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An integrated fuzzy optimization and simulation method for optimal quality-quantity operation of a reservoir-river system

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ABSTRACT

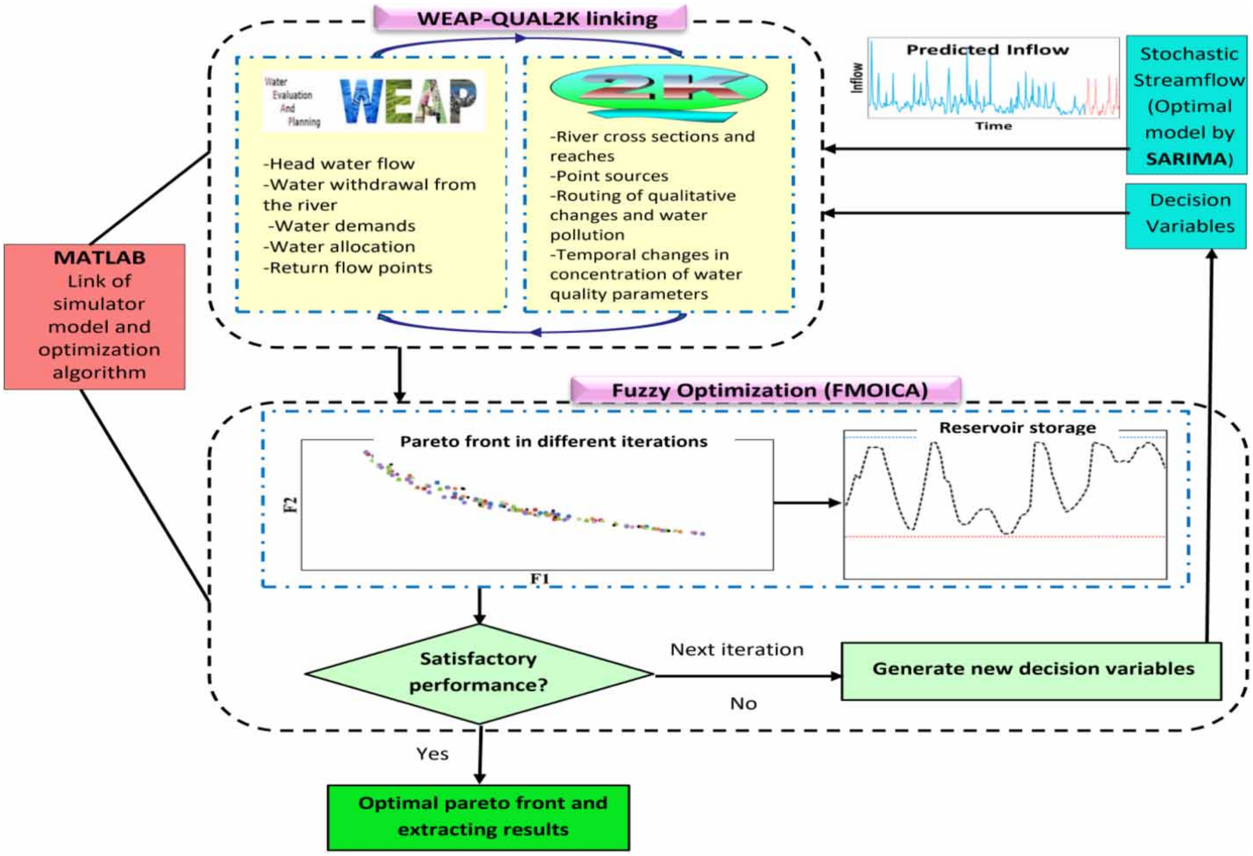
In this study, a novel optimization-simulation dynamic approach was developed for optimal water operation of reservoir-river systems to improve the water quality and supply the water demands along a river. To this purpose, the WEAP-QUAL2 K linked model was developed to simulate water quality and quantity, which is dynamically coupled to a fuzzy multi-objective imperialist competition algorithm (FMOICA). The approach's applicability is demonstrated through the case study of the Dez reservoir river in Iran. The simulation and optimization period used was six years (October 2019-September 2025). Stochastic models (SARIMA(1,0,1)(1,1,1)) were used to forecast inflow into the Dez dam reservoir for the simulation period. Given that in the verification stage of the QUAL2 K and WEAP model it was concluded that the model has high accuracy in simulating the parameters of water quality and quantity, two scenarios were considered: the first scenario was used for dynamic coupling of the quantity-quality model (reference scenario), and the second was the fuzzy optimization of a linked model (optimal scenario). The results show that average water supply reliability increased from 86.13% in the reference scenario to 95.76% in the optimal scenario. Also, under the optimal scenario, the river water quality improves. It was also found that environmental flow rate demands of the river are fully supplied in different months.

Key words: Dez river, dynamic linking, MOICA, QUAL2 K, SARIMA, water quality, WEAP

HIGHLIGHTS

- Development of a coupled quantity-quality-environment water allocation model.
- Links water quality and quantity models.
- Dynamic linking of fuzzy evolutionary optimization to linked water quantity and quality models.

GRAPHICAL ABSTRACT



INTRODUCTION

Rivers are an essential water source for drinking, and for industrial and agricultural use (Babamiri *et al.* 2020). Population growth and consumption competition have led to increased conflicts and contradictions, overexploiting rivers (Wang & Li 2019). The environmental status of rivers can be affected by human activities due to urbanization and industrialization (Singh *et al.* 2005; Hu *et al.* 2018). At the same time, the construction of dams on rivers alters the natural flow regime, slows the flow velocity, and weakens rivers' self-purification ability, which aggravates water pollution (Topping *et al.* 2000; Kileshye *et al.* 2006; Zhang *et al.* 2010a, 2010b). Thus, proper operation of rivers and dam reservoirs is necessary to maintain the health of rivers and human life (Campolo *et al.* 2002).

To properly operate reservoirs and rivers, it is essential to consider the water quantity and quality (Froebrich *et al.* 2007; Reis *et al.* 2015), and ecological demands (Symphorian *et al.* 2003; Shirangi *et al.* 2008; Steinschneider *et al.* 2014). In this vein, some studies have been conducted to incorporate both water quantity and quality into river basin modeling such as by Azevedo *et al.* (2000) which presented a combined surface water quantity (MODSIM) and quality (QUAL2E) model within the framework of a decision-support tool in an application applied to the Piracicaba River Basin in the state of Sao Paulo, Brazil. Their results showed that pathways for the solution to the very complex problems in the basin require increased levels of wastewater treatment and flow augmentation to meet growing water demands and maintain the diversion to Sao Paulo. Paredes *et al.* (2010) established a water quality support system to analyze the impact of reservoirs and sewage treatment on water quality improvement in the Manzanares River, Spain, and proposed methods to enhance the ecological environment. Zhang *et al.* (2010a, 2010b) proposed a water quantity and water quality coupling model and simulated the model's hydrodynamics and water quality process when applied to the Jiaojiang River basin (China) analyze two water allocation schemes. Their results show that the coupled model can help managers improve water and adjust water allocation between different users. Manshadi *et al.* (2015) assessed water quantity and quality based on virtual water, blue water, and transferred water in inter-basin water allocation. The results revealed that the proposed methodology could effectively develop sustainable inter-basin water allocation management. Da Silva & Alves (2016) integrated the WEAP and QUAL2 K models to evaluate the effect of population growth on BOD concentration changes in the Descoberto river basin under different management scenarios. The results showed that treatment efficiency at the wastewater treatment plant on the river should be enhanced under the population growth scenario. Given population growth and industry development, Jaramillo *et al.* (2016) integrated the WEAP and QUAL2 K models to examine the effect of domestic and industrial wastewater on biochemical oxygen demand (BOD) and dissolved oxygen (DO) changes in the Rio La Vieja, Colombia. The results showed that the status of the river does not exceed the local standards of using river water. Mishra *et al.* (2017) analyzed water quality parameters (BOD and DO) to evaluate the sustainability of the surface water resources of the Kathmandu Valley. For this purpose, they implemented current and future wastewater production and treatment scenarios based on two crucial aquatic health indicators. Ma *et al.* (2021) integrated numerical water quality and quantity models to manage water demand, basin outlet flow, and pollutant concentration in Nanning, China. Their results indicated that the error of the integrated model in terms of quantity and quality was below 5%.

Nevertheless, a comprehensive and well-organized model has not been provided for the operation of reservoir-river systems for which information can be easily updated. One of the practical approaches to water pollution control and supplying the demands of users is water quantity and quality optimal joint operation in the reservoir-river basin (Azevedo *et al.* 2000; Zhang *et al.* 2011; Piman *et al.* 2013). In this way, the integrated optimization and simulation approach is an economical and sustainable way to manage water resources properly. Simulation methods make it possible to model the water resource system in full detail and quickly understand the desired design. Similarly, during the optimization process, the most appropriate values can be found for the decision variables in a problem so that the objectives of the problem can be met with optimal utility.

Studies have been conducted on integrating simulation and optimization models, such as by Hayes *et al.* (1998) who integrated water quantity and quality modeling in an optimization model for regulation of multi-reservoir hydropower systems in the Cumberland River Basin, USA. The objective was to maximize hydropower revenue while meeting downstream water quality objectives. Dai & Labadie (2001) linked the extended model (MODSIMQ) with the U.S. Environmental Protection Agency's (QUAL2E) using a Lagrangian relaxation network solver with FrankWolfe non-linear programming to find solutions satisfying right water priorities while attempting to maintain minimum water quality requirements in the lower Arkansas River basin in Colorado, USA. Their results showed satisfaction of all water supply requirements with conjunctive use of surface and groundwater and dramatic improvement in water quality conditions but at the expense of increased water supply shortages. Nikoo *et al.* (2012) developed an optimization model by considering available water and water demand uncertainties every month for water and waste load allocation in a river basin. Also, they applied cooperative game theory to redistribute benefits to water consumers. Yuan *et al.* (2015) developed a water quantity and quality joint operation model of dams and floodgates coupled with a one-dimensional water quality model with flood control and pollution control for the Huai River basin in China. They used dynamic programming (DP) to solve the model. Their results demonstrated that the water quality of the main monitoring sections with joint operation was better than that with empirical operation under the same water quality standard. Azari *et al.* (2018) developed a WEAP-NSGA linking model for the hedging policy in the two-reservoir system on Gavoshan and Shohda dams located in the west of Iran. They argued that using a combination of a multi-objective optimization algorithm and simulation model can provide optimum solutions for hedging policy in multi-reservoir systems. Wang *et al.* (2019) proposed an optimization-simulation method that included water resources systems, multiple water resources such as local surface water and reused sewage, and multiagents to remit serious water problems in Guanzhong Plain China. Results showed that, compared to the current situation, the water quantity and environment agent guarantee rates could satisfy design requirements in future planning years. Saadatpour (2020) used simulation and optimization models for water quality-quantity management of the Meimeh Reservoir in Iran. This study evaluated upstream saline inflow using the CE-QUAL-W2 and WEAP model to determine the best inflow scenario. The adaptive surrogate-assisted water quality simulation model (WQSM) was linked to the hybrid NSGA-II_AMOSA algorithm to ascertain the desired operation policy. Farrokhzadeh *et al.* (2020) connected the WEAP model with multi-objective optimization to optimize water allocation for environmental requirements and benefits from agriculture in the Sistan region in Iran. By plotting Pareto sets, they investigated the trade-offs between the two conflicting objectives and evaluated a possible compromise. Masoumi *et al.* (2021) linked the two-dimensional hydrodynamics and water quality simulation model (CE-QUAL-W2) to Multi-Objective Particle Swarm Optimization (MOPSO) to develop a simulation-optimization approach. Using this model dramatically reduced the severity of failure periods in the water quantity quality and the sequence of failure periods. Muronda *et al.* (2021)

linked the WEAP model and the particle swarm optimization (PSO) algorithm to the optimal operation of the Amir Kabir Dam reservoir in Iran. Their results showed that the integrated model optimized the release of the reservoir in different periods properly.

In the last few years, with the development of optimization methods and the introduction of meta-heuristic methods, optimum operation of water resources systems has entered into a new stage. Meta-heuristic optimization can be equally applied to linear or non-linear constraints and objectives, as well as to either time-separable or non-separable objectives. Hence it can be applied to problems where complex decisions are investigated (Dobson *et al.* 2019). To date, many algorithms have been used in the context of optimization of water resources systems operation, such as genetic algorithms (GA) (Wardlaw & Sharif 1999; Hınçal *et al.* 2011; Azari *et al.* 2018), PSO (Nagesh Kumar & Janga Reddy 2007; Noory *et al.* 2012), honey bee mating optimization (Haddad *et al.* 2006), ant colony optimization (Kumar & Reddy 2006), simulated annealing (Georgiou *et al.* 2006) and the imperialist competition algorithm (ICA) (Afshar *et al.* 2015). A relatively new evolutionary algorithm, the ICA proposed by Atashpaz-Gargari and Lucas in 2007. The algorithm has been successfully applied to various single-objective engineering problems (Kaveh & Talatahari 2010; Nazari-Shirkouhi *et al.* 2010; Yousefi *et al.* 2011; Talatahari *et al.* 2012; Hosseini-Moghari *et al.* 2015), but few attempts have been made to utilize it in the multi-objective optimization area. Enayatifar *et al.* (2013) developed a multi-objective optimization based on the ICA (MOICA) and demonstrated its effectiveness on several benchmark functions. The results were compared with those of the NSGA-II, MOPSO and proved to be better or at least on par. Nazari & Deihimi (2017) developed fuzzy multi-objective optimization based on the ICA. A comparison with NSGA-II and MOPSO showed that MOICA is a more effective and reliable multi-objective solver covering the actual Pareto fronts.

Optimization in water resources systems is generally complex, as they are often associated with a large number of uncertain factors in combination with no commensurable objectives (Kamodkar & Regulwar 2014). Due to these uncertainties in objectives and model parameters, applying a fuzzy model instead of a crisp model can be helpful. In this regard, studies have been carried out on the fuzzy operation of water resources systems such as by Sasikumar & Mujumdar (1998), Tilmant *et al.* (2002), Sadegh & Kerachian (2011), Xu *et al.* (2013), Kamodkar & Regulwar (2014), Mirajkar & Patel (2016), and Morankar *et al.* (2016).

To date, no research can be found on optimal joint operation of water quantity and quality for water resources systems using linked water quantity and quality models and coupling it dynamically to a fuzzy meta-heuristic optimization algorithm for optimal function of a reservoir-river system. Thus, this study aims to develop a coupling fuzzy multi-objective algorithm (FMOICA) to the body of a linked WEAP-QUAL2 K model for the optimal quantity-quality operation of a reservoir-river system, based on objectives of: (i) supplying various water demands including for drinking, industry, agriculture and environmental flow rates, and (ii) maintaining the water quality of the river according to world standards.

MATERIAL AND METHODS

Study area

The Dez river basin is the third largest basin in Iran which plays a fundamental role in the economic, social, and environmental life of southwest Iran. Due to the various wastewaters (municipal, agricultural and industrial) that pollute the river, it is essential to develop a comprehensive quantitative-qualitative model for the operation of the Dez reservoir and river as the most important source of water supply in the region. In this way, it would be possible to address the water supply issue, the impact of water withdrawal, and the return of municipal, agricultural and industrial wastewater effluents in different parts of the river route on the qualitative process and pollution of the river. The study area has a semi-arid climate; its annual precipitation is 252.38 mm, its annual temperature is 25.1 °C, and the total evaporation is approximately 2,035 mm. As a result, the average water inflow to the reservoir is 152 m^3 /s (http://www.irimo.ir). The Dez river basin has an area of about 21,720 km^2, which is divided by the Dez dam upstream and downstream. It flows from north to south, with an average basin elevation of 1,603 m. The present study focuses on the downstream part of 173.78 km, from Dez dam to Bandeghir. The gross area of arable land around the Dez river from the Dez dam to Bandeghir is about 245,000 hectares. The surface water source in this area is the Dez dam reservoir and river. Another source in the area is the deep and semi-deep wells in the Dez plain. Both surface and groundwater sources supply the region's agricultural, drinking, and industrial requirements (KWPA 2001). Figure 1 shows the plains, rivers, and hydrometric stations of the study area.

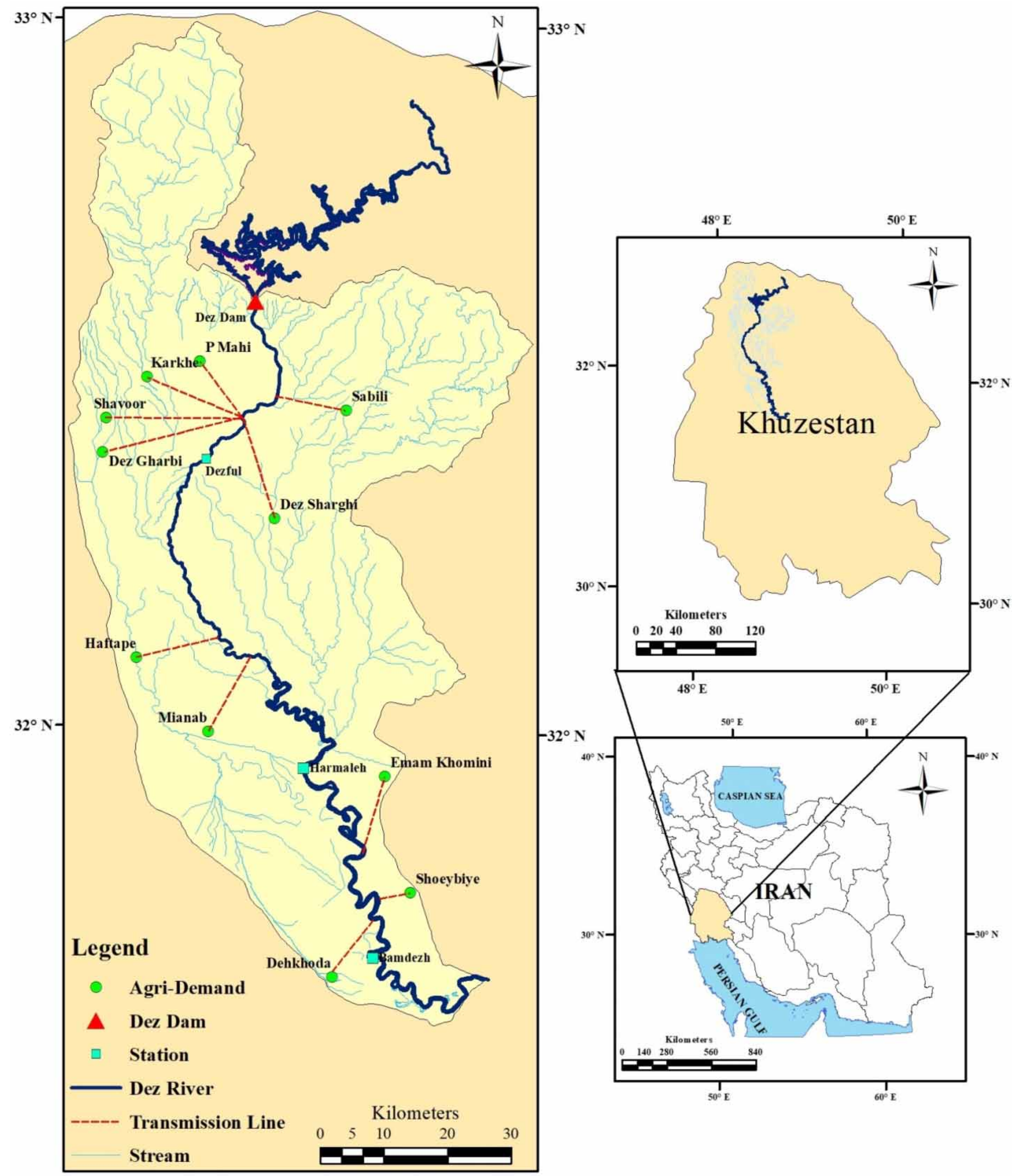


Figure 1 | Location of the study area in Iran and Khuzestan province.

Qualitative simulation

The QUAL2 K model is used for qualitative simulation of the Dez river (from the Dez dam to BandeGhir), shown in bold in Figure 1. QUAL2 K is the latest model of the QUAL model series, which was approved by the United States Environmental Protection Agency (USEPA) and is widely used to simulate river water quality (Kannel *et al.* 2007). The framework represents the river as a one-dimensional channel with a non-uniform, steady flow and simulates the impact of both point and non-point pollutant loadings. To determine the 'concentration of qualitative parameters' in this model, the Finite difference method is used for the numerical solution of the Advection-Diffusion Equation (Chapra *et al.* 2008). The Dez river section was divided into fragments (143 units) based on the river's hydraulic conditions and pollutant discharge site, as shown in Figure 2. The general mass balance equation in the *i* section water column for all constituent concentrations can be written as:

$$\frac{\partial C}{\partial t} = \frac{\partial\left(AD\frac{\partial C}{\partial x}\right)}{A\partial x} - \frac{\partial(AUC)}{A\partial x} - \frac{dC}{dt} + \frac{S_C}{V} \tag{1}$$

where C: concentration of the specific parameter; v: volume of the river; U: mean velocity; D: diffusion coefficient; A: river estuary section area; S_C: external sinks or sources of the C element; *t*: time (day) and *x*: the distance of each reach along the river in the flow direction.

Quality data

Many parameters are required for river water quality simulation (QUAL2 K), including hydraulic data in fragments (headwater flow, river bottom slope, riverside slope, river bottom width, and Manning's coefficient), meteorological data (temperature, wind speed, dew point temperature, solar radiation, and cloud cover percentage), and water quality of point sources and nonpoint sources (temperature, pH, EC, DO, BOD, NO_3-N, NH_4-N, and surface water inflow) (Chapra *et al.* 2008), which the Environmental Protection Agency of Iran collected. The detailed requirement can be found in Chapra *et al.* (2008). The Khuzestan Water and Power Authority (KWPA) and Khuzestan Department of Environment (KDOE) are the main authorities responsible for the Dez river water quality monitoring and supervision (KWPA 2001). Hydrometric and quality data from Dezful, Harmaleh, and Bamdezh stations were collected from KWPA, and wastewater discharge (point sources) was gathered from KDOE. Table 1 represents an average of quantitative and qualitative characteristics corresponding to the most important sources of pollutants in the study area. Moreover, hydrodynamic data were obtained from the Dezab Engineering Company (www.dezab.com).

Quantitative simulation

The Water Evaluation and Planning (WEAP) model was used for quantitative simulation of the Dez reservoir-river. WEAP is advanced-integrated modeling software that simulates and models water supplies, water demands, and environmental requirements as well as considering the effects of policies on water quantity, water quality, and the ecosystem, which was developed by the Stockholm Environment Institute (SEI 2012). Mass balance equations are the foundation of WEAP's monthly water accounting: total inflows equal total outflows, net of any change in storage (in reservoirs and aquifers). Every node and link in WEAP has a mass balance equation, and some have additional equations which constrain their flows (e.g., inflow to a demand site cannot exceed its supply requirement, outflows from an aquifer cannot exceed its maximum withdrawal, link losses are a fraction of flow, etc.). Each mass balance equation becomes a constraint in linear

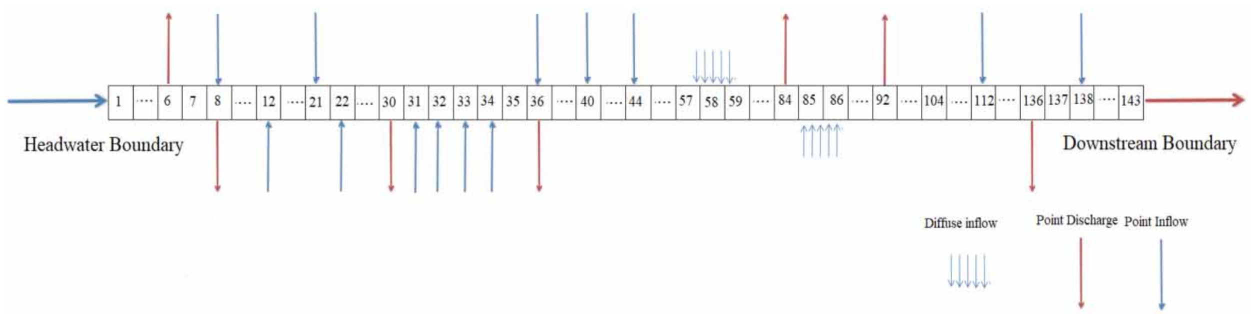


Figure 2 | Detachment pattern of the proposed simulation.

Table 1 | Average discharge and monthly wastewater of point source pollutants at various locations along the Dez river (Khuzestan Department of Environment)

Name		Distance Km	Q m^3/s	T °C	EC μmhos	pH	DO mg/L	BOD mg/L	NH_4-N μg/L	NO_3-N μg/L
Urban Pollutant Sources	Dezful	8.6	2.4	19	1,750	7.3	3.4	94.2	3,500.4	11,378.5
	Safiabad	26.6	0.4	17	1,780	7.2	4.7	40.8	2,457.1	956.1
	Hor	37.5	0.5	20	1,830	7.6	5.2	63.8	1,127.6	742.5
	Mianrood	40.3	0.6	20	1,740	7.1	4.8	75.6	2,832.1	662.3
Industrial Pollutant Sources	P. Mahi	23.2	5.2	19	1,700	7	2.5	22.1	480.6	3,688.5
	K. Hafttapeh	38	1.8	18	1,850	6.9	4	110.6	421.8	2,266.2
	Kagz Pars	69.2	0.6	19	1,450	6.8	2.2	150.3	1,300.5	2,026.3
Agricultural Pollutant Sources	Loor	4.7	1.3	16	697	7.8	6.2	6.8	856.3	1,638.5
	Sabzab	23.5	3	21	787	7.8	8.1	4.2	945.4	9,745.1
	Banehasan	31.4	1.3	22	778	7.8	7.6	7.2	1,089.9	8,683.2
	Sagari	33.2	4.2	19	708	7.4	8.7	3.7	1,154.3	9,596.4
	Haftapeh	43.3	1.3	20	1,345	7.6	7.6	5.4	784.1	2,230.7
	Salimeh	55	2.8	18	747	7.5	6	3.3	952.4	12,524.9
	Tapdarin	55.4	1.2	19	888	7.3	7.4	6.2	844.5	21,884.3
	Atij	65.2	2.3	22	1,242	7.7	6.9	4.3	621.6	5,920.5
	Mianab	107.5	3.5	21	3,310	7.5	3.1	7.8	951.7	9,180.6
	Kharvar	134.7	2.2	22	4,592	7.9	3.5	5.5	723.6	6,940.4
	Shoabiye	167.9	11.1	21	5,020	7.8	7.2	7.3	983.8	5,655.4
Hydrometric Stations	Dezful	0	174.9	16.2	607	7.4	10.6	3.6	410	3,410
	Harmaleh	81.5	123.4	18.6	1,520	7.8	7.5	4.5	450	8,120
	Bamdezh	136.6	116.9	19.7	2,100	7.8	5.8	4.8	318.4	7,415

programming (Muronda *et al.* 2021):

$$\sum_{Inflow} = \sum_{Outflow+Addition\ To\ Storage} \tag{2}$$

This can also be rewritten as: Inflow – Outflow – Addition To Storage = 0

Addition To Storage only applies to reservoirs and aquifers. Addition To Storage is positive for an increase in storage and negative for a decrease in storage. Outflow includes consumption and losses. To determine the basic framework of the model, basic maps were prepared in the GIS environment and then introduced into the WEAP model. For further familiarity with all the resources and applications in the study area, the schematic and framework of the developed model are shown in Figure 3. The framework indicates that each regional water resource, surface and underground, was connected by a transmission line to demand points or the node associated with each user. Then, a backflow line to the river was considered from each node that transported surface runoff and agricultural surplus water through drainage.

Quantity data

Stochastic linear models were used to predict the river flow into the Dez Dam for 2019–2025. The most common method in time series modeling is the autoregressive moving average (ARMA) based approach, such as autoregressive integrated moving average (ARIMA) and seasonal ARIMA (SARIMA). The formulation of SARIMA (p,d,q)(P,D,Q) is a complete stochastic model with differencing and seasonality as follows (Box & Jenkins 1976):

$$\Phi(B^{\omega})\phi(B)(1-B^{\omega})^{D}(1-B)^{d}x(t) = \Theta(B^{\omega})\theta(B)\varepsilon(t) \tag{3}$$

$$\Phi(B^{\omega}) = (1-\Phi_1 B^{\omega} - \Phi_2 B^{2\omega} - \Phi_3 B^{3\omega} - \ldots - \Phi_p B^{p\omega}) \tag{4}$$

$$\phi(B) = (1-\phi_1 B - \phi_2 B^2 - \phi_3 B^3 - \ldots - \phi_P B^P) \tag{5}$$

$$\Theta(B^{\omega}) = (1-\Theta_1 B^{\omega} - \Theta_2 B^{2\omega} - \Theta_3 B^{3\omega} - \ldots - \Theta_P B^{p\omega}) \tag{6}$$

$$\theta(B) = (1-\theta_1 B - \theta_2 B^2 - \theta_3 B^3 - \ldots - \theta_p B^p) \tag{7}$$

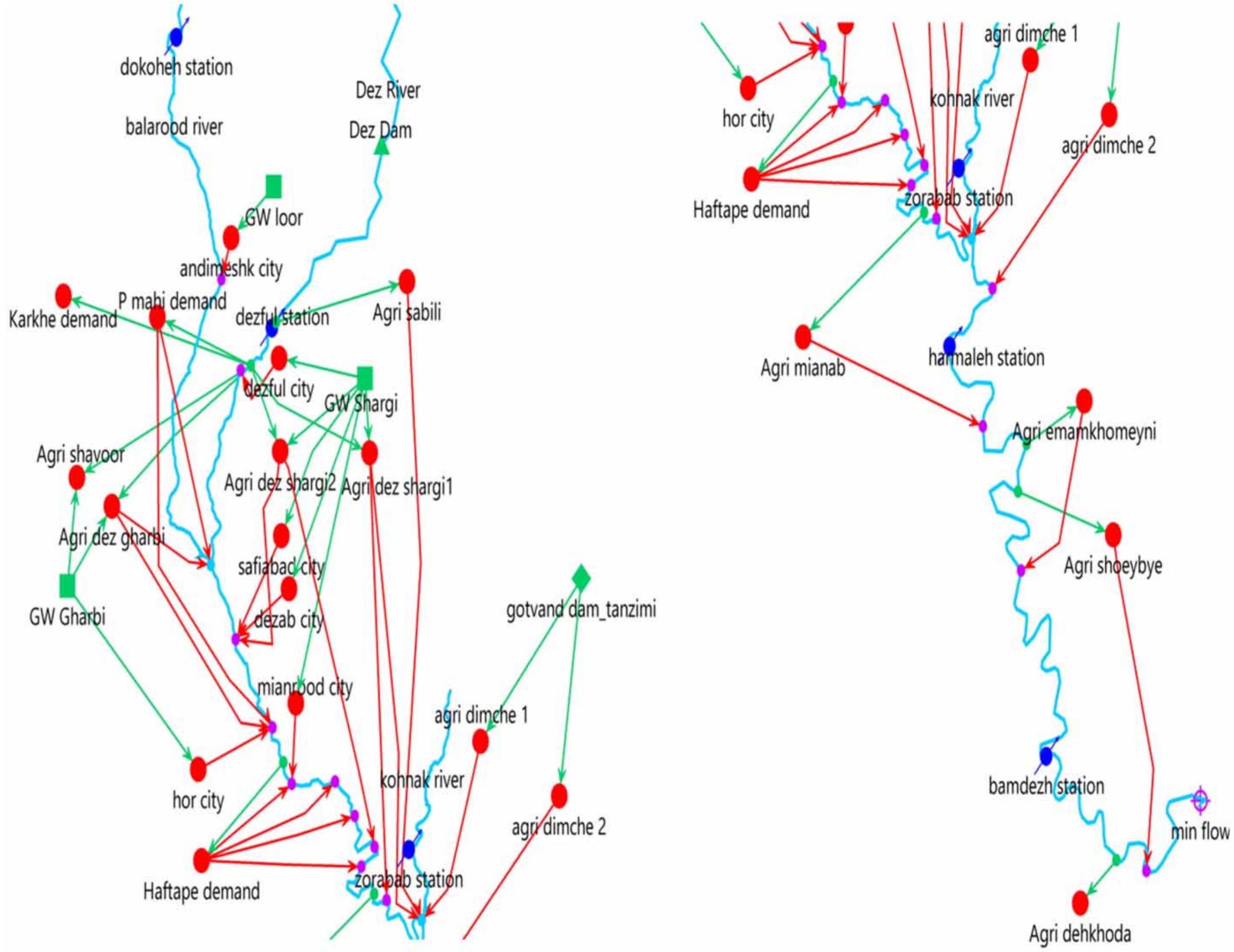


Figure 3 | Schematic and framework modeled in the WEAP model.

where, ε(t) is the residual, θ and φ are moving average (MA) and autoregressive (AR) parameters, Φ and Θ are seasonal AR and MA parameters, d is the non-seasonal differencing degree, and D is the seasonal differencing degree. Q, q, P, and p are the stochastic model's SMA, MA, SAR, and AR orders. The values of these orders are approximated using partial autocorrelation function (PACF) and autocorrelation function (ACF) diagrams (Cryer & Chan 2008). Figure 4 shows the predicted inflow into the Dez dam. The SARIMA (1,0,1)(1,1,1) model was determined as the best optimal model for river flow prediction with the lowest RMSE (8.74 m^3/s).

The environmental flow rate was estimated based on the river's natural flow regime in the desired nodes. The Tennant (or Montana) method, which is a hydrologic water allocating method, was employed to estimate the downstream (Bandeghir) environmental flow rate (Tennant 1976). From October to March, the minimum environmental flow rate was 28.7 (m^3/s), and for April to September, it was 86.2 (m^3/s).

Agricultural water demand in the study area was calculated based on the cultivation pattern of each plain and was considered to be constant over the following years. To calculate urban and rural drinking water demands, demographic information of all cities, villages, and settlements in the plain area according to 2006, 2011, and 2016 censuses were obtained from the Water and Sewer Administration of Khuzestan. Population growth rates between consecutive censuses were measured in each city and rural area, and finally, the future population was estimated according to the population at the base year and the population growth rate. Then, urban and rural demands for drinking water were calculated based on the population and per capita water consumption in each region for 2019–2025. The average monthly requests for each agriculture and industrial application are presented in Table 2 (www.dezab.com).

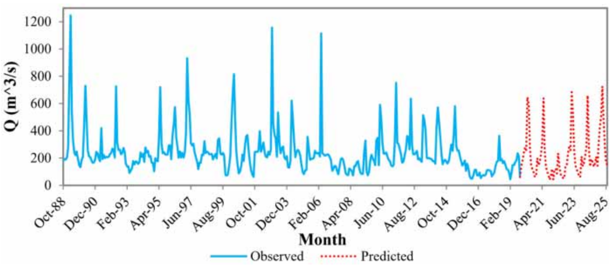


Figure 4 | Predicted inflow for the period of October 2019 to September 2025.

Table 2 | The average monthly demands for agriculture and industrial applications (m^3/s)

Name	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Agri Sabili	1.8	16.3	4.8	0.8	0	3.7	8.1	6.3	1.5	2.3	3.3	3.6
P. Mahi demand	1.4	1	0.6	0.5	0.5	0.75	0.85	1.2	1.5	1.6	1.6	1.5
Karkhe demand	23	26.1	30.3	27.5	22.6	24.4	20.5	21.8	25.2	23.9	23.9	21.9
Agri Shavoor	21.7	7.4	7.7	3.3	2.3	13.2	20.7	8.6	16.7	17.3	29.6	32.5
Agri Dez Shargi	27.2	20.1	16.7	29.7	34.4	22.7	55.2	39.5	47	52.4	47.3	56.3
Agri Dez Gharbi	37.2	12.9	13.8	10.4	3.1	23.8	35.7	14.9	28.9	29.6	50.2	55.5
K. Haftape demand	1.7	3.65	3.5	3.5	3.6	3.65	2.7	3.4	3.4	2.25	1.65	1.65
Agri Dimche	19.8	11.2	6.4	2.8	3.1	6.4	16.9	21.4	27.6	28.9	28.8	31.4
Agri Mianab	5.29	5.66	6.55	4.13	5.94	4.52	6	5.25	8.52	6.96	8.94	6.67
Agri Emamkhomeyni	2.68	2.87	3.32	2.09	3.01	2.29	3.05	2.66	4.32	3.53	4.53	3.38
Agri Shoeybye	2.1	2.98	0.45	0.96	4.72	9.05	12.84	6.65	1.69	1.81	4.03	3.1
Agri Dehkhoda	9.87	10.57	12.23	7.7	11.09	8.44	11.22	9.79	15.9	12.99	16.69	11.5

To simulate the flow discharged from the Dez dam as one of the surface water supply sources, the required data, including reservoir storage volume at the minimum and the maximum level, the inactive volume of the reservoir, and hydropower plant capacity, were defined in the model. These data are shown in Table 3.

Calibration and validation of models

Calibration aims to minimize the difference between the predicted output from the model and observational data, usually by accurate estimation of parameters or by optimization techniques. The parameters for the QUAL2 K model are ISS settling velocity, fast CBOD oxidation rate, organic nitrate settling velocity, organic nitrate hydrolysis, ammonium nitrification,

Table 3 | Operation characteristics of Dez dam during the simulation period (KWPA 2001)

Parameter	Amount
The total storage volume of the reservoir after sedimentation	2,857 MCM
The average storage volume level of the reservoir	352 m
Minimum operation level	310
Reservoir storage volume at the maximum operating level	2,857 MCM
Reservoir storage volume at the minimum operating level	942.33 MCM
Reservoir useful storage volume	2,600 MCM
Maximum turbine flow	473.6 m^3/s
Average of hydropower plant factor	35.6
Generating efficiency	89%

MCM = million cubic meters

nitrate denitrification, and sediment denitrification transfer coefficient, and for the WEAP model they are crop coefficient, soil water capacity, root zone conductivity, and preferred flow direction. The QUAL2KW model minimizes the difference between observational and computational results using fitness relationships, for which the RMSE relation is most applicable. The genetic algorithm then uses the fitness result for automatic model calibration. The validated model is re-run with a new set of information to measure the error rate between the calculations and the observations in the validation phase. The WEAP model minimizes the difference between observational and computational results using the PEST method (parameter estimation); PEST optimizes the parameters by non-linear regression. The models were calibrated using monitoring data from three stations, namely, Dezful, Harmaleh, and Bamdezh. Field data from October 2015 to September 2018 were used for model calibration. Data from October 2018 to September 2019 were used for model validation. The calibration and validation accuracy is based on calculation of NSE (Nash and Sutcliffe error), standard error (SE), and mean absolute error (MAE).

Dynamic linking of WEAP and QUAL2 K

The integration of the water quality model (QUAL2 K) and WEAP (SEI 2012) (decision support system) was evaluated, considering its effectiveness to represent the water quality impacts on different river discharge and planning alternatives. The two models were linked using the available tools in the WEAP model. In the coupled model, the WEAP model simulates quantitative values such as dam release and river water withdrawal, and water return from drainage, while the QUAL2 K model tracks the qualitative changes and water pollution at all time intervals and for all river basins (SEI 2012).

Multi-objective imperialist competition algorithm (MOICA)

The ICA is an example of a population-based algorithm. The algorithm is inspired by imperialist competition, and individuals in ICA are called countries. Countries are within different parts of the problem space, called empires. The strongest country in an empire is called the imperialist, and other countries within that empire are named colonies. Iterations are called decades. Imperialists tend to attract colonies towards themselves in every decade (Atashpaz-Gargari & Lucas 2007). In the Multi-objective method, rather than finding the lowest cost associated countries as in the original algorithm, the non-dominated solutions are found (Enayatifar *et al.* 2013).

Simulation-optimization modeling framework

In the proposed structure, a series of decision variables were generated by the FMOICA algorithm in each iteration and entered as input variables in the WEAP-QUAL2 K linked model. After running the model based on the decision variables, the results were evaluated according to the fuzzy objective functions and defined constraints. If the objective functions were not met after running the model, the new variables were introduced into the linked model by applying new management conditions, and then the objective functions were re-tested. This cycle was repeated until optimal values were obtained.

The structure of the proposed operation model

The first objective was to maximize the percentage of water supply (coverage) during the planning period, while the second objective was to minimize violations from permissible quantities of qualitative parameters during the operational period (by the qualitative utility function). Decision variables of the optimization problem included the monthly environmental flow rates in BandeGhir, which needed to be supplied from the surface water within the range of 28.7–86.2 m^3/s (the maximum value was 86.2 m^3/s for the dry season, and the minimum value was 28.7 m^3/s for the wet season). Given that the environmental flow rate was determined for the river's natural flow regime, this amount should be optimized in different months in dams and withdrawals that change the river's natural flow. The equations of the objective functions and constraints are defined as follows:

1. **Objective functions**

Maximize the coverage percentage of water demands for the whole period

$$F_1 = Maximize\ (Coverage) = Maximize\left(\sum_{t=1}^{n}\sum_{z=1}^{nz}\sum_{d=1}^{nd}(Cov_{tzd})\right) = Maximize\left(\sum_{t=1}^{n}\sum_{z=1}^{nz}\sum_{d=1}^{nd}\left(\frac{TAW_{tzd}}{DM_{tzd}}\right)\right) \tag{8}$$

Since the optimization algorithm attempts to minimize the objective functions, the function mentioned above can be written as follows:

$$F_1 = Minimize\left(\sum_{t=1}^{n}\sum_{z=1}^{nz}\sum_{d=1}^{nd}(1 - Cov_{tzd})\right) = Minimize\left(\sum_{t=1}^{n}\sum_{z=1}^{nz}\sum_{d=1}^{nd}\left(1 - \frac{TAW_{tzd}}{DM_{tzd}}\right)\right) \tag{9}$$

where Cov_{tzd} is coverage, TAW_{tzd} is the amount of water allocated to zone z in period t for d type, DM_{tzd} is the water demand of zone z in period t for type d, n is the number of times planned, nz is the number of zones, nd is the number of water-demand types in each zone.

Minimizing the violations from permissible quantities of qualitative parameters over the whole period is given by:

$$F_2 = Minimize\left(\sum_{t=1}^{n}\sum_{p=1}^{q}\sum_{r=1}^{nr}\left(\frac{Concentration_{tpr} - Accepted\,Concentration_p}{Accepted\;Concentration_p}\right)\right) \tag{10}$$

where $Concentration_{tpr}$ is the concentration of p parameter in period t at river interval (r), $Accepted\ Concentration_p$ is the permissible concentration of each parameter, q is the number of simulated qualitative parameters, nr is the number of river intervals.

2. **Constraints**

$$V_{\min}(t) \leq V(t) \leq V_{\max}\ (t) \tag{11}$$

where $V_{\min}(t)$ is the minimum storage capacity of the Dez reservoir at time t, $V_{\max}(t)$ is the maximum storage capacity below the flood-control water level.

$$TAW_{tzd} = RS_{tzd} + RG_{tzd} \quad t = 1,\ \ldots.., m \times y, \quad z = 1,\ \ldots.nz, \quad d = 1,\ \ldots.nd \tag{12}$$

where RS_{tzd} is the amount of surface water allocated to zone z in period t for type d, RG_{tzd} is the amount of groundwater allocated to zone z in period t for type d, m is the number of planning courses per year, y is the number of years.

$$RS_{tzd} = \left\{\begin{array}{cc} DM_{tzd} & if\left(TSR_t - \sum_{z=1}^{z-1}\sum_{d=1}^{d} DM_{tzd} - \sum_{z=1}^{z}\sum_{d=1}^{d-1} DM_{tzd}\right) \geq DM_{tzd} \\ \left(TSR_t - \sum_{z=1}^{z-1}\sum_{d=1}^{d} DM_{tzd} - \sum_{z=1}^{z}\sum_{d=1}^{d-1} DM_{tzd}\right) & Otherwise \end{array}\right\} \tag{13}$$

where TSR_t is the whole amount of surface water allocated in t period.

$$TDF_{tdz} = DM_{tdz} - RS_{tdz} \tag{14}$$

TDF_{tdz}: is the amount of water shortage which not supplied by surface water.

$$RG_{tzd} = \left\{\begin{array}{cc} TDF_{tzd} & if\left(G_{t-Max} - \sum_{z=1}^{z}\sum_{d=1}^{d-1} TDF_{tzd}\right) \geq TDF_{tzd} \\ \left(G_{t-Max} - \sum_{z=1}^{z}\sum_{d=1}^{d-1} TDF_{tzd}\right) & Otherwise \end{array}\right\} \tag{15}$$

where G_{t-Max} is groundwater withdrawal limit (this limitation was assumed to equal the current maximum withdrawal and not exceed that value).

The maximum transfer capabilities of the Sabili, Dez Shargi, Dez Gharbi, and Gotvand channels were defined as constraints in the model.

$$R_{c-s} \leq 16\frac{m^3}{s} \quad R_{c-sh} \leq 92\frac{m^3}{s} \quad R_{c-gh} \leq 157\frac{m^3}{s} \quad R_{c-g} \leq 60\frac{m^3}{s} \tag{16}$$

where R_{c-s} is the maximum transfer capability of the Sabili canal, R_{c-sh} is the maximum transfer capability of the Dez Shargi canal, R_{c-gh} is the maximum transfer capability of the Dez Gharbi canal, R_{c-g} is the maximum transfer capability of the Gotvand canal.

3. **Fuzzy-compromised approach**

Imprecision is often involved in reservoir-systems operation, as these systems are too complex to be defined precisely. Fuzzy programming has an essential role in fuzzy modeling, which can formulate uncertainty in the actual environment. In the present study, the reservoir operation model is developed by addressing uncertainty in the release. Due to release uncertainty in the model, the model's objectives also become fuzzy. In the proposed model, each objective is represented by fuzzy sets and defined by a linear membership function: $\mu_k(x)$. This can be stated as follows:

$$\mu_k(x) = \begin{cases} 0 & F_k \leq l_k \\ (F_k - l_k)/(u_k - l_k) & l_k \leq F_k \leq u_k \\ 1 & F_k \geq u_k \end{cases} \tag{17}$$

where F_k denotes the k^{th} objective function and is the monotonically increasing function that shows the degree to which x satisfies the fuzzy value in the $\mu_k(x)$ inequality; l_k and u_k values are the lower and upper bounds that represent the subjectively chosen intervals for the objective function for each k (Arikan & Güngör 2007).

Model assumptions and scenarios

- **Reference Scenario:** The reference scenario represents the continuation of existing conditions without significant changes in future management policies in which quantitative-qualitative simulations were carried out for six years, from October 2019 to September 2025. In this scenario, stochastic linear models were used to predict the river flow into the Dez dam, agricultural water demands in the study area were calculated based on the cultivation pattern of each plain and were considered to be constant over the following years, and drinking demand in the next years was estimated according to population growth rate and introduced into the model. According to the current exploitation status, the environmental flow rate downstream of the river was considered to be equal to the recorded flow rates at the end of the river route. In this scenario, drinking water is entirely provided by groundwater sources. The industrial, environmental, agricultural demands and Karkhe demand were defined to the model as the first, second, and third priorities of surface water withdrawing, respectively. Surface water and groundwater are the first and second priorities to supply water demands.
- **Optimal Scenario:** This scenario was designed to optimize release from the reservoir and reduce pollution along the river. In this scenario, all demands, supply priorities, and allocations were similar to the first scenario, with the difference that the importance of the distribution is related to the environmental request in Bandeghir. At the end of the optimization process, the optimal environmental flow values obtained for the downstream of the river were used to manage the exploitation of water resources in the study area.

RESULTS AND DISCUSSION

Models calibration and validation

The r-squared, NSE, SE, and MAE calculations are presented to evaluate the simulation results, as shown in Table 4. According to the parameters mentioned above, the closer the value of MAE and SE to zero, and the r-squared and NSE value to one, the more accurate the model will be. A perfect NSE is noted in simulation for all parameters. For calibration and validation, NSE lies within the range of 0.779–0.995 and 0.916–0.996, respectively, which indicates a good simulation when using the present model. For calibration, the highest SE is 16.16% for discharge in Bamdezh station, and the lowest SE value is

Table 4 | The r-squared, NSE, SE, and MAE criteria values for calibration and validation of the WEAP and QUAL2 K models

		Calibration				Validation			
		r-squared	NSE	SE%	MAE	r-squared	NSE	SE%	MAE
Discharge (m^3/s) (WEAP)	Dezful station	0.99	0.995	6.23	3.12	0.99	0.996	6.11	2.87
	Harmaleh station	0.99	0.983	10.10	3.42	0.99	0.994	6.40	3.30
	Bamdezh station	0.98	0.968	16.16	8.3	0.99	0.997	4.78	0.23
Water Quality parameters (QUAL2 K)	Temperature (°C)	0.97	0.905	6.2	3.18	0.98	0.941	5.2	3.14
	pH	0.98	0.922	15.4	6.42	0.98	0.952	9.2	6.72
	EC (μmhos)	0.97	0.921	10.3	12.3	0.97	0.934	7.3	11.52
	DO (mg/L)	0.99	0.956	5.78	0.19	1	0.995	3.04	0.09
	BOD (mg/L)	0.93	0.779	5.74	0.10	0.94	0.916	6.38	0.16
	$N\text{-}NH_4$ (μg/L)	0.93	0.815	9.58	19.50	0.96	0.988	2.34	4.90
	$N\text{-}NO_3$ (μg/L)	0.98	0.961	8.65	83.18	0.98	0.971	5.11	51.96

5.2% for temperature. For validation, the highest SE is 6.40% for release in the Harmaleh station, and the lowest value is 2.34% for $N\text{-}NH_4$. The range of r-squared (0.93–1) calculated from the present simulation indicates how good the validated model is. Also, the low MAE means a good simulation when using the current models. The calibration error results are along with Da Silva & Alves (2016).

The results of implementing scenarios

As mentioned above, the optimization process was performed using FMOICA. In this process, 12 decision variables (environmental flow rate downstream of the river in different months) were optimized using a multi-objective function. Repeated running of the model showed that the initial number of countries must be at least twice the number of decision variables; hence, the initial population was 24. The results showed that in lower repetitions, both the function of water supply (coverage) (the first objective) and the function of violation from the permissible values of qualitative parameters (the second objective) experience significant changes. In contrast, in the higher iteration, the variation amplitude of the coverage function was fixed, and the model focuses on reducing the violation from the permissible values of qualitative parameters. The number of algorithm iterations to achieve convergence was estimated to be about 500. Given the initial population (24), the quantitative-qualitative linked model was implemented 12,000 times. In the FMOICA algorithm, the best solutions in each repetition are selected based on the evaluation of the objective functions and stored as an optimal repository to move to the next step. The optimal Pareto optimal front curve was obtained in the last iteration between the optimization objectives. Figure 5 shows the Pareto optimal front curve where the points offer the optimal solutions of the model, and the axes represent the number of objective functions. The last iteration of the model produced 18 optimal solutions, of which the best solution (9) with the highest percentage of coverage and lowest violation from the permitted values of the qualitative parameters was

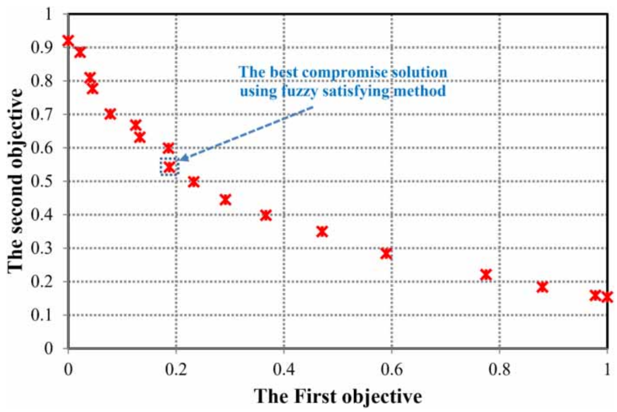


Figure 5 | The Pareto optimal front curve of objective functions (in iteration 500).

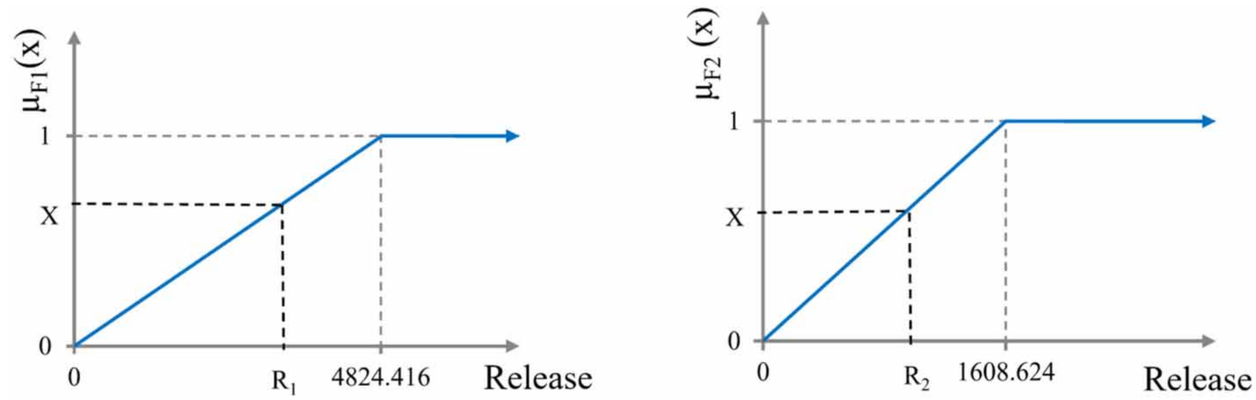


Figure 6 | Linear membership functions for releases from the Dez dam (MCM).

selected according to the evaluation of the objective functions, and the results of its implementation were evaluated in the quantitative-qualitative model.

The linear membership functions are given by Equation (17) for objective functions. Figure 6 shows graphical representation of the membership functions. The degree of satisfaction (X in Figure 6) achieved by solving linear membership

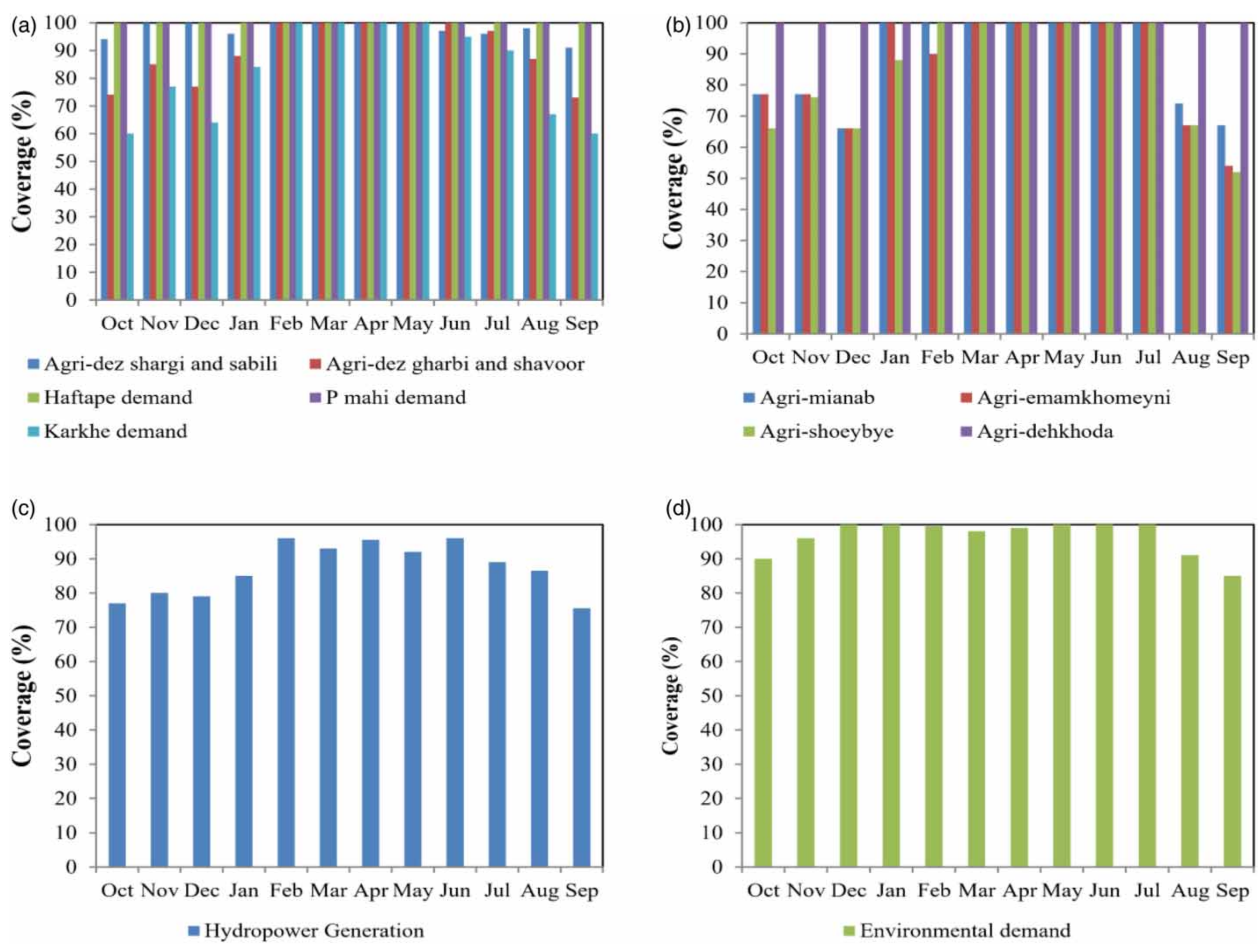


Figure 7 | (a) Coverage percentage of Dez plain upstream; (b) coverage percentage of Dez plain downstream; (c) power coverage percentage of Dez dam power plant; (d) environmental demand coverage (the reference scenario).

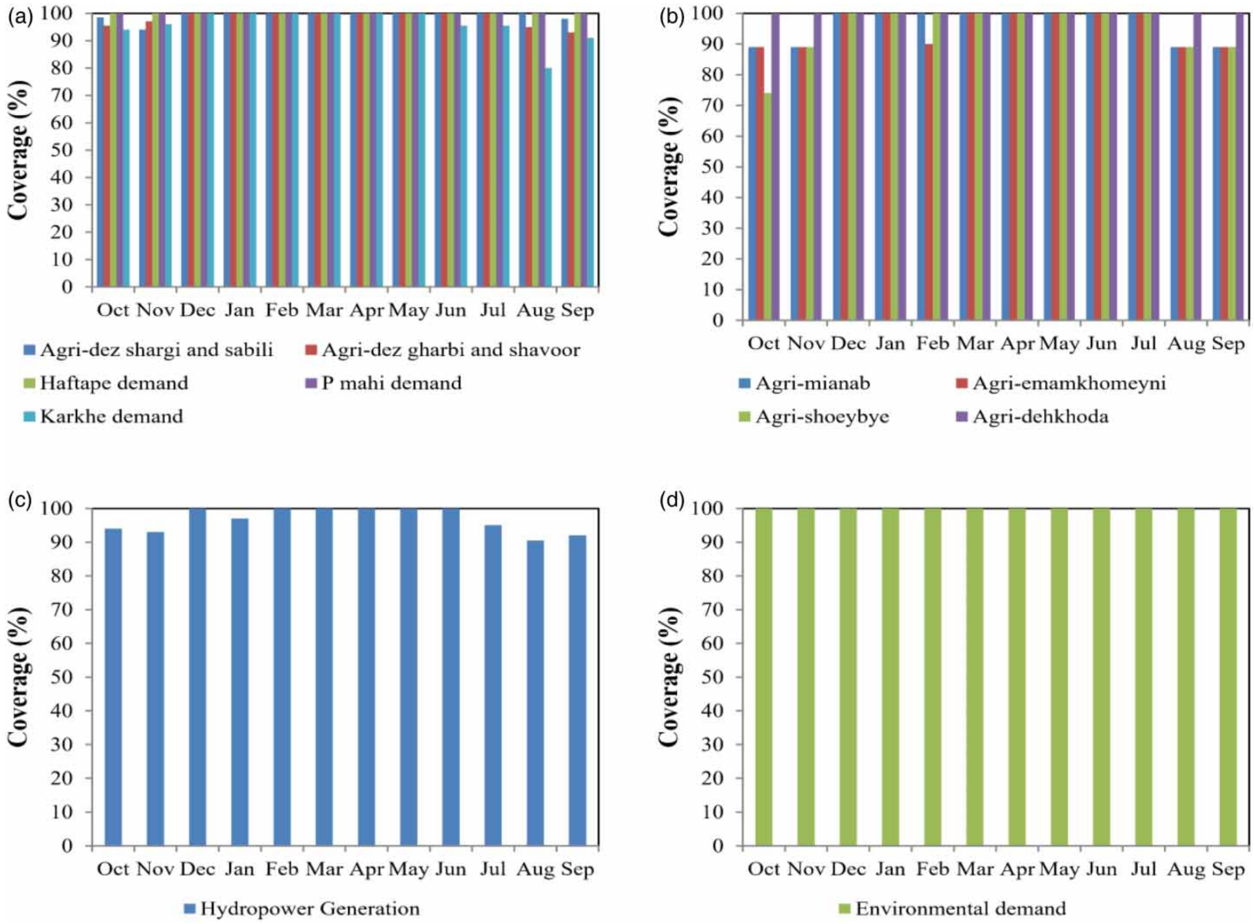


Figure 8 | (a) Coverage percentage of Dez plain upstream; (b) coverage percentage of Dez plain downstream; (c) power coverage percentage of Dez dam power plant; (d) environmental demand coverage (the optimal scenario).

Table 5 | The reliability of the water supply in the Dez plain

	Scenario	
Demand	**Reference**	**Optimal**
Agri-Dez Shargi & Sabili	88.19	98.83
Agri-Dez Gharbi & Shavoor	78	95.44
Agri-Dimche	100	100
Agri-Mianab	79.91	95.44
Agri-Emamkhomeyni	77.46	88.45
Agri-Shoeybye	76.25	89.5
Agri-Dehkhoda	100	100
Municipal demand	100	100
K. Haftape and P. Mahi demands	100	100
Karkhe demand	61.56	85.73
Environmental demand	86.1	100

functions are equal to 0.187 and 0.541 for objectives one and two, respectively, and the corresponding release values for them are R1 (3,936.88 MCM/year) and R2 (738.35 MCM/year), respectively.

The average monthly coverage percentage of water demands under the reference scenario is shown in Figure 8. The coverage percentage of water demand for each upstream user of the Dez Plain is shown in Figure 7(a). Since the priority of this scenario is to respond to the requests of large industries (K. Haftape and P. Mahi demand), these demands are fully supplied in all months. However, there has been some shortage in satisfying agricultural land demands in some of the summer and autumn months, which are simultaneously supplied by surface and groundwater. The lowest percentage of coverage is related to Karkhe water demand (60.2%), which is delivered only from the Dez river.

According to Figure 7(b), the coverage percentage of agricultural water demands is lower downstream of the river than that of upstream due to the downstream users of the Dez plain being supplied by surface water. Agri-Dehkhoda demand has been fully supplied throughout the year since it is located at the end of the river and following the environmental demands of the Bamdezh station. The lowest percentage of coverage was 52% for Agri-Shoeybye in September. Figure 8(c) represents the percentage of the Dez dam power coverage. The lowest rate of power coverage was 75.5% in September; also, the reliability of the power generation obtained was 58.3%. The lowest coverage percentage of environmental demand was 85% for September, as shown in Figure 7(d).

The percentage coverage for the upstream and downstream users of the Dez plain is shown in Figure 8(a) and 8(b) for the optimal scenario. The percentage of upstream coverage is over 90% for all users except for Karkhe demand. Figure 8(c) shows the percentage of power coverage generated by the Dez dam power plant in the optimal scenario. The power plant generates the power demands in this scenario with 91.67% overall reliability months. The optimal scenario considers the environmental coverage as the priority, and thereby the percentage of environmental coverage was calculated as 100% as shown in Figure 8(d). In this regard, Ma *et al.* (2021), in research to optimize water allocation for Nanning City in China, showed that using an optimization model increases the percentage of allocation to demands.

The reliability of water supply for the study area users, which are supplied simultaneously from surface and groundwater, is shown in Table 5. This table shows that the reliability of the water supply is improved in most cases in the optimal scenario compared to the reference scenario. Average water supply reliability increased from 86.13% in the reference scenario to 95.76% in the optimal scenario.

Fluctuations in the reservoir storage volume of the Dez dam in the optimal scenario were compared with fluctuations in the reference scenario. As seen in Figure 9, because of applying the constraint of non-violation of the reservoir storage minimum level during the planning period, the reservoir storage in the optimal scenario was never lower than the minimum storage level. This helps to manage the reservoir storage volume under severe drought conditions.

Since most of the water withdrawal from the Dez river is to supply the agricultural demands of the plain, the trends of the qualitative parameters of pollution changes including, temperature (T), pH, electrical conductivity (EC), ammonium-nitrogen ($N\text{-}NH_4$), nitrate-nitrogen ($N\text{-}NO_3$), biochemical oxygen demand (BOD), and DO (dissolved oxygen) were investigated at the agricultural water withdrawal point, between Dez dam and Bandeghir.

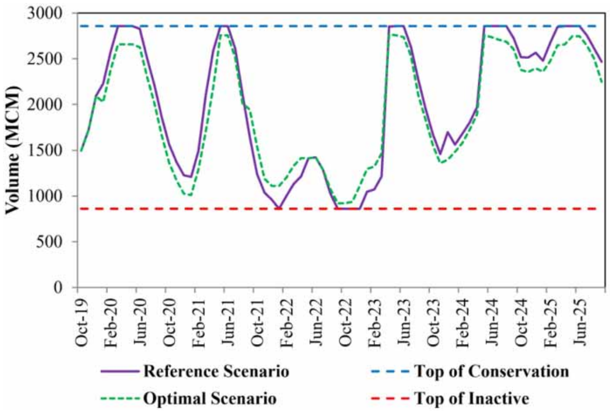


Figure 9 | Fluctuations in the reservoir storage volume of the Dez dam during the 6-year operation period for the reference and optimal scenarios.

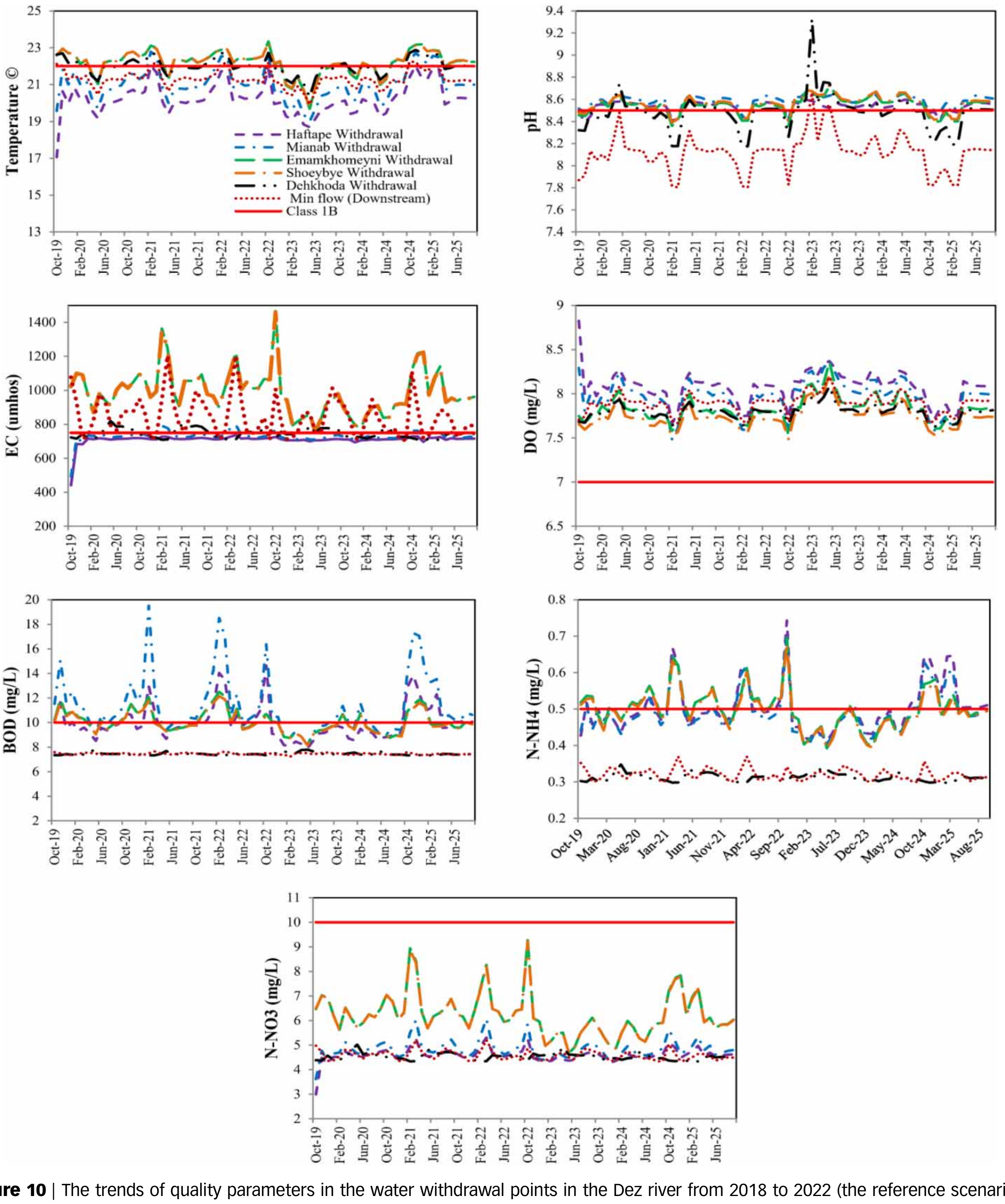


Figure 10 | The trends of quality parameters in the water withdrawal points in the Dez river from 2018 to 2022 (the reference scenario).

Figure 10 shows the trend of each parameter change at the agricultural water withdrawal site along the river under the reference scenario. According to Figure 10, the variations in BOD and N-NH_4 concentration, in most of the months in the water withdrawal sites except Min flow (downstream) and Dehkhoda, which are under the permissible limit, are more significant than the standard value considered for this parameter (standard Class1B), and thereby evaluated as undesirable. The amount of DO was higher than the permissible limit of this parameter in most months along the river; hence, the river

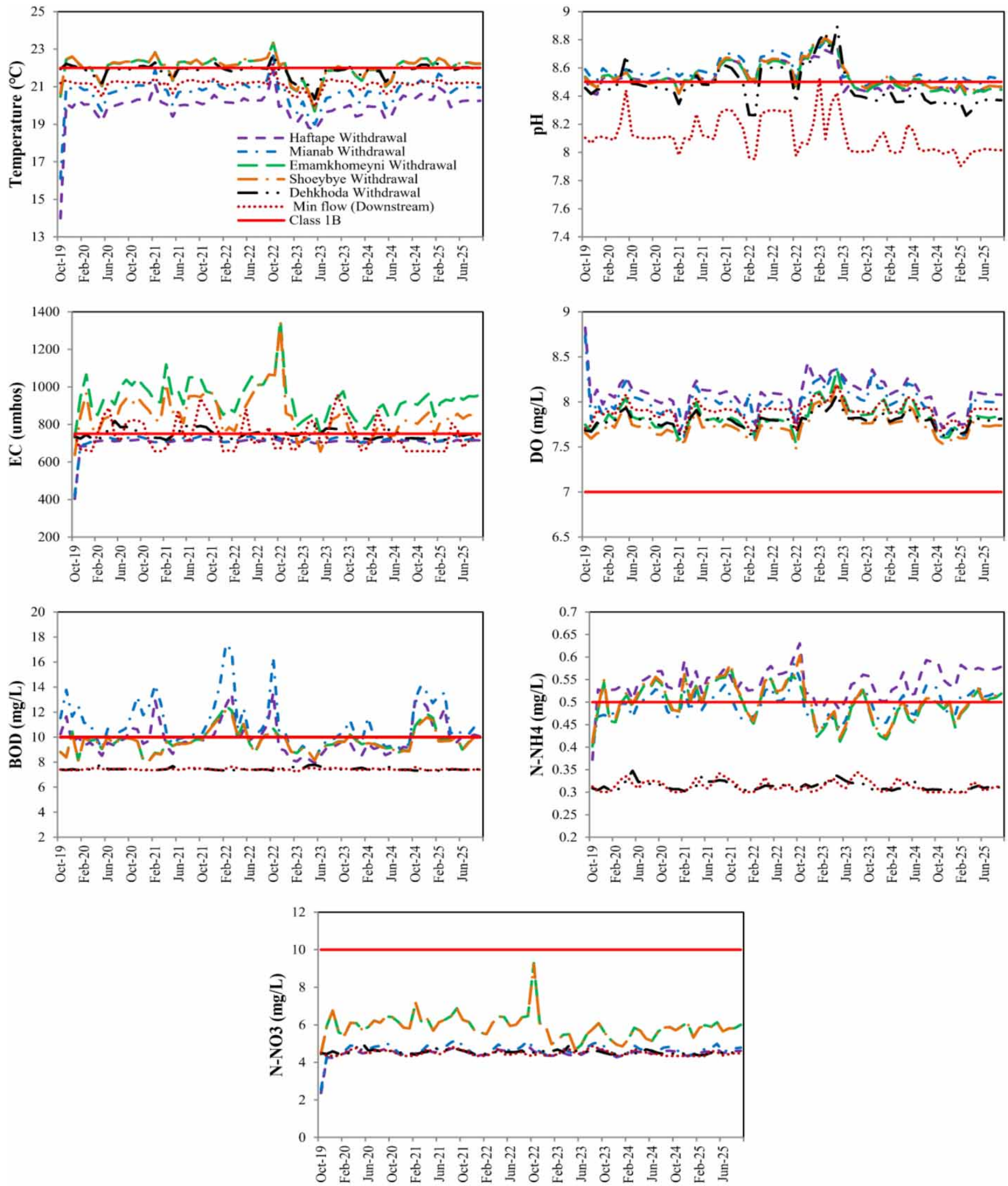


Figure 11 | The trends of quality parameters in the water withdrawal points in the Dez river from 2018 to 2022 (the optimal scenario).

status is favorable in this respect. The EC of water exceeds the permissible limit of this parameter in the standard Class1B in the water withdrawal sites except for K. Haftape, which is also considered undesirable. Also, this scenario results show that the river status in terms of N-NO_3 concentrations is quite favorable according to standard Class1B. Moreover, water temperature and pH trends in the water withdrawal sites of Emamkhomeyni, Shoeybye, and Dehkhoda are more significant than the standard value considered for this parameter.

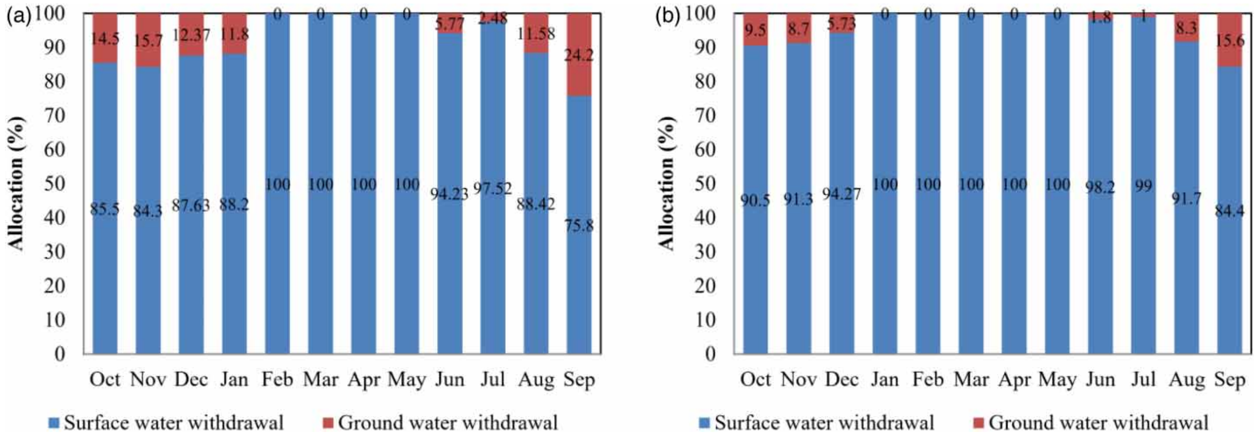


Figure 12 | Percentage of allocation from surface and groundwater sources of Dez Shargi demand under the reference (a) and optimal (b) scenarios.

Figure 11, shows the trend of qualitative parameters under the optimal scenario at agricultural water withdrawal sites. Due to using the optimization model and applying the qualitative objective function and the requirement of the system to supply the environmental flow rate along the river, the quality status of the river is more desirable in this scenario. This figure further shows that in the optimal scenario, the highest concentration of quality and pollution parameters and the least dissolved oxygen during the planning period is related to the Emamkhomeyni, Mianab, and Shoeybye withdrawal sites located downstream of the plain. However, the values of these parameters have significantly improved compared to the reference scenario. These changes are particularly evident for the parameters of BOD and N-NH_4. This demonstrates the efficiency of the optimization model in providing a solution that, in addition to supplying the demands with optimal reliability, also enhances the environmental status of the river in terms of quality changes and pollution. In other words, the amount of self-purification under the optimal scenario increased compared to the reference scenario.

As mentioned earlier, among the upstream agricultural lands, the Dez Shargi, Dez Gharbi, and Shavoor plains withdraw water from surface and groundwater resources simultaneously. Figure 12 show the percentage allocations of surface and groundwater resources under the reference and optimal scenarios in the Dez Shargi plain. As can be seen, the amount of groundwater harvested under the optimal scenario is 4.2%, which is reduced compared to the reference scenario (8.2%). In other words, under the optimal scenario, groundwater is conserved.

Figure 13 show the percentage allocations of surface and groundwater resources under the reference and optimal scenarios in the Dez Gharbi plain. As can be seen, the amount of groundwater harvested under the optimal scenario is 4.4%, which is reduced compared to the reference scenario (8.73%). In other words, under the optimal scenario, groundwater is conserved.

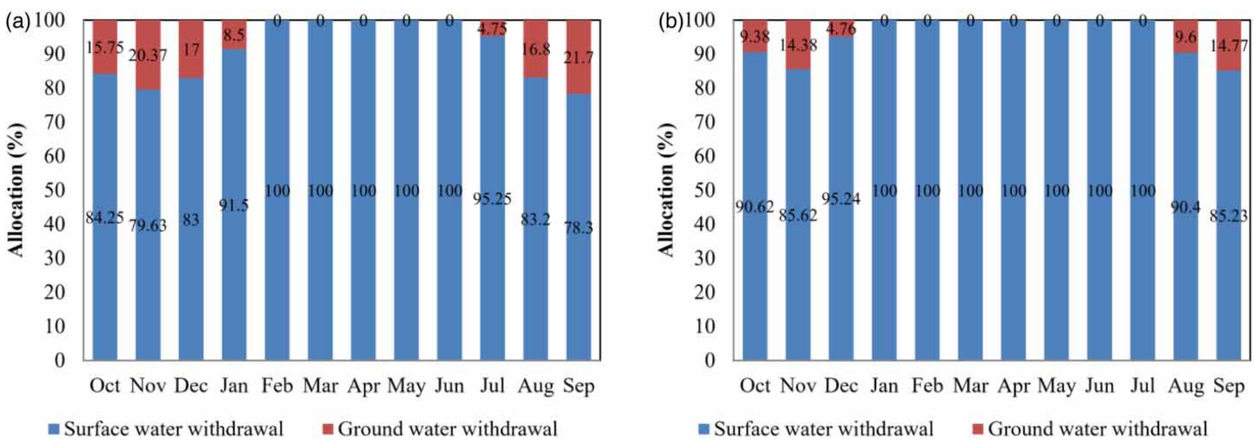


Figure 13 | Percentage of allocation from surface and groundwater sources of Dez Gharbi demand under the reference (a) and optimal (b) scenarios.

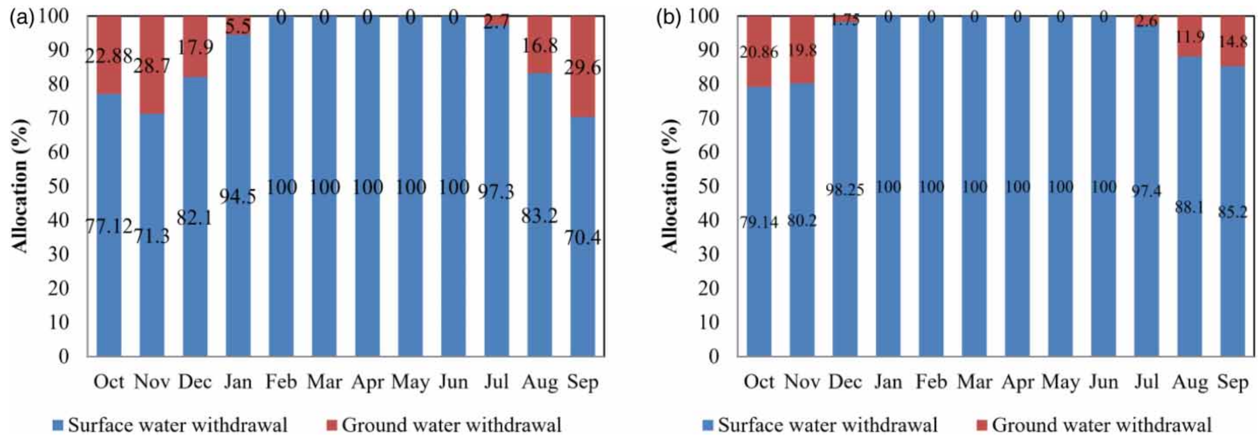


Figure 14 | Percentage allocation from surface and groundwater sources for Shavoor demand under the reference (a) and optimal (b) scenarios.

Figure 14 show the percentage allocations of surface and groundwater resources under the reference and optimal scenarios in the Shavoor plain. As can be seen, the amount of groundwater harvested under the optimal scenario is 5.97%, which is reduced compared to the reference scenario (10.34%). In other words, under the optimal scenario, groundwater is conserved.

CONCLUSION

The recorded values of qualitative and pollution parameters in the quality monitoring stations along the Dez River showed that the river is in critical condition in BOD pollution (due to discharge of urban and industrial wastewater) and EC pollution (due to drainage of agricultural lands). This study further showed no clear plan for controlling the water withdrawal rate throughout the river or controlling the concentration of these parameters and other important parameters such as DO, pH, N-NO_3, and N-NH_4. Therefore, it seemed necessary to use a comprehensive operation model that maintains water quality at the optimal level along the river. The proposed optimal model showed that the water quality along the river has improved, and the minor violations from the water quality standards for the river have occurred, especially in agricultural water withdrawing sites. Additionally, the environmental demand, which has changed due to the dam's construction and withdrawals from the river, was supplied and optimized. On the other hand, the plain's water demands were provided with higher reliability than the current condition, while the dam's storage capacity has been consistently above the minimum operating level. This helps to manage the reservoir storage volume under severe drought conditions. Under the optimal model, the amount of groundwater harvest in the downstream plains of the Dez Dam was reduced, which in turn preserved groundwater resources. Morever, the results of this study showed that linear stochastic models have high accuracy for predicting the inflow into the Dez dam reservoir. Also, since the objective functions were two different types, using the fuzzy function in the optimization algorithm helped prevent the scattering of the decision space by dimensioning the functions. According to the results, the dynamic linking of the WEAP and QUAL2 K models and then coupling the linked model to the body of a fuzzy optimization algorithm can provide better planning for proper operation of reservoir-river systems. This can be used as a model for water resource planners, especially in areas with different procedures and a variety of pollutants. But to run the coupled model requires robust computer systems and a long time, for this study took about 15 days, which was done with a 16-core system.

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AUTHORS CONTRIBUTION

Omid Babamiri presented the idea, performed the numerical modeling optimization coding, and wrote the paper; Arash Azari advised and observed the paper's scientific content; Safar Marofi edited and supervised the form of the document and methodology.

ETHICAL APPROVAL

The authors have agreed on submitting this article, and it is not currently under any consideration for publication in other journals.

CONSENT TO PARTICIPATE

The authors voluntarily agreed to participate in this research study.

CONSENT FOR PUBLICATION

The authors approved the publication of this study.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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