Operation of two major reservoirs of Iran under IPCC scenarios during the XXI Century.

by

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Abstract

We assess the effects of prospective climate change until 2100 on water management of two major reservoirs of Iran, namely Dez ($3.34x10^9$ m^3), and Alavian ($6x10^7$ m^3). We tune the *Poly-Hydro* model suited for simulation of hydrological cycle in high altitude snow fed catchments. We assess optimal operation rules (ORs) for the reservoirs using three algorithms under dynamic and static operation, and linear and nonlinear decision rules during control run (CR,1990-2010 for Dez and 2000-2010 for Alavian). We use projected climate scenarios (plus statistical downscaling) from three general circulation models (GCMs), EC-Earth, CCSM4 and ECHAM6, and three emission scenarios, or representative concentration pathways (RCPs), RCP2.6, RCP4.5 and RCP8.5, for a grand total of 9 scenarios, to mimic evolution of the hydrological cycle under future climate until 2100. We subsequently test the ORs under the future hydrological scenarios (at half century, and end of century), and the

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need for re-optimization. *Poly-Hydro* model, when benchmarked against historical data well mimics the hydrological budget of both catchments, including the main processes of evapotranspiration and stream flows. Teaching-learning based optimization (TLBO) deliver the best performance in both reservoirs according to objective scores, and is used for future operation. Our projections in Dez catchment depict decreased precipitation along the XXI century, with -1% on average (of the nine scenarios) at half century, and -6% at the end of century, with changes in stream flows on average -7% yearly, and -13% yearly, respectively. In Alavian precipitation would decrease by -10% on average at half century, and -13% at the end of century, with stream flows -14% yearly, and -18% yearly, respectively. Under the projected future hydrology reservoirs' operation would provide lower performance (i.e. larger lack of water) than now, especially for Alavian dam. Our results provide evidence of potentially decreasing water availability, and less effective water management in water stressed areas like Northern Iran here during this century.

Key words: Climate change, hydrological projections, reservoir operation, uncertainty, Iran.

1. Introduction

Efficient operation of reservoirs in water stressed countries plays nowadays a tremendously important role worldwide, and increasingly so under transient climate change (IPCC, 2013). Central Asia is particularly at stake, given the largely threatened water resources therein under present management, demography, and climate change (UNEP-DHI, 2016). Water resources management is particularly important in arid, and semi-arid basins of Middle East countries relying on water resources from the mountains, heavily sensitive to climate change. Climate change affects in practice all hydrological components (precipitation, evaporation, stream flows, e.g. Groppelli et al., 2011a; Bocchiola, 2014), carrying a bearing on water availability and even water demand for all purposes, and may therefore affect optimal operation of water resources (Ehsani et al., 2017). Snow/ice cover influences freshwater availability, and future cryospheric dynamics is of tremendous interest (Kaser et al., 2010; Soncini and Bocchiola, 2011). Modified hydrology under future climate cascades into modified water allocation, and successful development programs in the area of water resources, for agricultural, industrial, irrigation, sanitation, and even ecological purposes, require understanding of the current and future climate, and impact upon the hydrological cycle therein. Some studies have hitherto addressed modified hydrological cycle under future climate change (Bocchiola et al., 2011; Groppelli et al., 2011a; Migliavacca et al., 2015; Soncini et al., 2015; 2016; 2017; Aili et al., 2018), and impact on water allocation and potential conflicts in shared catchments (e.g. Ansink and Ruijs, 2008; Bocchiola et al., 2017). Recently several scientists focused on the need for testing, and possibly redesigning current system operation (Anghileri et al., 2011; Ashofteh et al., 2105a,b,c; Giuliani et al., 2016), mimicking rule curve extraction under climate change conditions, and uncertain hydrology (Yao and Jeorgakakos, 2001; Wurbs et al. 2005; Langsdale et al., 2009; Pianosi and Soncini-Sessa, 2009; Lee et al., 2011; Golombek et al, 2012; Vicuna et al, 2011; Georgakakos et al., 2012a and 2012b; Majone et al, 2012; Ashofteh et al., 2015a; Feng et al., 2017; Salazar et al., 2017). Among others Ashofteh et al. (2015b) used multi-objective genetic programming (MO-GP) to extract the optimal rule curves during the historical period, and under climate change conditions for the Aidoghmoush reservoir in Iran, and Ashofteh et al. (2015c) investigated the risk of increasing water demands under climate change conditions during 2026-2039 for a wide range of agricultural products, watered by an irrigation networks supplied from the Aidoghmoush reservoir in Iran, highlighting the importance of water management issue in this country.

In this study we investigated the present and prospective water management for two important, and recently investigated reservoirs of Iran, namely Dez (Dariane and Sarani 2013), and Alavian (Abeshzadeh et al., 2008). Among others, Alavian dam regulates inflow in the Urmia lake, the largest endorheic lake of Iran, an UNESCO reserve of biosphere ever since 1976, and very important from the ecological, and touristic point of view.

In these two reservoirs (i.e. in their upstream catchments) hydrological cycle is driven by precipitation during Spring and Winter at the lowest altitudes, and snow melt in Spring from the highest altitudes. Henceforth the (potential) impact of future climate change may explicitly include modification of the cryospheric cycle. Further, evapotranspiration is an important term of the water budget in semi-arid areas, primarily depending upon temperature, and therefore sensitive to climate change.

We here present a flexible methodology to model the hydrology of semi-arid high altitude catchments as here, to project forward hydrology in time, and to optimize reservoirs' operation under present, and future climate, and we demonstrate such methodology for the Dez, and Alavian reservoirs.

First, we properly tuned the hydrological model *Poly-Hydro* (Bocchiola et al., 2010; Soncini et al., 2015; 2106; 2017), able to represent the main hydrological processes in high altitude watersheds, namely precipitation, snow accumulation and melting against altitude, evapotranspiration during warm seasons, and stream flows. The model was tuned against stream flow, and validated against evaporation data to verify accurate depiction of the basin wide hydrological cycle.

We then assessed optimal reservoirs' operation rules (ORs). We used three algorithms, under dynamic and static operation, and linear and nonlinear decision rules, during control run periods CR (eleven years depending on data availability, 1990-2010 for Dez and 2000-2010 for Alavian). We benchmarked operation efficiency with the chosen approaches for the CR, based on a set of objective indicators. We then used climate scenarios (plus statistical downscaling) from the fifth assessment report (AR5) of the IPCC to provide hydrological scenarios until the end of the century in the two catchments, using our properly tuned hydrological model.

We used three emission scenarios, i.e. representative concentration pathways (RCP2.6, RCP4.5, and RCP8.5) and three general circulation models GCMs (EC-Earth, CCSM4 and ECHAM6) to explore uncertainty of the results against unknown future climate evolution. Representative periods were selected for the two basins (2040-2060, and 2080-2100 for Dez; 2045-2055, and 2090-2100 for Alavian) for comparison against the CR, where we investigated changes in temperature, precipitation, evapotranspiration, and stream flows.

We performed reservoirs' operation under future conditions with i) unchanged rule curves as from the CR, and ii) via re-optimization under climate change conditions. We quantified the modified performance under climate change conditions by way of our objective indicators, and we assessed the potential for improvement via re-optimization.

We provide here discussion of the results, we briefly benchmark our finding against notable case studies in the middle east and worldwide, we provide suggestions for application of the method to other case study areas, and we discuss limitations and future developments

2. Region of investigation

The case study reservoirs are Dez, and Alavian, and their upstream basins (Figure 1a). Dez dam is located in Western Iran. The climate here is arid-desert, with transition (West to East) between hot and cold (BWH, and BWK, Peel et al., 2007). The construction of this double arched concrete dam began in February 1957, and it was completed in December 1962. It was designed and implemented to supply water for drinking, industrial, and agricultural purposes, and for flood control. Dez dam Irrigates 125000 hectares of downstream land.

Alavian dam is located on the Sufichay river in the Northwest of Iran. Sufichai river originates from the Sahand mountain and flows to Urmia lake downstream of Alavian dam. Climate therein is in transition (South to North) between temperate/cold with dry and hot Summers (CSA and DSA, Peel et al., 2007). Alavian dam is designed to supply drinkable water demand to Maragheh city and agricultural water to an area of 13900 hectares downstream, for approx. 123×10^6 m^3. The main characteristics of the dams are given in Table 1.

Figure 1. a) Region of investigation: Dez and Alavian basins, Iran. b) Proposed methodology for hydrological modeling, water resources projections under climate change, and operation of reservoirs under present and future conditions. In the flow chart the necessary tools are reported, as per 7 categories, i.e. domain (*e.g.* hydrology, reservoir operation), tools (*e.g.*

hydrological model, optimization algorithms), functions (*e.g.* snow melt M_s as a function of temperature, and radiation M_s (T, G), etc..), data (weather, terrain models, etc..), model outputs (*e.g.* snow melt in time and space M_i (t,s)), and model accuracy (*e.g.* Bias, NSE). Division in present, and future (projections) reported. Four main blocks in the four black frames are highlighted, numbered 1-4, and namely 1 hydrological modeling in present conditions, 2 reservoir operation in present conditions, 3 hydrological projections, 4 reservoir re-operation under future projected conditions. In **bold,** the most important outputs for each block are reported. The large black arrows numbered 1-4 indicate the notable input passed from one block to another. Block 1 passes observed, and modeled discharge, Q(t), Q_m(t) to block 2 for reservoir operation setup. Block 1 also delivers a tuned hydrological modeling to block 3 for hydrological projections under future climate scenarios from GCMs. Block 2 passes information of best optimization algorithms to block 4 for reservoir operation under future scenarios. Block 3 then passes future projected discharges Q_f(t) to block 4, also necessary for reservoir operation, and re-operation. T(t) is daily temperature, P(t) daily precipitation, Ev(t) evaporation data from pans, G(t) is solar radiation, Q(t) is daily observed discharge at outlet section, Q_m(t) is daily modeled discharge at outlet section, M_s (t,s) is daily snow melt in a given place (cell) *s*. D_t(t) is water demand in time, $R_{t,f}$(t) is reservoirs' release, present, future. $OR_{R,N}$ operation rules, reference, new for re-optimization. Optimization function *Def*, and performance indices *RT, RV, φ, η, I,* as defined in text. Bias is systematic error on average, NSE is Nash-Sutcliffe Efficiency. T_f'(t), P_f'(t) are (future/projected) temperature and precipitation from GCMs before downscaling (biased), T_f(t), P_f(t) future daily temperature and precipitation after downscaling (unbiased), Q_f(t) is projected discharge.

Table 1. Dez and Alavian reservoirs. Main characteristics.

3. Database

3.1. Historical data

We could gather for this study daily data of temperature (2 for Dez, 2 for Alavian), evaporation (6 for Dez, 2 for Alavian), rainfall (16 for Dez, 3 for Alavian) and discharge (1 for Dez, 1 for Alavian, both slightly upstream of the dams), in a number of stations within the two considered catchments (Figure 1). Further, we could gather monthly values of water demand for multiple uses, *i.e.* drinkable water, agricultural, industrial, ecological flows from the Ministry of Energy in Iran. These data could be used after a preliminary check for quality, and completeness.

3.2.GCM data

To depict potentially modified hydrological cycle during the XXI century, which includes large room for uncertainty, we fed the *Poly-Hydro* model with weather projections from three GCM models, downscaled to the area of interest. The chosen GCMs come from the Coupled Model Intercomparison Project, release 5 (CMIP5, Alexander et al., 2013), namely ECHAM6 (European Centre HAmburg Model, version 6, Stevens et al., 2013), CCSM4 (Community Climate System Model, version 4, Gent et al., 2011), and EC-Earth (European Consortium Earth system model, version 2.3, Hazeleger et al., 2011). These GCMs were used in former studies, providing acceptable depiction of weather seasonality in Europe and Asia, and the authors have large experience of downscaling of their outputs, so being confident in their use (e.g. Soncini et al., 205-2016; Aili et al., 2018). Climate projections (i.e. temperature, and precipitation) were provided under three representative concentration pathways (RCPs, Moss *et al.*, 2010 ; IPCC, Intergovernmental Panel for Climate Change, 2013), namely RCP2.6 (peak in radiative forcing at 3 Wm^{-2}, *i.e.* 490 ppm CO_2 equivalent at 2040, and subsequent decline to 2.6 Wm^{-2}), RCP4.5 (stabilization to 4.5 W m^{-2}, *i.e.* 650 ppm CO_2 eq. at 2070), and RCP8.5 (radiative forcing up to 8.5 W m^{-2}, *i.e.* 1370 ppm CO_2 eq. by 2100). Here we used RCP2.6, RCP4.5, and RCP8.5, because RCP6.5 is somewhat similar to RCP4.5.

In principle, all RCPs may be though as equally likely to happen in the future until the end of the century, so they all represent plausible evolutions of the climate, and they therefore need to be explored, to gather a full spectrum of potential evolution of hydrology, and water resources availability (however recent climate evolution mimics more closely RCP8.5, e.g. Fuss et al., 2014). Different GCM models in turn provide different potential evolution of the climate under the same RCP, especially as far as precipitation is concerned. Exploring more models allows exploiting of a wider array of possible future evolutions (and possibly worst case scenarios), and of adaptation therein.

3.3. Topography and land cover

The digital terrain model (DTM) from SRTM (NASA) for the study area was used, with a spatial resolution of 90 m (http://www2.jpl.nasa.gov/srtm/). This has vertical, and horizontal accuracy of ~ 20 m and 30 m, respectively. For hydrological modeling we used a land use map produced from the Ministry of Agriculture of Iran for the whole country. This map includes general categories like agricultural, urban, forest, rangeland, desert, ponds, lakes, mainly used here to assess soil properties (i.e. maximum soil water content).

4. Methods

4.1.The proposed methodology

Here we propose a template for hydrological modeling in high altitude catchments like here, where snow, and in some case (not here) ice dynamics are relevant, and yet little information is available, and for projections of the hydrological cycle under future climate change.

The template is sketched in a flow chart in Figure 1b. The framework builds upon the authors' experience in monitoring, and modeling mountain areas, in the Italian Alps (Bocchiola et al., 2010; Groppelli et al., 2011a; Soncini et al., 2017), and worldwide (Migliavacca, 2015; Soncini et al., 2015, 2016), and it is extended to pursue reservoirs' operation using the present/future hydrological fluxes as an input. In the flow chart in Figure 1b we report the necessary components, divided into 7 categories. These are domain of investigation, tools, functions, field surveys, data from measuring stations and other sources, model outputs, and model accuracy. A distinction is made between the present time (i.e. for assessment of the present hydrological conditions and reservoir's operation), and the future (i.e. for projection of the future conditions using GCM scenarios, re-operation of the reservoirs). The information necessary to model each component and the interactions between the components is also sketched. Data gathering strategies aimed at hydrological modeling are presented. The proper implementation of the method is clearly specific for each case study, and depends on the available data, and tools. Here each component of the methodology is illustrated, with specific reference to the Dez, and Alavian catchments, and dams, and application to other case study reservoirs is discussed in Section 6.

4.2. Hydrological model

We used here the *Poly-Hydro* model, a semi-distributed, cell based (with variable resolution, 2km x 2km for Dez, and 400m x 400m for Alavian) hydrological model, developed at Politecnico di Milano (Bocchiola, et al., 2010; Groppelli et al., 2011a; Soncini et al., 2015;

Migliavacca et al., 2015), and used to model vegetation dynamics, for pasture (Addimando et al., 2015; Bocchiola and Soncini, 2017), and crops (Bocchiola, 2015). The main equations are reported elsewhere (see Aili et al., 2018), and we provide here a brief description. The model tracks the daily variation of water content in the ground within any cell, as given by inputs of liquid rain and snowmelt, and outputs of (actual) evapotranspiration.

Potential evapotranspiration is calculated here using Hargreaves equation, requiring temperature data, which we validated against evaporation data from evaporation pans.

Poly-Hydro model's equations are solved using a semi-distributed cell based scheme (Migliavacca et al., 2015; Aili et al., 2018). Flow discharges from each cell are routed to the outlet section through a semi-distributed flow routing algorithm, based upon the conceptual model of the instantaneous unit hydrograph, IUH (Rosso, 1984). For calculation of the in stream discharge the model uses two (parallel) systems (groundwater, overland) of linear reservoirs (in series) each one with a given number of reservoirs (n_g and n_s). Each of such reservoirs possesses a time constant (*i.e.*, t_g, t_s). For each cell the lag time is proportional to the hydraulic path to the outlet section. Snow ablation is modeled by way of a degree-day approach (Bocchiola et al., 2010).

Given the lack of snow depth data within the catchments or nearby, the melting factor for snow was assessed by model tuning against timing and amount of stream flows at thaw in each watershed.

4.3. Downscaling of GCM projections

A key feature in climate change impact studies is the choice of best methods for downscaling of the outputs of global circulation models GCMs, especially precipitation (Groppelli et al., 2011b). Benchmarking of some studies entailing use of both statistical and dynamic (e.g. nested regional climate models) methods for downscaling showed that statistical methods may lead to equivalent results with less mathematical burden (Murphy, 1999; 2000; Kidson and Thompson, 1998). Wilby and Wigley (1997) and Wilby et al. (1998) used a variety of statistical downscaling models showing that weather generators are powerful in sketching dry and wet spells, and the distribution in time of precipitation. Zorita et al. (1995) and Zorita and Von Storch (1999) studied the CART method, and showed that simple analog methods have the same results as more complex, physically based methods.

Here for downscaling of precipitation we used a statistical approach based on stochastic space random cascades (SSRCs), which we developed for the purpose (see full account in Bocchiola, 2007; Groppelli et al., 2011b). The model was tuned for each GCM during control run periods CR, 1990-2010 for Dez, and 2000-2010 for Alavian. We used daily series of precipitation at the P measuring stations available. The downscaling procedure corrects precipitation from GCMs by a random multiplicative process, considering intermittence (i.e. dry spells). A constant term is used to fix daily bias. Here, the adopted GCMs overestimated precipitation as observed on the ground in the Dez and Alavian catchments, with a bias factor of to 3 to 6. A β model (binomial distribution 0/1) generator gives the probability that the rain rate in a given day is zero, conditioned upon GCM precipitation being positive (Over and Gupta, 1994). Then a "strictly positive" generator adds proper variability to precipitation during wet spells. The so tuned model was used to downscale future precipitation projected by the GCMs under the three RCP scenarios. Temperature downscaling was carried out using temperature series for the same CRs. A monthly averaged ΔT approach was used (explained in Groppelli et al., 2011a). We obtained series of daily projected precipitation and temperature for each GCM and RCP, for a grand total of 9 climate scenarios until 2100, which we used to feed the glacio-hydrological model.

4.4. Modeling of reservoir system operation

Operation of the reservoirs is pursued primarily based upon a monthly continuity equation expressed as

$$S_{t+1} = S_t + Q_t + \mathrm{Re}_t + Sp_t - Ev_t\left(A_t + A_{t+1}\right)/2 \qquad \forall t = 1,\ldots,N\,, \tag{1}$$

with t time (month), N number of months, S_t storage volume at month t, S_{t+1} storage volume of reservoir at month $t+1$, Q_t inflow to reservoir during period t, Re_t release from reservoir during period t (decision variable), Sp_t outflow from reservoir during period t, all expressed in m^3. Ev_t is the evaporation from the reservoir during period t [mm], and A_t, A_{t+1} area of the reservoir at the beginning/end of period t [m^2]. As an objective function to optimize the operation of the reservoirs, we used here the (minimum of) the squared difference between supplied water, and total downstream demand D_t

$$\underbrace{\mathrm{Def} = \sum_{t=1}^{N}\left(1 - \frac{\mathrm{Re}_t}{\mathrm{D}_t}\right)^2}_{\min}\,, \tag{2}$$

where *Def* is an index of total deficiency during an operation period of N months (e.g. Ashofteh *et al.*, 2015a). The purposes of water management (i.e. water use) change between the two reservoirs as reported. Allocation is pursued based on an a priori ranking of the water needs. In Dez one has i) drinking, ii) ecological, iii) industrial, iv) agricultural, v) fishing, and in Alavian one has i) drinking, ii) ecological, iii) agriculture. In Figures 2, and 4 monthly demand for each purpose is given.

4.5. Decision rule curves

In this study, the reservoirs' management is optimized under two different optimization policies. First, monthly operation is pursued using a long historical series, and assuming it is repeated in the future (called long term, LT), to be used as a benchmark of other operation rules ORs. Second, the release from the reservoirs is assumed to be a function of parameters such as inflow discharge *Q*, reservoir storage *S* and demand *D* in each period. This second category is called real time operation. In real time operation the rate of reservoir release is a function of the decision-making parameters above, and this function could be linear (Revelle et al., 1969) or nonlinear (Akbari-Alashti et al., 2015, Pan et al., 2015). Also, the ORs can be static, or dynamics (i.e. changing with time, e.g. monthly) as

$$\begin{aligned} \mathrm{Re}_t &= f\left(S_t, Q_t, D_t\right) \\ \mathrm{Re}_{m,t} &= f'(S_{m,t}, Q_{m,t}, D_{m,t}), \end{aligned} \tag{3}$$

where $f(...)$ and $f'(...)$ can be any type of linear or nonlinear functions, and *m* is month index. The decision rules may be linear (LDR), or nonlinear (NLDR), for instance

$$\begin{aligned} \mathrm{Re}_t &= a_1 S_t^2 + a_2 S_t + a_3 Q_t^2 + a_4 Q_t + a_5 \\ \mathrm{Re}_{m,t} &= a_{m,1} S_{m,t}^2 + a_{m,2} S_{m,t} + a_{m,3} Q_{m,t}^2 + a_{m,4} Q_{m,t} + a_{m,5}, \end{aligned} \tag{4}$$

where all a_i, and $a_{m,i}$ are factors tuned via optimization according to target functions, like e.g. *Def* in Eq.(2). In this paper, both LDR (i.e. with $a_1 = a_3 = 0$, or $a_{m,1} = a_{m,3} = 0$), and NLDR approaches are tentatively employed to set up the real-time ORs under both the hypotheses of static and dynamic operation for the two target reservoirs. For the static operation case, one rule curve is extracted valid for all months, based on the historical data. In the dynamic approach, for each month specific rule curves are extracted. The different options are then benchmarked against a set of performance indicators, and the best rules curve(s) is selected and used for future operation under climate change conditions.

4.6. Optimization algorithms

Teaching-learning based optimization (TLBO) is a recently developed class of optimization algorithms, introduced by e.g. Rao et al. (2011a), well-known for solving optimization problems effectively, according to recent findings (Rao et al., 2011a, 2011b, 2012; Rao, 2012; Rao and Patel, 2012; Rao and Kalyankar, 2013; Togan, 2012; Zou et al., 2013). The TLBO algorithms' mechanism consists broadly speaking of two parts, i.e. a *teaching* phase, improving knowledge of the problem by the algorithm (class), and a *learning* phase, with the role of interacting and reviewing lessons by algorithm (class).

All evolutionary and swarm intelligence based optimization algorithms require common control parameters, such as population size, number of generations, etc, as well as their own algorithm-specific parameters. TLBO algorithms do not require algorithm-specific parameters, so decreasing the tuning effort in their use (Niknam et al, 2012a, 2012b; Satapathy et al., 2012; Rao and Patel, 2013a; Rao, 2016).

Interior search algorithms (ISAs) are inspired from architectural processes, where placement of decorative elements is changed iteratively until they create a satisfying view. Any element may change place whenever better fitness (e.g. decorative view) is obtained, and constraints (resources and needs) are better fulfilled. In this process mirrors are placed near the most beautiful element(s) to emphasize their value. Such aesthetic concept is implemented within ISA algorithms by placing mirrors near the global best(s) or fittest element(s) to find other beautiful views (Gandomi, 2014). The elements are divided into two groups. One of these groups, the composition one, is used for optimization. The second, or mirror group, is used for mirror search (Gandomi and Roke, 2014).

Genetic algorithms (GAs) are promising techniques introduced recently, receiving a great deal of attention in the field of optimization. These techniques are generally speaking derived from Darwin's principle of survival of the fittest, and subsequent adaptation (Holland, 1992). A population of creatures evolves over generations, and characteristics of the individuals useful for survival are passed over to next generations. Information is passed from parents to offspring using the mechanism of natural genetics, resulting in a structured yet randomized exchange of information. Future generations will hence display the most favorable characteristics (Sivapragasam et al., 2007). During each generation, the individuals are rated in term of performance, and a new population of candidate solutions is formed using genetic operators such as reproduction, crossover, and mutation (Grefenstette and Fitzpatrick, 1985).

4.7. Performance Indices of Reservoir System

Further to the use of *Def* as an objective function to be minimized by optimization, we used reservoirs' performance indices to objectively benchmark optimization methods, namely *reliability*, *resiliency*, and *vulnerability* (Hashimoto et al. 1982). Reliability can be divided into two categories, i.e. time-based reliability *RT*, and volumetric reliability *RV* (Akbari-Alashti et al., 2014). Time-based reliability *RT* is

$$RT = \frac{1}{N} \underset{t=1}{\overset{N}{Nu}}_{RT} (\mathrm{Re}_t \geq D_t) \quad , \tag{5}$$

with *Nu* number of periods (out of *N*) when release is equal to or greater than total downstream demand (i.e. water requirements are fulfilled). Volumetric reliability is

$$RV = \frac{1}{N}\sum_{t=1}^{N} g\left(\frac{\mathrm{Re}_t}{D_t}\right)$$
$$g\left(\frac{\mathrm{Re}_t}{D_t}\right) = \frac{\mathrm{Re}_t}{D_t} \; if \; \mathrm{Re}_t \leq D_t;\; 1 \; if \; \mathrm{Re}_t > D_t \;, \tag{6}$$

giving in practice the average share of water volume released against demand. Resiliency φ reports how fast a reservoir may solve a failure (water lack) situation, as

$$\varphi = \frac{\sum_{t=1}^{N-1} Nu_1(\mathrm{Re}_t < D_t | \mathrm{Re}_{t+1} < D_{t+1})}{\sum_{t=1}^{N} Nu_2(\mathrm{Re}_t < D_t)} , \tag{7}$$

with Nu_1 number of multiple consecutive failures, and Nu_2 total number of failures during the period of operation. Vulnerability η can be calculated as

$$\eta = \operatorname*{Max}_{t=1}^{N}\left(\frac{D_t - \mathrm{Re}_t | D_t \geq \mathrm{Re}_t}{D_t}\right), \tag{8}$$

i.e. the largest share of water failure during the regulation period. To further aid comparison of the performance in the periods P1, P2 against the performance during CR we defined a lumped performance index *I*, as

$$I = \frac{(\mathrm{RT} + \mathrm{RV} + \varphi + (1 - \eta))}{4} . \tag{9}$$

4.8. Reservoir operation under past, and future conditions.

Here we carried out optimization of the Dez and Alavian reservoirs during control run CR periods, and future periods. CR for Dez dam is 1990-2010, and CR for Alavian is 2000-2010, as given by available weather and flow data. Future hydrology and operation under climate change were simulated for periods of equivalent length for comparison, at half century and end for century (2040-2060, and 2080-2100, for Dez, and 2045-2055, 2090-2100 for Alavian). For CR optimal operation was carried out using both static and dynamic operation rules. To extract rule curves for both static and dynamic operation, LDR and NLDR rule were tested. The *Def* index was used for optimization, and the performance indices (*RT*, *RV*, φ, η) were used for benchmarking. For future operation under climate change, the best algorithm during the CR period was chosen. First, we tested operation under future hydrological conditions (3 GCMs, 3 RCPs, two periods, half century P1, and end of century P2, 18 scenarios in total), using the rule curves from the base (CR) periods, or reference rule OR_R. Second, we pursued re-optimization (based on *Def*) of reservoirs' operation, to extract new rule curves OR_N based on hydrological conditions under climate change. We then evaluated the performance of both OR_R and OR_N optimization rules (based on performance indices) under all the so obtained 18 scenarios, with and without re-optimization.

5. Results

5.1. Hydrological model

In Table 2 we report the goodness of fit statistics for the *Poly-Hydro* model based on daily values, namely *Bias* (i.e. volumetric error in simulation), and determination coefficient R^2, for calibration and validation periods. The first verifies that on average stream flow volume is well represented (i.e. water mass budget is conserved yearly). The second is used to assess the capability of the model to mimic flow variability (i.e. second order statistics, or variance), so including occurrence of high flows, or floods. Calibration was pursued by maximizing R^2 with a constrain to minimize *Bias* (never to exceed ± 5%). Clearly the combined use of both indices leads to a trade-off situation, where the model mimics reasonably well mean flows, and low to high flow variability, with possibly some loss of accuracy in depiction of large flood events.

In the Figures 2 and 4 we report the monthly water demand Q_D split for different purposes, compared against monthly flows, for Dez, and Alavian, respectively. Clearly the total demand for Dez dam on average yearly is slightly smaller than the total availability ($E[Q_D] = 201$ m^{3}s^{-1} *vs* $E[Q] = 255$ m^{3}s^{-1}), while in Alavian dams Q_D is larger than Q for most of the year (E[Q_D] = 4.5 m^{3}s^{-1} *vs* E[Q] = 2.9 m^{3}s^{-1}). Accordingly, on average in the Alavian dam total demand for the region exceeds the total available water, and part of this demand must be provided via integration with underground water.

Figures 3, and 5 report observed, and modeled daily stream flows, for Dez, and Alavian respectively. In Dez, estimated snow melt contribution (not shown for shortness) starts in in March (ca. 50%), and ends in may (ca. 10%), with a total yearly share of ca. 20%. In Alavian, estimated snow melt contribution (not shown for shortness) starts in in March (ca. 75%), and ends in may (ca. 20%), with a total yearly share of ca. 22%.

Also, we report in the Figures 3 and 5 the modeled values of potential evapotranspiration *ETP* against the measured values at some stations within Dez (6 stations), and Alavian (3 stations) catchments. Evaporation pans measure evaporation *Ev* in full water availability conditions, and over water bodies. Accordingly, evaporation on the pan Ev_p is comparable with potential evapotranspiration *ETP*. We here report the average measured *ETP* from the stations, against average modeled *ETP* within the models' cells containing these stations. Reservoir's operation (Eq. 1) considers explicitly an evaporation term Ev_t from the lake surface, which is normally approximated by *ETP* as taken from some reference equation. Here, the *ETP* term as provided by *Poly-Hydro* model could be confidently used to estimate Ev_t, which makes more accurate reservoirs' budget, and operation. This is especially important when carrying out water budget, and reservoirs' operation exercise under projected hydrological conditions for the future, given that no evaporation measures can be provided therein.

Table 2. *Poly-Hydro* model. Goodness of fit.

Figure 2. Dez catchment. Monthly demand split as per different purposes.

Figure 3. Dez catchment. Daily stream flows (observed and modeled), and potential evapotranspiration (observed and modeled). Evapotranspiration is on the right y axis, with values upside down.

Figure 4. Alavian catchment. Monthly demand split as per different purposes.

Figure 5. Alavian catchment. Daily stream flows (observed and modeled), and potential evapotranspiration (observed and modeled). Evapotranspiration is on the right y axis, with values upside down.

5.2. Projected climate and hydrology

We here report briefly about future climate (not shown for the sake of shortness), and hydrology in the two target areas. Temperature *T* in Dez catchment always increases in the future, yearly and monthly under any RCP. At half century P1 (2040-2060) yearly temperature would reach as high as +1.32 °C, +1.66 °C, and +2.36 °C against CR under RCP2.6, RCP4.5, and RCP8.5, respectively, with largest increase in Summer JAS, likely to increase (potential) evapotranspiration largely. At the end of century P2 (2080-2100), the temperature would reach as high as +1.09 °C (thus decreasing under RCP2.6 against P1), +2.70 °C, and +5.11 °C, respectively Precipitation *P* displays a more variable pattern. At P1 yearly *P* would change from -16% (EC-Earth, RCP4.5) to +21% (ECHAM6, RCP2.6), with unchanged value on average (-1%). During P2, EC-Earth (RCP4.5) would project decreased *P* down to -31%, and ECHAM6 8.5 would give *P* increased until +11% (-6.4% on average). In the Alavian catchment *T* also would increase in the future yearly, but with room for monthly decrease under RCP2.6. At half century P1 (2045-2055) yearly temperature would reach as high as high as +1.11 °C, +1.28 °C, and +2.15 °C under RCP2.6, RCP4.5, and

RCP8.5, respectively. At the end of century P2 (2090-2100), temperature would reach as high as +1.03 °C, +2.48 °C, and +4.93 °, respectively under ECHAM6 8.5, with largest increase in February, and September. Precipitation *P* displays again a variable pattern. At P1 yearly *P* would change from -31% (EC-Earth, RCP4.5) to +7% (CCSM4, RCP4.5), with large decrease on average (-10%). During P2 EC-Earth (RCP4.5) would project decreased *P* down to -24%, and only ECHAM6 8.5 would give unchanged *P*, with on average -13% *P* yearly.

The hydrological regime within our two target rivers also display large changes. In Dez dam (Figure 6) during P1 large flow decrease would be seen during late Winter and early Spring (MA), presently the period of snow melt, depending on decreased precipitation under most scenarios. During P2 however, RCP2.6 provides somewhat increased flows during Spring, in response to increased precipitation (Especially EC-Earth). For RCP4.5, and especially RCP8.5 in spite of some possible increase of *P*, stream flows are largely decreased during P2, also in response to increased *T*, leading to increased *ETP*, and *ET* until soil moisture is available.

In the Alavian catchment, stream flows always decrease under any RCP and GCM, unless for some slight increase during Winter, possibly given by earlier snow melt contributing in those months with low flows however. Here, in spite of possible precipitation increase in some periods, ever increasing temperature would reduce stream flows, and increasingly so as one moves towards the end of the century.

Figure 6. Hydrological projections of the Dez river closed at Dez dam. The monthly river flow is reported as per each GCM model, and stationary scenario, *vs* the calibration period. Left y axis, 2040-2060. Right y axis, values upside down, 2080-2100. a) RCP2.6 b) RCP4.5 c) RCP8.5.

Figure 7. Hydrological projections of the Alavian river closed at Alavian dam. the monthly river flow is reported as per each GCM model, and stationary scenario, *vs* the calibration period. Left y axis, 2045-2055. Right y axis, values upside down, 2090-2100. a) RCP2.6 b) RCP4.5 c) RCP8.5.

5.3. Reservoir operation during CR period.

In Table 3 (optimization target, *Def*) and 4 (performance indices, *RT*, *RV*, φ, η) we report our operation exercise during the CR period for Dez and Alavian dams. Optimization with Long term LT option is pursued using both the observed discharges, and the modeled ones, to test the potential for use of the *Poly-Hydro* model to simulate hydrological input for optimization of the reservoirs. This is necessary given that the optimization under future scenarios during P1 and P2 periods can only be pursued using model outputs, and accordingly testing of the optimization algorithm in the CR period needs to be carried out coherently using modeled input flows at the reservoir. Given that the performance of the LT algorithm as mapped by the *Def* target function does not change largely when using either the observed discharges or the modeled ones (Table 3), we assume that the modeled discharges from *Poly-Hydro* represent well the stream flow dynamics for the purpose of optimization, and we proceed henceforward to optimization using the modeled series. The LT optimization procedure so obtained allows to pursue a comparison between optimization algorithms, and provides a benchmark for the tested operation rules, either linear or not. From the analysis of the results in Table 3, TLBO and ISA algorithms under dynamic operation (i.e. with monthly fixed parameters), and LDR (linear) approach give the best performance in both our case study reservoirs, in practice reaching LT in term of performance. GA algorithm under LT approach in Dez is outperformed by LDR (0.17 *vs* 0.20), which is counterintuitive because the results of long-term (LT) operation should be better than real-time operation. GA algorithm under LT conditions has been run several times, always with more than 10000 iterations, and yet such issue was not solved. This may indicate the relative (to other models) weakness of the algorithm in reaching global optimal solution under the LT scheme.

NLDR nonlinear algorithms under dynamic hypothesis do not converge to an optimal solution, so meaning that monthly estimation of models' parameters may not be suitable. Also under LDR approach the GA algorithm does not provide an optimal rule curve.

Accordingly, and because no sensible improvement was found using NLDR instead of LDR (see *Def* value in Table 3) we discarded NLDR approach. Also, from our preliminary analysis the dynamic approach under LDR provided slightly better results than the static approach in some cases, but it appeared less efficient in others (e.g. GA algorithms in both dams), while static approach always provided similar results. Given also that dynamics approach required much longer simulation time (normally static approach obtained converged to optimal results after one single run, while NLDR method would require 2-3 runs with more iterations), we decided to use the static approach.

Among the three algorithms applied with the static approach, performing in practice equivalently (Table 4), TLBO provides slightly better, and more stable results than ISA and GA. We therefore decided to use TLBO algorithm for operation under future climate for the purpose of the present manuscript.

Table 3. Optimal operation in CR period. Comparison of methods based on *Def* index. NaN means lack of convergence.

Table 4. Optimal operation in CR period. Comparison of methods based on performance indices (all expressed as % values).

5.4. Reservoir operation during P1, P2 periods.

In Table 5, and 6 we report the performance of the reference operation rule OR_R under future hydrological scenarios during periods P1, P2 according to our 9 proposed climate scenarios, for Dez and Alavian respectively. This performance indicates the potential change in reservoirs' operation effectiveness under the modified hydrological conditions, at half century, and at the end of century. In Table 7, and 8 we report the same performance, after re-optimization, i.e. with new operation rules OR_N. These findings display the potential for adaptation of reservoirs' management strategies under climate change.

From Table 5, in Dez reservoir most of the time during P1, and P2 *Def* index slightly increases under OR_R (to 0.19 during P1, and P2 against 0.17 during CR) so indicating slightly worse capacity of the reservoir to fulfill the water demand. The performance indices are decreasing during P1 under OR_R (26.2 on average *vs* 29.5 in CR period), and again slightly decreasing after (P2, 26.5 on average *vs* 29.5 in CR period). When re-optimizing operation under modified hydrological cycle (Table 7) *Def* increases slightly (to 0.18 during P1, and 0.19 during P2). The performance index increases slightly on average (28.4 during P1, 26.7 during P2, *vs* 29.5 in CR). In Figure 8 we report *I* value under each scenario (GCM, RCP) against the CR value, for present and future operation rules OR_R, OR_N. The largest decrease of *I* (OR_R) is seen under ECHAM6 model, displaying as reported the largest decrease of water availability. After re-optimization OR_N, *I* increases slightly on average, and especially under ECHAM6, demonstrating some potential for adaptation when re-optimizing reservoirs' operation.

In Alavian reservoir (Table 6) the situation under climate change seems slightly worse than in Dez. During P1 the *Def* index increases under OR_R (on average from 0.18 during CR to 0.21 during P1, and 0.22 during P2), so indicating a decreased capacity of the reservoir to fulfill the water demand. The performance index *I* would clearly decrease during P1 under OR_R (22.6 on average *vs* 29.5 in CR period), and further so during P2 (20.6 on average). When re-optimizing operation under modified hydrological cycle (Table 8) *Def* is indeed slightly decreasing with respect to OR_R (to 0.20 during P1, and 0.21 during P2). The performance index *I* however increases slightly on average, but still below CR (23.6 during P1, 21.2 during P2, *vs* 29.5 in CR). From Figure 9a during P1 *I* would decrease visibly under all scenarios unless for CCSM4 4.5, which displays a somewhat similar water availability to now (Figure 7b). At P2 again all scenarios would give a lower value of *I*, unless for the scenario ECHAM6 2.6, somewhat unexpectedly given the low water availability therein (Figure 7a). The re-operation of the Alavian reservoir OR_N (Figure 9b) does not improve largely the situation as reported, and an improvement is seen in practice only during P1, for ECHAM6 4.5/8.5, and CCSM4, same RCPs. Accordingly, the management of Alavian dam would be visibly less performing than now in the future under climate change.

Table 5. Dez reservoir. Optimal operation in P1/P2 periods using CR operation rule.

Table 6. Alavian reservoir. Optimal operation in P1/P2 periods using CR operation rule.

Table7. Dez reservoir. Optimal operation in P1/P2 periods with re-optimization.

Table 8. Alavian reservoir. Optimal operation in P1/P2 periods with re-optimization.

Figure 8. Average performance index *I* of Dez reservoir system. Left y axis, P1 2040-2060. Right y axis, values upside down, P2 2080-2100. a) Future (control run operation rule OR_R). b) Future (re-optimization with new rule OR_N).

Figure 9. Average performance index *I* of Alavian reservoir system. Left y axis, P1 2045-2055. Right y axis, values upside down, P2 2090-2100. a) Future (control run operation rule OR_R). b) Future (re-optimization with new rule OR_N).

6. Discussion

6.1. Reservoirs' operation under climate change in Iran

Our results demonstrate that use of operation rules developed during past periods may result into worse performance during the century under a changing climate. In Dez under OR_R rule (Table 5) the deficit index *Def* would increase mostly during P1 (on average +2.1), and P2 (+1.9) with exceptions however (ECHAM6, RCP2.6, and CCSM4, RCP4.5). Reliability (time-based *RT*, and volume based *RV*) indeed would decrease under all scenarios during P1 (*RT* -15.7% on average, *RV* -6.3%), and P2 (*RT*, -15%, *RV*, -8.3%). Resiliency φ would increase in one case only during P1(ECHAM6, RCP2.6), but it would be much smaller on average (-3% in P1, and -3.9% in P2). Vulnerability η would be instead smaller under any scenario (-44.9% in P1, and -26.3% in P2). Vulnerability η accounts for one only value (i.e. a maximum deficit), being possibly less representative of the general behavior of the reservoirs. When re-operating the reservoir with a new rule OR_N (Table 7) the situation changes only slightly (*Def* +1.2, P1 +2.4, P2; *RT* -12.7, P1, and -14.9, P2; *RV* -5.1, P1, -8.9 P2; φ -3.2 P1, -4.4, P2), with η worsening after re-operation (-16.9% in P1, and -17.4% in P2), which may indicate little influence of single shortage events on general optimization. When looking at the lumped index *I* (Figure 8) one gathers the idea that overall management under climate change may result into a sensible loss of performance. On average during P1 *I* under OR_R (Figure 8a) is smaller than during CR (-3.15). Notice however that the increased values of *I* with respect to CR are due to an increase in vulnerability η, which again accounts for one extreme event. When excluding the term 1-η from the calculation of *I*, lower values than during CR are always found, so witnessing always decreased performance under climate change. During P2 one has *I* decreased by -3.04, and again here excluding 1-η one has always lower values of *I*. On average during P1 under OR_N (Figure 8b) one has decreased *I* (-1.09, P1, -2.76, P2) with some improvement. Again here, exclusion of 1-η carries always worse performance. Therefore, for Dez dam modified hydrology under climate change carries large potential for decreased efficiency in the operation, especially without re-operation.

For the Alavian dam a possibly worse picture is seen. Under the OR_R rule (Table 6) the deficit index *Def* would increase (+3.4, P1, +3.8, P2), again with exceptions (CCSM4, RCP4.5, and ECHAM6, RCP8.5, during P1, and ECHAM6, RCP2.6 during P2). The reliability in Alavian decreases under most scenarios during P1 (*RT* -5.2%, *RV* -7.6%), and P2 (*RT*, -7.6%, *RV*, -15.4%). The resiliency φ is always much lower than now (-8.3% in P1, and -7.8% in P2). The vulnerability η is variable, but smaller on average than during CR (-3.6% in P1, and -4.7% in P2), however changing much less than in Dez. When re-operating the Alavian reservoir with a new rule OR_N (Table 8), the situation changes slightly (*Def* +1.9, P1 +2.7, P2; *RT* -3.2, P1, and -5.4, P2; *RV* -10.9, P1, -16.4 P2; φ -6.2 P1, -6.8, P2), with η in practice constant after re-operation (-3.4% in P1, and -4.4% in P2). Concerning *I* (Figure 9), on average under OR_R (Figure 9a) it would be in practice always smaller than during CR (-6.86, P1, -8.86, P2), unless for slightly increased values in two cases. Here η does not affect largely the calculation of *I*, and exclusion of vulnerability leave things unchanged. When re-operating the dam with the rule OR_N (Figure 9b) the values of *I* improve visibly against OR_R, especially on the short term P1, remaining however below CR values (-4.88, P1, -7.7, P2). Accordingly, on average during the XXI century the Alavian dam would be operating less efficiently than now, in response to the largely decreased stream flow availability. Adaptation via operation may improve the results, but apparently the efficiency of operation would be lower than now, and integration via other water sources (e.g. groundwater) would be more necessary.

From Table 3 one finds that *Poly-Hydro* model seems not as effective for the Alavian reservoir as it is for Dez, given that *Def* statistic for Alavian under LT option is different for the modelled discharges than for the observed ones. This may indicate a slight difference in optimization performance when using modeled discharges. However, Alavian is a small dam with demand largely exceeding water availability, so it seems that optimization may be weakly performing independently of input flows origin. Future scenarios for reservoirs' operation may only be done using a hydrological model, and the results here can be taken indicative of potential future changes of operation of the Alavian reservoir under modified stream flows.

Our results here are seemingly consistent with the available literature covering water allocation in the area of study and generally in the middle east. Among others Ashofteh et al. (2015b) used multi-objective genetic programming (MO-GP) to extract optimal rule curves for the Aidoghmoush reservoir in Iran, under climate change conditions simulated using HadCM3 model under the A2 storyline of IPCC. Narrative Storylines (A1, A2, B2, B2) were previously used by IPCC (e.g. AR4), while in AR5 the concept of RCP was introduced. However, storylines and RCPs can be roughly correlated given that they represent in practice similar paths (for example RCP8.5 very pessimistic, can be roughly speaking linked to Storyline A2, also called "business as usual").

Ashofteh et al. (2015b) found that the ranges of vulnerability and reliability indices were larger under climate change conditions, in response to larger flow variability. They concluded that modified reservoir's rule curves under climate change may improve performance scores as compared to control period rules.

Zarghami et al. (2016) proposed a decision support system for Yamchi reservoir operation in North West of Iran. They studied future stream flows in response to changes in temperature and precipitation under A2 scenario (HadCM3 downscaled with LARS-WG model), and under RCP2.6, RCP4.5, and RCP8.5 (statistical downscaling model SDSM). Average temperature until 2030 would increase in their results by +0.77 °C, and precipitation would decrease by 11 mm. Water shortage in different sectors (including agriculture, domestic, industry, and environmental users) would be increased in the case of business as usual strategy (OR_R here).

Gohari et al. (2014) tackled reservoir operation, and adaptation strategies under climate change until half century for the Zayandeh-Rud river east of Dez dam. They projected on average until 2044 a monthly increase of temperature by +0.46°C to +0.76 °C, and an annual decrease of precipitation by -14% to -38%, resulting into reduction of the Zayandeh-Rud's stream flows, and of the amplitude of its seasonal range. They demonstrated that under climate change smaller storage levels, and greater water releases would be necessary to meet increasing water demand, with agriculture undergoing severe water shortage.

6.2. Reservoirs' operation under climate change in notable areas worldwide

The need for modified reservoirs' operation under climate change is important worldwide (e.g. Haddeland et al., 2014), and we report here for reference some notable studies in the present literature.

In India, Raje and Mujumdar (2010) recently studied the impact of climate change on multipurpose (hydro-power, irrigation, flood control) operation of the Hirakud reservoir in the Mahanadi river (145818 km^2 in Orissa state), using three GCMs during 2046-2065 and

2075-2095 for the A2, A1B and B1 storylines. They showed that under most scenarios hydropower production would be greatly reduced when using standard operation policy (Figure 10 therein), and irrigation would be less reliable, and increasingly so at the end of the century (Table 2 therein, SOP option). Adaptation with modified operation may only partly make up for both purposes (Table 2 therein, SDP option).

Abera et al. (2018) studied optimal operation (using HEC-ResPRM model) under climate change for the Tekeze (hydropower) reservoir on the Eastern Nile (294040 km^2 in Ethiopia and Sudan, see also Kim and Kaluarachchi, 2009). Outputs of the Downscaling Experiment over African domain (CORDEX-Africa) under RCP4.5 and RCP8.5 resulted into an increase of power storage potential up to +25% and +30% under RCP4.5 and RCP8.5 until 2100, in response to an increase of monthly inflows except in May-June. They conclude that use of optimized operation rules instead of current standard operating policy may increase hydropower production in the future.

In South East Asia, Giuliani et al. (2016) provided climate sensitivity analysis for operation of three largest reservoirs on the Red river (mostly used for agricultural supply), covering 169000 km^2 in China, Laos, and Vietnam, monsoon driven and expectedly sensitive to climate changes. They projected future hydrology of the river using two models (1 GCM, one Regional Circulation Model RCM), and the HBV model to project forward hydrology under A1B storyline until 2100. Reservoir operation is projected to change on average from −7 to +5% in hydropower production, +35 to +520% in flood damages, and +15 to+160% in water supply deficit. Under the assumption of full adaptation, the system performance can be improved, and yet the projected reduction of hydropower production by the end of the century would raise significant concerns about securing energy to support the rapid development of the country.

Also in this region, Lauri et al. (2012) studied optimal (cascading downstream) operation of 126 (some existing or under construction, some planned) reservoirs in the Mekong basin (795000 km^2 in six countries from China to Vietnam), and impacts on downstream river discharge therein. They pursued the maximization of annual outflow from a reservoir through hydropower turbine, also forcing the filling of the reservoir during the wet season and emptying during the dry season. They used scenarios from 5 GCMs (A1B, B1 of AR4) until 2050 to simulate future hydrology via the VMod model. They concluded that until 2050 the operation of the planned hydropower reservoirs is likely to have a larger impact on the Mekong hydrograph than the impacts of climate change, particularly during the dry seasons. However, climate change will increase the uncertainty of the estimated reservoir operation impacts. Even the direction of the flow-related changes induced by climate change is partly unclear. Consequently, both dam planners and dam operators would need to pay attention to the cumulative impacts of climate change and reservoir operation on aquatic ecosystems, including the largely profitable Mekong fisheries.

In Southern Europe, the Po valley of Italy is largely affected by modified cryospheric cycle under present and prospective climate change (Bocchiola, 2014), and multipurpose water management is challenged therein. Among others, Anghileri et al. (2011) proposed a framework for assessing climate change impact on the (lake) reservoir's operation of the very important Lake Como of Northern Italy, taking water from the largely snow/ice fed 4550 km^2 Adda river. They used climatic multi-model ensembles from PRUDENCE project (Christensen and Christensen, 2007) during 2071-2100 under storyline A2 to feed the HBV (Bergström, 1995) hydrological model and obtain future flows in the catchment.

They subsequently operated the Lake Como reservoir jointly with hydropower reservoirs at the highest altitudes (lumped into one reservoir), to optimize two indicators of revenue from hydropower, and deficit of water supply. They demonstrate that under climate change the system performances worsen with respect to both objectives, and particularly irrigation (Figure 5 in Anghileri et al., 2011). Climate scenarios indeed project a significant reduction of water availability in late Spring and Summer, when the water demand for irrigation is higher, and the lake cannot store the required volumes in anticipation of the dry period. Accordingly, failures of water supply would be more frequent. Hydropower revenue is mainly sensitive to the total volume of available water, which is only slightly reduced in the forecast scenario, because the ratio of reservoir capacity to mean annual inflow is quite high (60 %, against 6% for Lake Como). They further performed an analysis of the fallout of several sources of uncertainty upon reservoirs' operation, and they demonstrated that the contribution of natural climate uncertainty is remarkable and that, among different modelling uncertainty sources, the one given by climate modeling is largely significant.

In the Western US, Georgakakos et al. (2012) explored potential for adaptation to climate change in water resources management in Northern California (Sacramento+San Joaquin river) system.

They used two reservoir management policies (present, adaptive), and two hydrological scenarios (using CCSM3 model under A1B storyline, for historical 1970-2019, and future 2050-2099 hydrology). They qualitatively compared a number of indices, including energy production, and downstream release in the four scenarios, and report as main conclusions that the performance of the present policy may worsen under future hydrology, giving reductions in the minimum water deliveries (-25.2%), slight reduction in energy generation (-2.89%), and significant violations of the Delta water demand (X2, +35.6%). Adaptive policy improves, with modest differences between the future and the historical period. They conclude that water supply, energy, and environmental water uses cannot be effectively satisfied during future droughts, exposing the system to higher vulnerabilities and risks. By contrast, the adaptive policy maintains similar performance under both hydrologic scenarios, suggesting that adaptive management constitutes an effective mitigation measure to climate change.

Ehsani et al. (2017) tackled a large scale study to test resilience of reservoirs' operation (for 11000+ dams) in the North-Eastern United States (see Figure 1 therein) under climate change until 2100, which they projected according to all four RCPs from the HadGEM2-ES GCM. They used a general reservoir operation scheme GROS, optimized via neural network approach. globally in the region they projected increased precipitation (and more rain than snow) in Winters, and anticipated snowmelt in Spring may increase the aggregate regional total available water TAW, by up to +22% during December-March. However, in other seasons reduced precipitation and increased potential evapotranspiration and reduced recharge as from shifting of snowmelt will decrease water availability down to -54%. Accordingly, the existing dams and reservoirs in the region would be incapable of storing the added water in the wet season to supplement lower flows in dry months. Their results indicate that increasing the size and number of dams, in addition to modifying their operations, may become necessary to offset the vulnerabilities of water resources systems to future climate uncertainties, even neglecting the likely increase in future water demand, especially in the most densely populated areas.

In south America, among others Vicuña et al. (2012) recently analyzed the sensitivity to climate change (i.e. changes in temperature ΔT, and in precipitation ΔP) until 2100 of reservoir operation, and agricultural water availability in the Limarí river basin, covering ca. 12000 km^2 in the tropical Andes of Chile. The river is regulated through an interconnected system of three reservoirs (Paloma, Recoleta, and Cogoti) to then irrigate ca. 50000 ha of agricultural land, and sustain ca. 100000 people living nearby. They simulated 30-year long time series of monthly precipitation, by modifying the historical time series by a discrete set of delta values (ΔT +0 °C to +5°C, ΔP -30% to +30%) applied equally to all months, and mixed to obtain 25 scenarios in all. They mapped (Figure 8 therein) the decrease of irrigation water in response to increasing temperature, and decreasing precipitation. For ΔT, ΔP values comparable with storyline A1B, they quantified a decrease of available water from 88% of demand now, to 78% demand at 2040, and 63% demand at 2100 (Figura 8a).

From this very short review of recent studies in sparse areas worldwide, clearly reservoirs operation under present and prospective climate change is a critical issue globally.

In spite of some potential increase of precipitation, and stream flows in Winter, or early Spring, generally the dry season would display lower streamflows, as given by earlier snow melting in cryospheric catchments, and increased evapotranspiration. Accordingly, and also given the increased need of water under increased evapotranspiration, historical operation rules may lack efficiency, and modified operation would be necessary, however without certainty of full recovery.

6.3. Portability of the methodology

The methodology we proposed here (Figure 1b) for assessment of present and future hydrological conditions, and reservoirs' operation in semi-arid catchments is general in principle, and can be tailored depending upon local settings, and data and tools available. Topographic data are necessary, including in case (albeit not here) ice cover mapping. Then, climate data are required, including temperature and precipitation observations (rainfall plus snowfall, or snow depth), or their extrapolation at high altitudes. Reading of snow depth, i.e. snow water equivalent SWE at melt may be useful, but uneasily unavailable given harsh conditions at high altitudes (and not available here).

Indirect assessment of snow melt may be pursued with remotely sensed SCA (e.g. Parajka and Blöschl, 2008; Corbari et al., 2009; Bocchiola et al., 2011).

In lack of in situ measures, cryospheric contribution may be indirectly inferred, e.g. by analysis of hydrograph flow components, and sensitivity analysis (Ragettli et al., 2015), however entailing possible uncertainty due to equifinality problems (e.g. Konz and Seibert, 2010; Soncini et al., 2017). Hydrological measurements would clearly be necessary for model's assessment (Soncini et al., 2015; Ragettli et al., 2015). Evapotranspiration ET is considered in our model, and successfully benchmarked against pan evaporation Ev_p data. Evapotranspiration is a very important component of the water budget in semi-arid catchments like here, and increasing under increasing temperature (see e.g. potential increase of ET for two mountain catchments in Groppelli et al., 2011a; Ravazzani et al., 2014).

A distributed, or semi-distributed glacio-hydrological model should be used, which i) accounts for flow partitioning (liquid/solid precipitation, snow melt), ii) simulates credibly water inputs from snow melt, and outputs of evapotranspiration, and iii) operates fast enough to support repeated simulations for long term projections as we did here. Subsequently for reservoirs operation one needs i) water demand, at least monthly, or seasonal, ii) main geometric (volumetric) properties of the dam, and iii) reservoirs release over a long enough period for tuning of the optimization algorithms. Several potential optimization methods are available, and one may pursue a benchmark exercise, as we did here.

Eventually, one needs to use outputs of GCMs models (or similar meteorological models) covering the area, possibly after statistical/dynamical downscaling, aimed at fixing bias, and at capturing the variability of weather inputs (at least precipitation, and temperatures). Ideally, more GCMs, under different RCPs would be used to explore the large uncertainty embedded in projection exercise.

6.4. Limitations and outlooks

Our results seem consistent as reported against the present literature. Some uncertainty is entailed into the hydrological projections, especially concerning the projections of precipitation as reported. However, our GCM models from the most recent AR5 of IPCC project precipitation to be more likely constant, or decreasing in the target area, which together with much less uncertainly increasing temperature would result into less water available, and more challenging efforts to comply with water demand.

Here we assumed that the demand remains constant in time, which is possibly leading to an underestimation of the water needs under future population growth, and climate change. Preliminary work to investigate the prospective water demand indicated an increase especially in term of potential evapotranspiration, known to increase water demand for agricultural purposes as demonstrated worldwide (Bocchiola et al., 2014; Nana et al. 2014; Ashofteh et al., 2015c; Palazzoli et al., 2015). In the future the modified water demand will also need to be investigated, and likely the increase of water demand will make reservoirs' operation more challenging.

We haven't focused here on flood variability, and potential for flood dampening at the dams, which however may be of interest in the future, as given by the increased flood variability under climate change in several areas worldwide (Bocchiola et al, 2011; Soncini et al, 2016), and possibly expected also in Iran (Masih et al., 2011). Here we decided to use TLBO algorithm, which gave slightly better results against GA, and ISA. Use of either one of the other algorithms, or of even other ones may provide (slightly) different results, and in the future other algorithms may be used for benchmarking of options. It seems worth noting that the results of the optimization exercise seem more sensitive to the formulation of the decision rules, and yearly *vs* monthly, than to the choice of the optimization algorithm (see Table 3). Accordingly, proper formulation of the ORs may be as much as important as (or even more important than) the choice of the optimization algorithms, and more investigation on this facet is warranted.

An inherent assumption here is that operators will follow optimized/re-optimized rules in the future, or more broadly that real-world decision making processes can be represented by mathematical rules as here. It is possible that in the real world educated guess and experience from operators mostly drive operation. However, use of optimization algorithms as here provides an objective tool to i) demonstrate potential for decreased water availability for multipurpose use under climate change, and ii) benchmarking of management strategies under such changing conditions, and seemingly it represents an interesting support for water managers.

7. Conclusions

Transient climate change as expected during the XXI century is going to affect the water resources worldwide, and largely in arid and semi-arid regions relying upon water from the mountains. Water resources management under multiple purpose perspective will be therefore more challenging. Water managers therefore need tools to i) model hydrology of complex, high altitude catchments, ii) project forward hydrological scenarios in response to transient climate variations as projected by climate models, and iii) re-optimize water allocation strategies under modified hydrology. Here we presented a template approach to deal with such issue, and demonstrated it for two case study reservoirs of Iran.

We used the *Poly-Hydro* model to mimic hydrology of two catchments, paradigmatic of the conditions of basins in Iran, and central Asia. We subsequently applied locally based downscaling of climate scenarios from the IPCC panel, and we used these downscaled scenarios to project forward until 2100 the hydrology of the study catchments. We then set up a tool for optimal water allocation via benchmarking of different optimization strategies and algorithms. We demonstrated that application of the optimal rule curves for the present falls short in fulfilling the water demand in the future, and that even under re-optimization the hydrological modification pending climate change would affect negatively the water management exercise. Our effort demonstrates that indeed climate change as expected for the XXI century may affect the capacity of water management in Iran, and in areas with similar hydrology. At the same time, it provides a support for hydrologically based study of water allocation issues under climate change, and for benchmarking of adaptation strategies (e.g. reservoirs' relining, use of different management strategies, change in optimization methods).

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Table 1. Dez and Alavian reservoirs. Main characteristics.

Variable	Unit	Dez	Alavian
Height from foundation	[m]	230	76
Reservoir storage capacity in normal water level	[10^6 m^3]	3340	60
Reservoir storage capacity in minimum water level	[10^6 m^3]	831.1	3
Average inflow discharge	[$m^3 s^{-1}$]	255.20	2.85
Area of catchment basin	[10^6 m^2]	17430	317.1

Table 2. *Poly-Hydro* model. Goodness of fit.

			Dez		Alavian	
Variable	**Unit**	**Description**	**Bias (calib/valid)**	**R^2 (calib/valid)**	**Bias (calib/valid)**	**R^2 (calib/valid)**
Q	[m^3 s^{-1}]	Discharge	1.98% / -5.07%	0.44 / 0.62	−2.30% / −1.97%	0.48 / 0.59

Table 3. Optimal operation in CR period. Comparison of methods based on *Def* index. NaN means lack of convergence.

		LT		Rule Curve			
				Yearly		Monthly	
		Obs.	**Model**	**LDR (SQ)**	**NLDR (S2Q2)**	**LDR (SQ)**	**NLDR (S2Q2)**
Dez	**TLBO**	0.01	0.01	0.17	0.16	0.01	NaN
	GA	0.25	0.20	0.17	NaN	0.20	NaN
	ISA	0.01	0.01	0.17	0.16	0.01	NaN
Alavian	**TLBO**	0.24	0.10	0.18	0.16	0.11	0.11
	GA	0.28	0.12	0.18	0.19	0.26	NaN
	ISA	0.24	0.11	0.18	0.16	0.11	NaN

Table 4. Optimal operation in CR period. Comparison of methods based on performance indices (all expressed as % values).

Res.	Rule	Ind.	Yearly			Monthly		
			TLBO	**GA**	**ISA**	**TLBO**	**GA**	**ISA**
Dez	**SQ**	**RT**	31	31	31	51	56	51
		RV	73	73	73	99	108	99
		φ	4	4	4	29	44	29
		η	97	94	98	51	100	51
	S2Q2	**RT**	27	33	26	NaN	NaN	NaN
		RV	73	77	73	NaN	NaN	NaN
		φ	7	21	6	NaN	NaN	NaN
		η	85	98	85	NaN	NaN	NaN
Alavian	**SQ**	**RT**	21	21	21	2	17	5
		RV	59	59	59	61	54	62
		φ	16	16	16	32	23	31
		η	77	77	77	83	99	90
	S2Q2	**RT**	29	21	29	2	NaN	NaN
		RV	60	59	60	61	NaN	NaN
		φ	16	16	15	32	NaN	NaN
		η	78	77	78	83	NaN	NaN

Table 5. Dez reservoir. Optimal operation in P1/P2 periods using CR operation rule.

Dez	RCP	GCM	Def	RT [%]	RV [%]	φ [%]	η [%]
CR			0.17	29	73	13	97
P1	2.6	EC	0.19	22	72	16	78
		CC	0.17	15	68	10	70
		EA	0.23	17	65	10	0
	4.5	EC	0.17	14	70	9	95
		CC	0.18	19	68	9	81
		EA	0.22	10	56	6	0
	8.5	EC	0.17	15	70	11	68
		CC	0.17	15	68	10	77
		EA	0.22	14	63	9	0
P2	2.6	EC	0.15	17	70	11	77
		CC	0.19	17	70	11	83
		EA	0.21	18	65	11	89
	4.5	EC	0.18	15	69	10	70
		CC	0.16	15	68	10	73
		EA	0.21	9	56	5	0
	8.5	EC	0.20	13	66	10	79
		CC	0.19	11	62	7	83
		EA	0.21	11	56	7	82

Table 6. Alavian reservoir. Optimal operation in P1/P2 periods using CR operation rule.

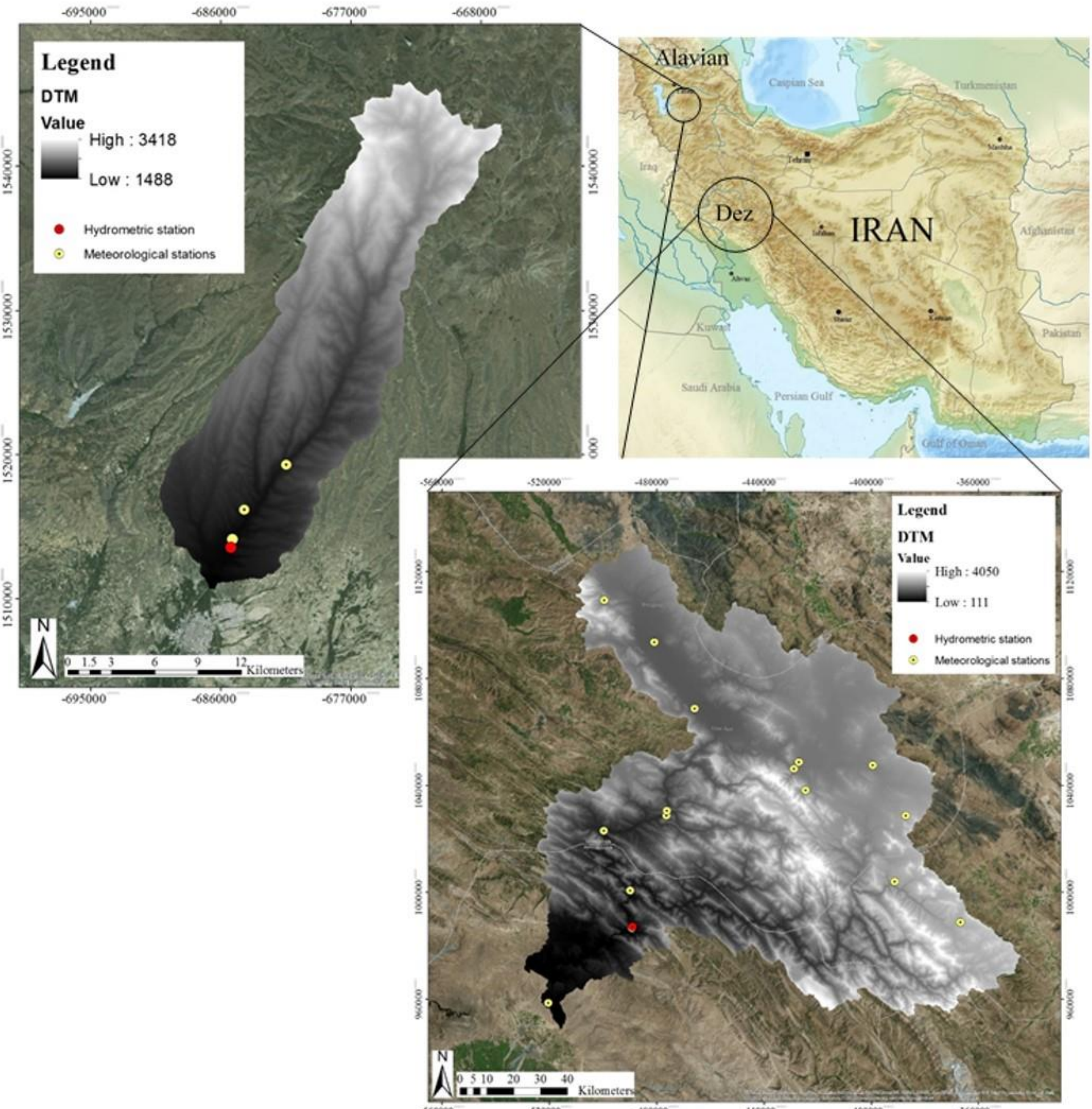
Alavian	RCP	GCM	Def	RT [%]	RV [%]	φ [%]	η [%]
CR			0.18	21	59	15	77
P1	2.6	EC	0.18	20	55	8	80
		CC	0.20	13	50	6	78
		EA	0.23	11	49	7	85
	4.5	EC	0.19	18	53	6	73
		CC	0.17	29	57	11	76
		EA	0.31	5	37	2	87
	8.5	EC	0.17	16	52	8	80
		CC	0.19	23	49	9	82
		EA	0.29	7	36	3	84
P2	2.6	EC	0.16	22	61	12	73
		CC	0.22	12	46	7	79
		EA	0.23	10	46	6	76
	4.5	EC	0.20	14	48	8	80
		CC	0.19	14	47	6	83
		EA	0.25	7	37	4	83
	8.5	EC	0.20	17	40	9	84
		CC	0.25	14	35	8	90
		EA	0.26	11	32	5	87

Table 7. Dez reservoir. Optimal operation in P1/P2 periods with re-optimization.

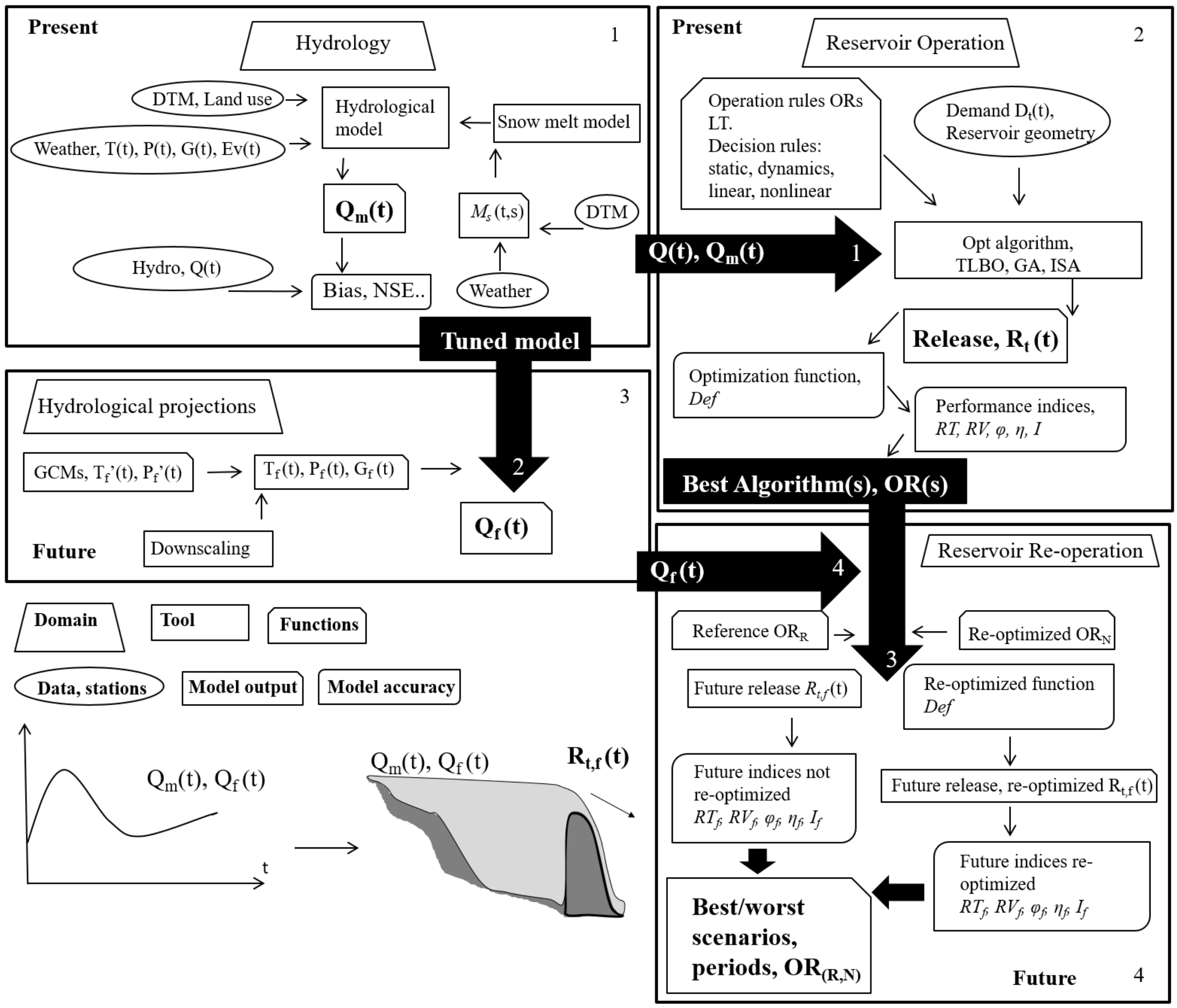
Dez	RCP	GCM	Def	RT [%]	RV [%]	φ [%]	η [%]
CR			0.17	29	73	13	97
P1	2.6	EC	0.19	21	69	14	76
		CC	0.16	14	72	10	70
		EA	0.21	17	59	9	78
	4.5	EC	0.17	15	72	9	93
		CC	0.17	19	71	10	86
		EA	0.22	10	54	5	81
	8.5	EC	0.15	22	83	13	64
		CC	0.16	15	73	9	78
		EA	0.21	14	58	9	95
P2	2.6	EC	0.13	23	85	11	72
		CC	0.19	15	66	10	84
		EA	0.21	18	60	10	86
	4.5	EC	0.18	16	69	10	74
		CC	0.16	15	70	10	73
		EA	0.29	9	54	5	79
	8.5	EC	0.19	10	60	7	84
		CC	0.19	11	60	7	83
		EA	0.21	10	53	7	81

Table 8. Alavian reservoir. Optimal operation in P1/P2 periods with re-optimization.

Alavian	**RCP**	**GCM**	**Def**	**RT** [%]	**RV** [%]	φ [%]	η [%]
CR			0.18	21	59	15	77
P1	2.6	EC	0.18	18	55	7	79
		CC	0.19	16	49	8	79
		EA	0.21	18	48	9	85
	4.5	EC	0.18	17	52	7	73
		CC	0.16	23	56	12	74
		EA	0.26	14	37	10	87
	8.5	EC	0.16	14	51	7	79
		CC	0.19	20	48	9	81
		EA	0.26	20	37	10	87
P2	2.6	EC	0.15	17	59	9	73
		CC	0.21	16	46	8	79
		EA	0.22	14	45	8	78
	4.5	EC	0.19	15	46	9	80
		CC	0.19	17	46	7	83
		EA	0.24	17	37	9	84
	8.5	EC	0.18	17	39	9	81
		CC	0.24	15	34	9	88
		EA	0.24	12	31	6	87


Legend
DTM
Value
High : 3418
Low : 1488
Hydrometric station
Meteorological stations
Kilometers
Alavian
Caspian Sea
IRAN
Dez
Persian Gulf
Legend
DTM
Value
High : 4050
Low : 111
Hydrometric station
Meteorological stations
Kilometers

a



b

Figure 1

a) Region of investigation: Dez and Alavian basins, Iran. b) Proposed methodology for hydrological modeling, water resources projections under climate change, and operation of reservoirs under present and future conditions. In the flow chart the necessary tools are reported, as per 7 categories, i.e. domain (*e.g.* hydrology, reservoir operation), tools (*e.g.* hydrological model, optimization algorithms), functions (*e.g.* snow melt M_s as a function of temperature, and radiation M_s (T, G), etc..), data (weather, terrain models, etc..), model outputs (*e.g.* snow melt in time and space M_i (t,s)), and model accuracy (*e.g.* Bias, NSE). Division in present, and future (projections) reported. Four main blocks in the four black frames are highlighted, numbered 1-4, and namely 1 hydrological modeling in present conditions, 2 reservoir operation in present conditions, 3 hydrological projections, 4 reservoir re-operation under future projected conditions. In **bold,** the most important outputs for each block are reported. The large black arrows numbered 1-4 indicate the notable input passed from one block to another. Block 1 passes observed, and modeled discharge, Q(t), Q_m(t) to block 2 for reservoir operation setup. Block 1 also delivers a tuned hydrological modeling to block 3 for hydrological projections under future climate scenarios from GCMs. Block 2 passes information of best optimization algorithms to block 4 for reservoir operation under future scenarios. Block 3 then passes future projected discharges $Q_f(t)$ to block 4, also necessary for reservoir operation, and re-operation. T(t) is daily temperature, P(t) daily precipitation, Ev(t) evaporation data from pans, G(t) is solar radiation, Q(t) is daily observed discharge at outlet section, $Q_m(t)$ is daily modeled discharge at outlet section, M_s (t,s) is daily snow melt in a given place (cell) *s*. $D_t(t)$ is water demand in time, $R_{t,f}(t)$ is reservoirs' release, present, future. $OR_{R,N}$ operation rules, reference, new for re-optimization. Optimization function *Def*, and performance indices *RT, RV, φ, η, I,* as defined in text. Bias is systematic error on average, NSE is Nash-Sutcliffe Efficiency. T_f'(t), P_f '(t) are (future/projected) temperature and precipitation from GCMs before downscaling (biased), $T_f(t)$, $P_f(t)$ future daily temperature and precipitation after downscaling (unbiased), $Q_f(t)$ is projected discharge.

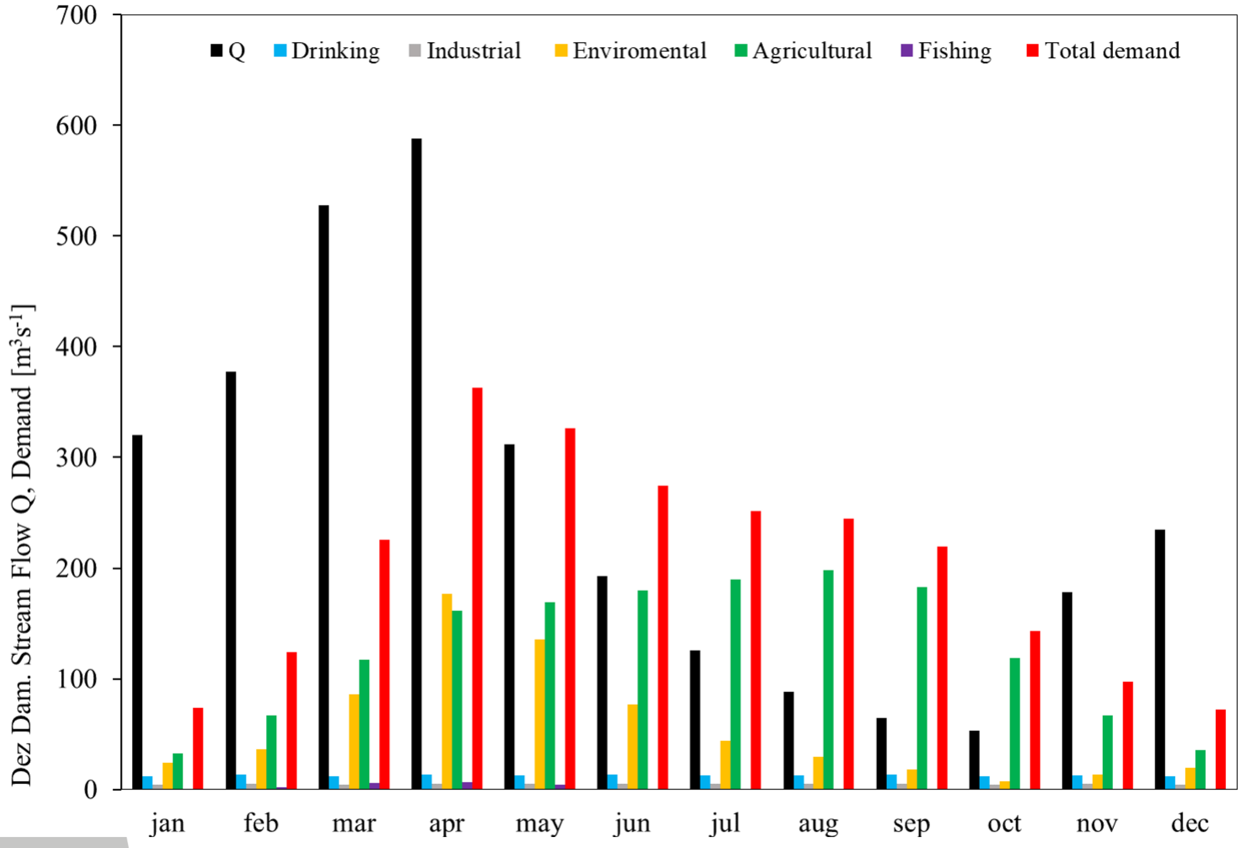


Figure 2

Dez catchment. a) Monthly demand split as per different purposes.

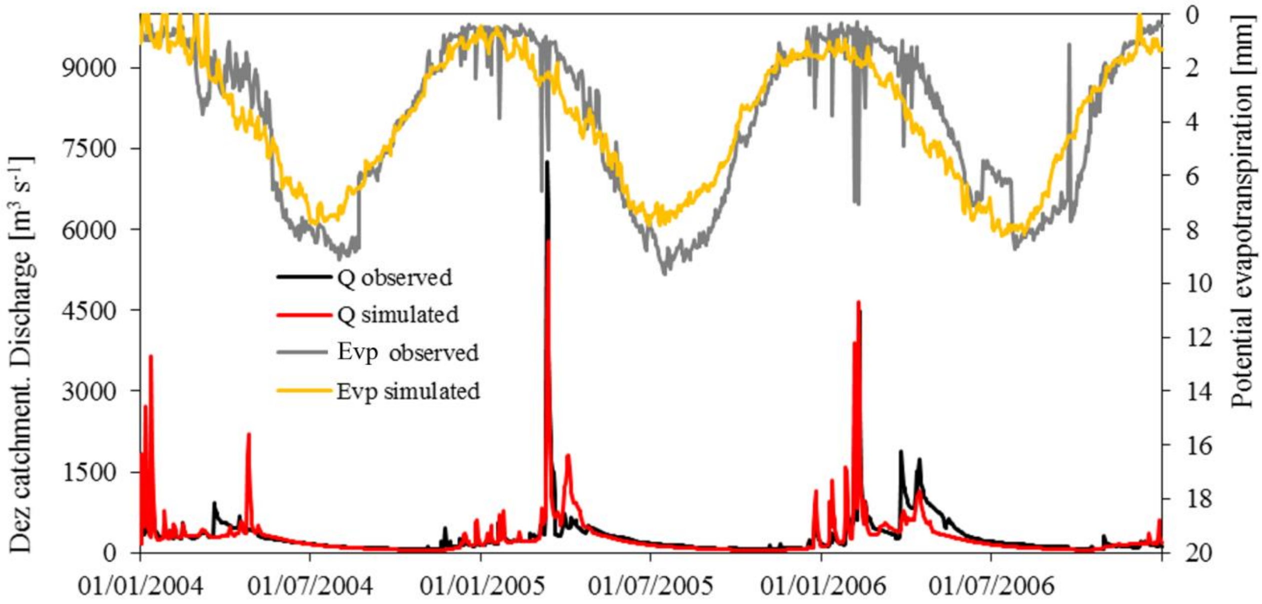


Figure 3

Dez catchment. Daily stream flows (observed and modeled), and potential evapotranspiration (observed and modeled). Evapotranspiration is on the right y axis, with values upside down.

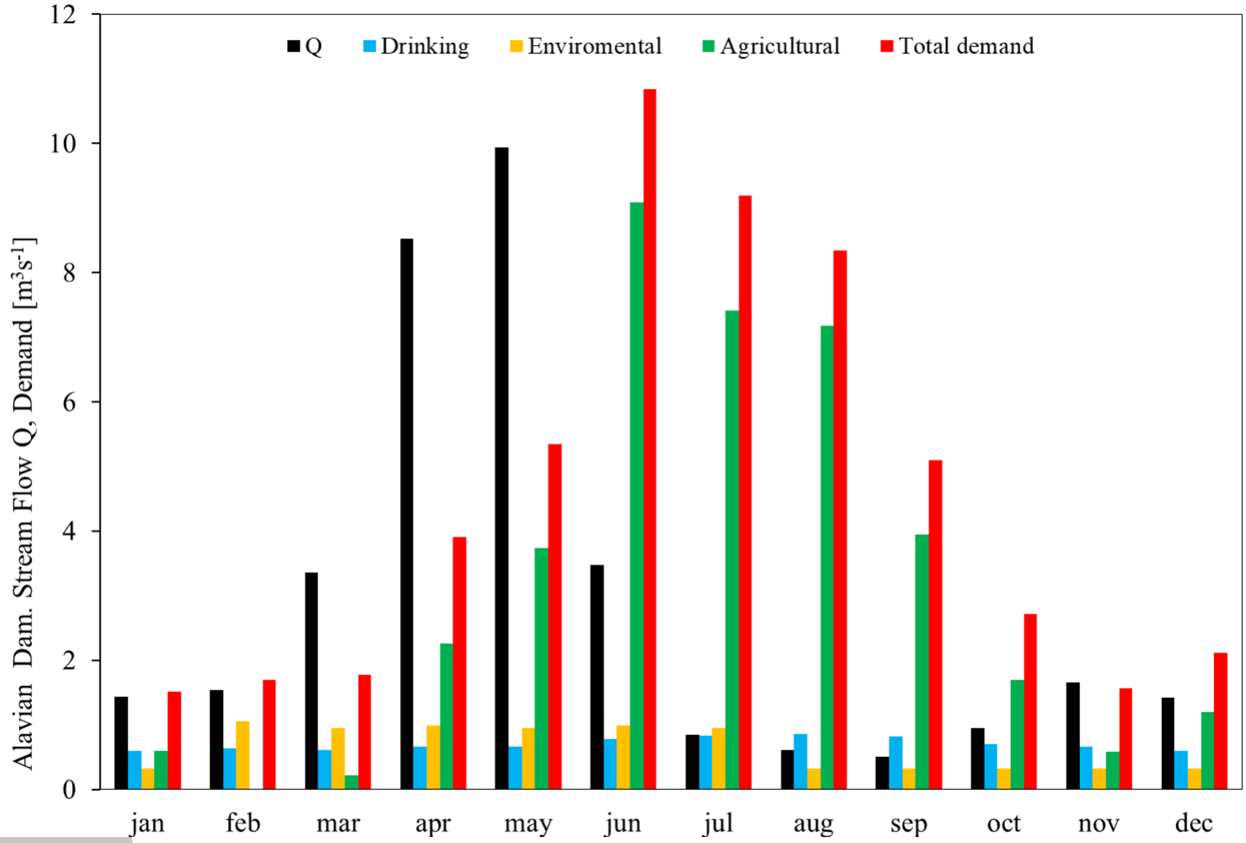


Figure 4

Alavian catchment. a) Monthly demand split as per different purposes.

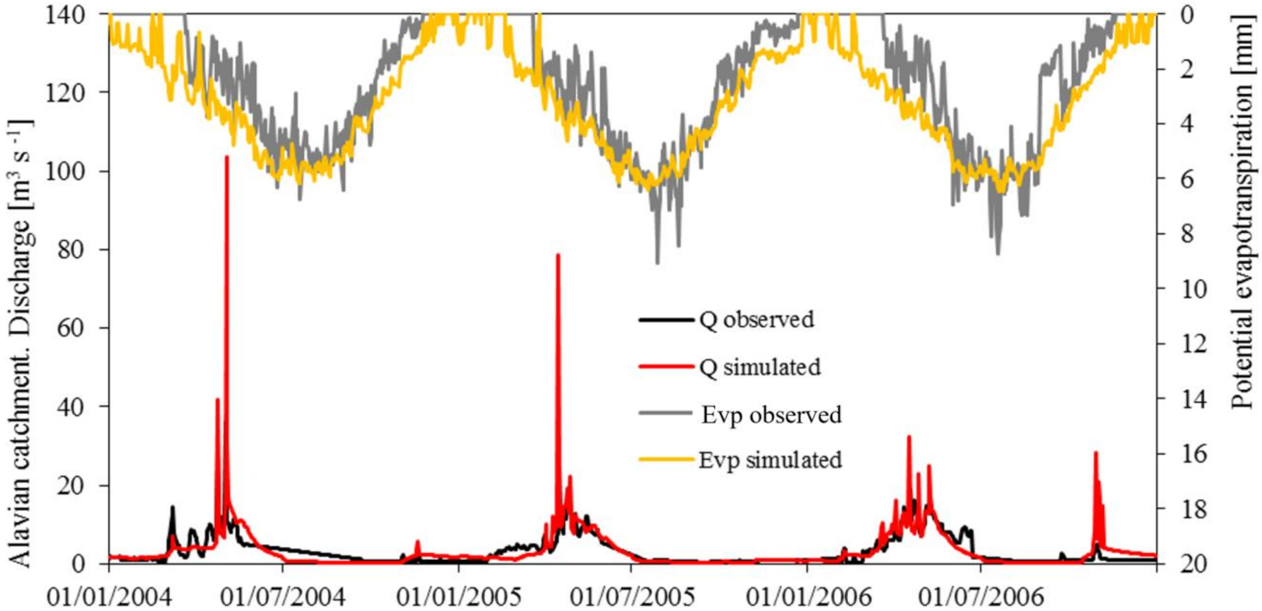
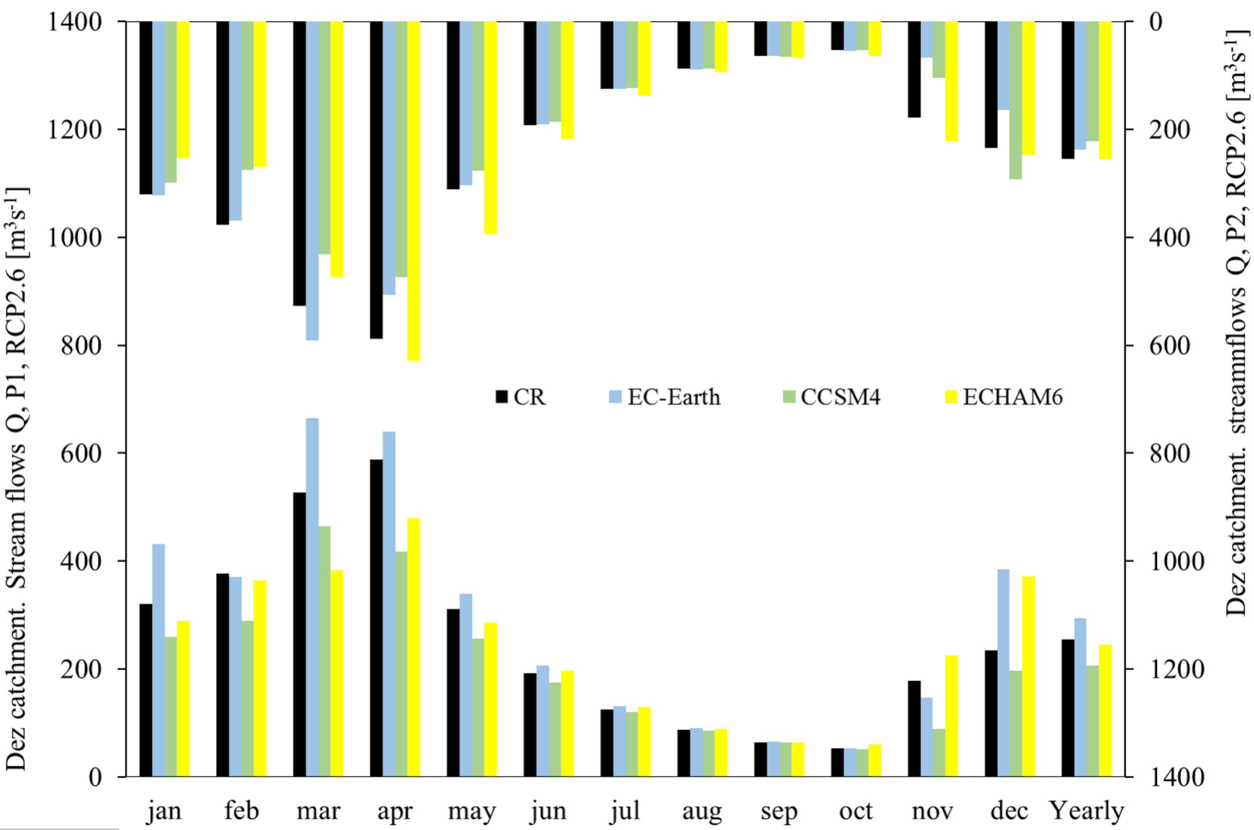
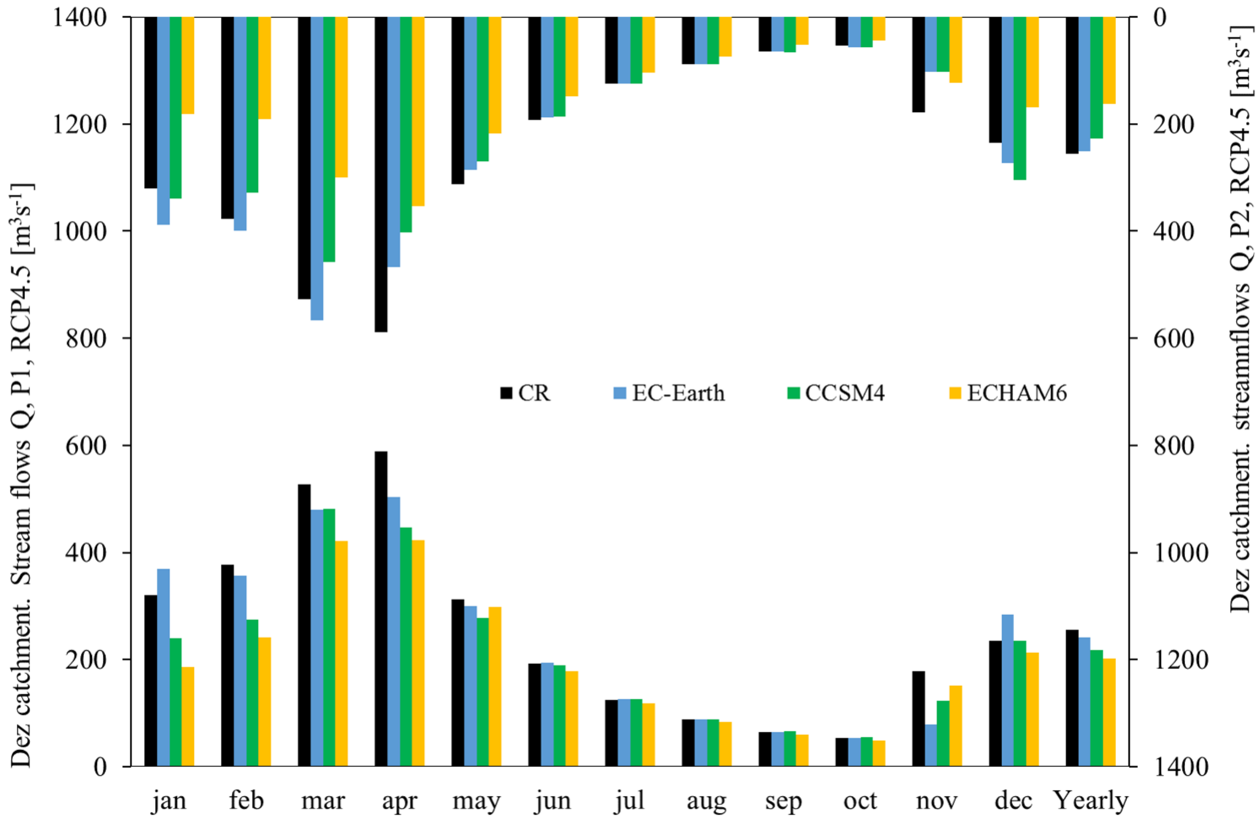


Figure 5

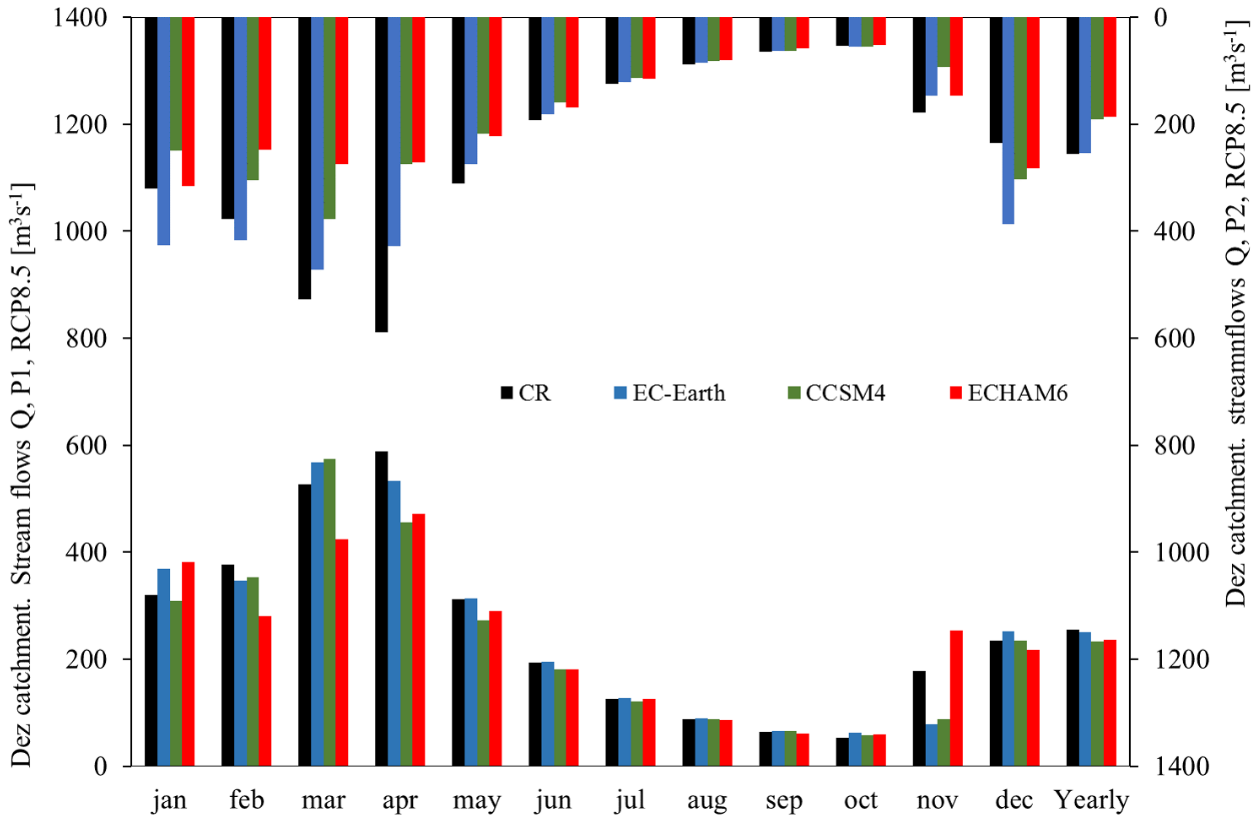
Alavian catchment. Daily stream flows (observed and modeled), and potential evapotranspiration (observed and modeled). Evapotranspiration is on the right y axis, with values upside down.


Dez catchment. Stream flows Q, P1, RCP2.6 [m3s-1]
Dez catchment. streamnflows Q, P2, RCP2.6 [m3s-1]
CR
EC-Earth
CCSM4
ECHAM6
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Yearly
0
200
400
600
800
1000
1200
1400

a


CR
EC-Earth
CCSM4
ECHAM6
Dez catchment. Stream flows Q, P1, RCP4.5 [m³s⁻¹]
Dez catchment. streamnflows Q, P2, RCP4.5 [m³s⁻¹]
0
200
400
600
800
1000
1200
1400
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Yearly

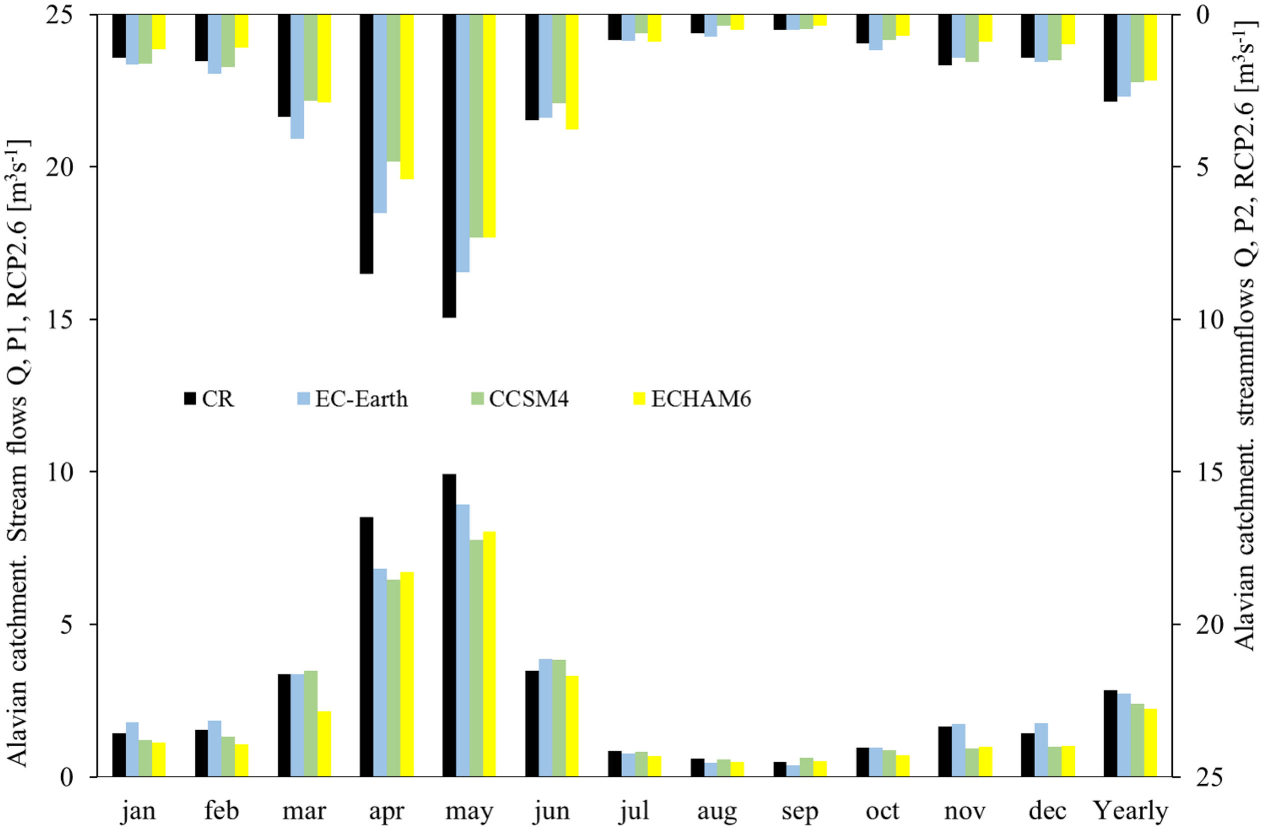
b



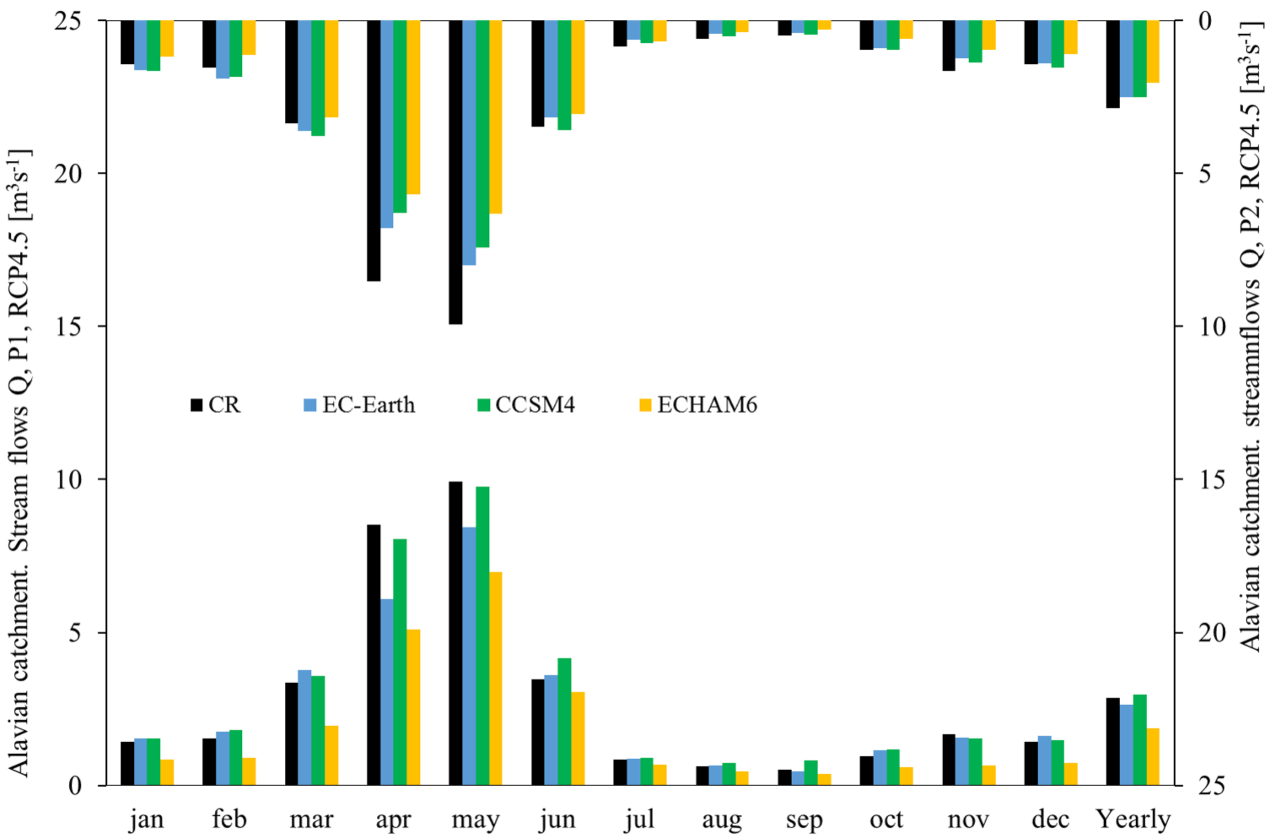
c

Figure 6

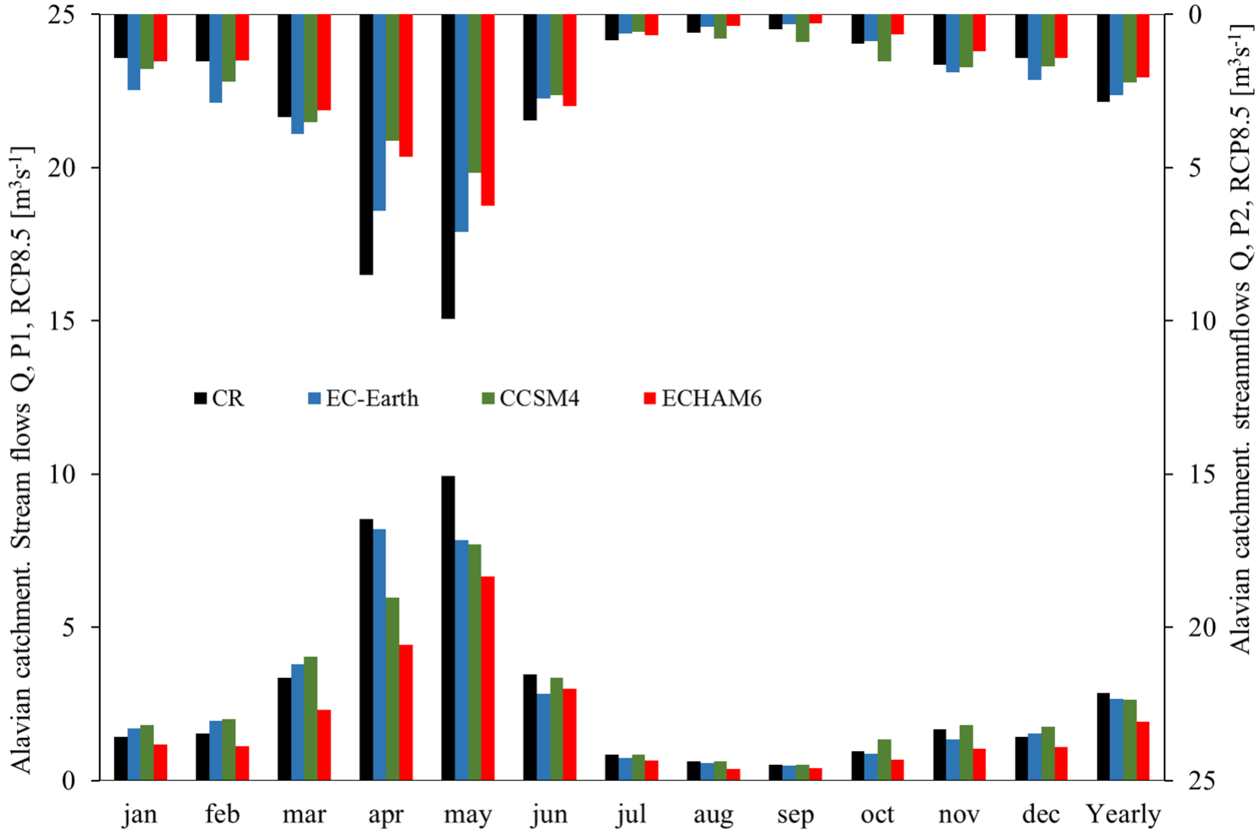
Hydrological projections of the Dez river closed at Dez dam. The monthly river flow is reported as per each GCM model, and stationary scenario, *vs* the calibration period. Left y axis, 2040-2060. Right y axis, values upside down, 2080-2100. a) RCP2.6 b) RCP4.5 c) RCP8.5.


Alavian catchment. Stream flows Q, P1, RCP2.6 [m^{3}s^{-1}]
Alavian catchment. streamnflows Q, P2, RCP2.6 [m^{3}s^{-1}]
CR
EC-Earth
CCSM4
ECHAM6
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Yearly

a


CR
EC-Earth
CCSM4
ECHAM6
Alavian catchment. Stream flows Q, P1, RCP4.5 [m3s-1]
Alavian catchment. streamflows Q, P2, RCP4.5 [m3s-1]
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Yearly

b



c

Figure 7

Hydrological projections of the Alavian river closed at Alavian dam. the monthly river flow is reported as per each GCM model, and stationary scenario, *vs* the calibration period. Left y axis, 2045-2055. Right y axis, values upside down, 2090-2100. a) RCP2.6 b) RCP4.5 c) RCP8.5.


100
90
80
70
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90
100
I, P2. OR$_R$
Dez reservoir. I, P1. OR$_R$
CR
EA 2.6
EA 4.5
EA 8.5
CC 2.6
CC 4.5
CC 8.5
EC 2.6
EC 4.5
EC 8.5

a

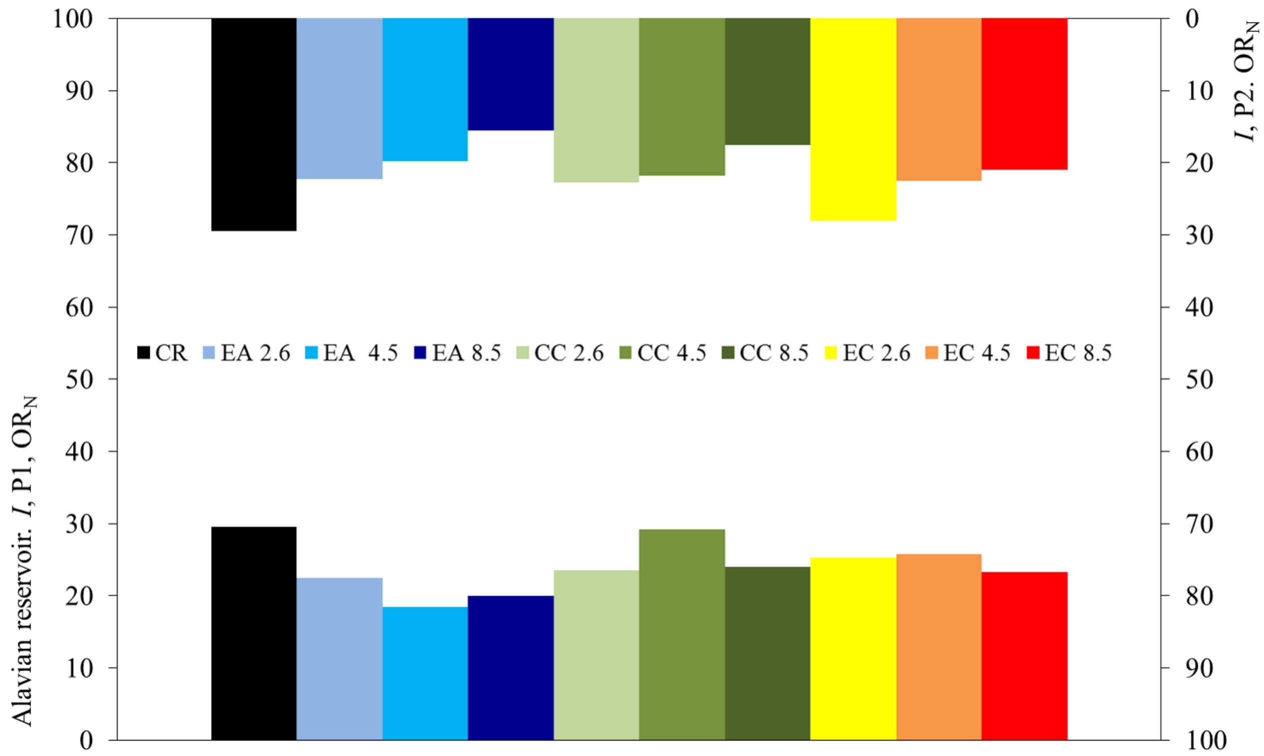
b

Figure 8

Average performance index *I* of Dez reservoir system. Left y axis, P1 2040-2060. Right y axis, values upside down, P2 2080-2100. a) Future (control run operation rule OR_R). b) Future (re-optimization with new rule OR_N).


100
90
80
70
60
50
40
30
20
10
0
Alavian reservoir. I, P1. OR_R
0
10
20
30
40
50
60
70
80
90
100
I, P2. OR_R
CR
EA 2.6
EA 4.5
EA 8.5
CC 2.6
CC 4.5
CC 8.5
EC 2.6
EC 4.5
EC 8.5

a



b

Figure 9

Average performance index *I* of Alavian reservoir system. Left y axis, P1 2045-2055. Right y axis, values upside down, P2 2090-2100. a) Future (control run operation rule OR_R). b) Future (re-optimization with new rule OR_N).