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Research Article

Application of modified two-point hedging policy in groundwater resources planning in the Kashan Plain Aquifer

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Abstract: Effective management of water resources, especially groundwater, is crucial and requires a precise understanding of aquifer characteristics, imposed stresses, and the groundwater balance. Simulation-optimization models plays a vital role in guiding planners toword sustainable long-term aquifer exploitation. This study simulated monthly water table variations in the Kashan Plain over a ten-year period from 2008 to 2019 across 125 stress periods using the GMS model. The model was calibrated for both steady-state and transient conditions for the 2008–2016 period and validated for the 2016–2019 period. Results indicated a 4.4 m decline in groundwater levels over the 10-year study period. Given the plain's location in a arid climatic zone with limited effective precipitation for aquifer recharge, the study focused on groundwater extraction management. A modified two-point hedging policy was employed as a solution to mitigate critical groundwater depletion, reducing the annual drawdown rate from 0.44 m to 0.31 m and conserving 255 million cubic meters (mcm) of water annually. Although this approach slightly decreased reliability (i.e. the number of months meeting full water demands), it effectively minimized the risk of severe droughts and irreparable damages. This policy offers managers a dynamical and intelligent tool for regulating groundwater extraction, balancing aquifer sustainability with agricultural and urban water requirements.

Keywords: Calibration; GMS; Groundwater simulation-optimization model; Modified two-point hedging policy; Sustainable operation

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Introduction

In recent years, Iran has experienced rapid population growth, limited surface water resources, and excessive groundwater extraction, resulting in a significant and often irreparable damage to natural resources. As a critical strategy, measure must be taken to prevent further deterioration of the current situation. According to an empirical rule, when water usage exceeds 30% of the total stored water of a source, water resource management becomes a vital component of the national economy (Vander Bruggen etal. 2003).

Groundwater resources, being closely interconnected with natural ecosystems and climatic conditions, are significantly affected by variations in temperature and precipitation. These changes directly impact water availability, particularly in arid regions. Considering these changes, the continuation of current trends in water supply and consumption is unsustainable for the country's water resources. Therefore, planning for the optimal and sustainable utilization of water resources has become increasingly important in recent years.

Given the variability in the temporal and spatial distribution of precipitation and its effects on water resources, optimizing water consumption is essential to maximize efficiency and maintain consumer satisfaction. This requires the formulation of decision-making frameworks that address multi-objec-

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tive approach from the outset, as these objectives are often conflict. Only through such a multi-objective approach can optimal solutions be developed to minimize social, economic, environmental, and political consequences, thereby enabling effective management of water supply and demand. Hence, devising optimal strategies for long-term water resource planning is both crucial and unavoidable.

In numerous studies, groundwater models have been integrated with optimization algorithms to develope water resource management strategies and identify optimal solutions based on specific objective functions and constraints (Ahlfeld et al. 2005; Yang et al. 2024). Typically, the optimization of groundwater reservoirs in a region begins with the development of a mathematical aquifer model. There are two primary approaches for utilizing such models to optimize groundwater reservoirs:

(1) Simulation-based approach: In this method the behavior of the aquifer, whether linear or nonlinear, is analyzed using a mathematical simulation model. The relationship between extraction rates and groundwater level decline is calculated, enabling optimization of the groundwater system based on these relationships.

(2) Combined simulation-optimization approach: In this approach, the hydrodynamic parameters of the aquifer are determined following the calibration of the simulation model. Subsequently, the objective function and constraints for the optimization model are defined simultaneously, leading to the integration of simulation and optimization models. A key strength of this method lies in its ability to re-run the simulation model for each adjustment in decision variables during the optimization process. This iterative approach ensures continuous refinement, resulting in a higher degree of accuracy compared to the first approach (Saghi Jadid et al. 2020).

In an ideal scenario, water allocation should be economically efficient, technically feasible, and socially equitable. Therefore, the development of an appropriate water allocation system that recognizes water as both a social and economic commodity is essential (Babel et al. 2005).

The construction of a simulation-optimization model that can: (1) capture the impacts of groundwater depletion on various decision-making processes, and (2) simultaneously address water allocation and consumption to formulate an effective aquifer management plan, is of particular importance.

Numerous studies have focused on the integration of simulation-optimization models and proposed effective solutions for achieving water resource sustainability. The following section provides a brief overview of some of these studies.

Shourian and Jamshidi (2022) explored the optimal performance of the Javah dam reservoir in western Iran by integrating hedging policies with the bat algorithm. The objective function was to minimize water shortage caused by the dam. Their results demonstrated that while the bat algorithm effectively optimizes reservoir performance, water scarcity is further reduced when a higher degree of freedom is incorporated into the operation rules. Men et al. (2019) improved the objective function of the hedging rule in Tianjin, China, by prioritizing water supply and accounting for the economic losses associated with water scarcity across various user groups. Using improved hedging rules (IHR) for urban water supply, their findingsindicated that these rules significantly increase the reliability of domestic water supply with high priority while mitigating detrimental water scarcity in agriculture. Sadeghi-Tabas et al. (2017) combined the multi-objective optimization algorithm (AMALGAM) with a groundwater model (Modflow 2005-NWT) in MATLAB to determine the optimal pumping rates for the Birjand Plain aquifer. The model aimed to minimize three objectives: Water shortages caused by unmet demands, water table declines, and Modified Shortage Index (MSI). One pareto-optimal solution revealed that maintaining a stable water table would result in 14.4 million cubic meters of unmet demands and an MSI of 3.95. The study highlighted the high efficiency of this approach in determining optimal aquifer management strategies. Srinivasan and Kranthi (2018) employed a multi-objective simulation-optimization (S-O) framework to develop piecewise linear hedging policies. By initializing an initial feasible solution based on a constant hedging parameter S-O framework, they enhanced pareto-optimal solutions and improved the computational efficiency of the multi-objective stochastic search-based optimization algorithm. Liu et al. (2018) established the optimal reservoir operation rules by integrating piecewise linear hedging with environmental flow and economic objectives. Similarly, Xu et al. (2017) employed two criteria, namely Conditional Value-at-Risk (CVaR) and forecast uncertainty, to improve reservoir operations under dry and extremely dry hydrological conditions. Their findings indicated that CVaR-based hedging outperformed traditional expected value-based hedging policies. Spiliotis et al. (2016) utilized a particle-swarm-optimization algorithm to derive optimal drought hedging rules. Their approach relied on identifying activation thresholds and rationing factors, with predefined activation functions reducing the number of parameters required for optimization. Wang and Liu (2013) proposed a framework that integrates inflow forecasting with a naïve hedging strategy to assess the performance of a water supply reservoir. Using gridded precipitation forecasts from a climate model, they forecasted reservoir inflows. Shiau (2011) derived analytical solutions for optimal hedging policies for a water supply reservoir, explicitly integrating reservoir release and carryover storage targets. These solutions were applied to two-point and one-point hedging strategies. Finally, Neelakantan and Pundarikanthan (2000) introduced an ANN-based Parameterization-Simulation-Optimization (PSO) framework to determine releases for a multi-reservoir system. This framework employed discrete hedging policies to optimize operational decisions effectively.

Considering that groundwater is the primary source of water supply in the study area, and recognizing the significant reduction in its volume in recent years due to population growth and drought, there is a pressing need for the optimal management of this resource to minimize damages caused by water scarcity. Achieving this goal requires revising current groundwater withdrawal policies to ensure sustainable use of these resources. While implementing such policies may temporarily result in water stress and reduced water supply, the long-term outcome will be less severe and less frequent water stress, thereby reducing associated damages over time.

This study aims to achieve the optimal management of groundwater resources by using a modified two-point hedging rule through Simulation-optimization models (MODFLOW-ACOA). The objective is to determine the best groundwater extraction strategy. With optimal extraction, the rate of groundwater depletion will be significantly reduced compared to the current trend scenario. Adopting this policy will help moderate existing stresses on water supply and lead to a more uniform and manageable failure process.

1 Materials and procedures

1.1 Geographical location of the study area

The unconfined aquifer of Kashan Plain covers an area of 1736 square kilometers and is situated at the foothills of the Karaks mountains, adjacent to the central desert of Iran. It lies approximately 240 kilometers south of Tehran, between longitudes 51°5' and 51°54' and latitudes 33°45' and 34°23'. According to the Domarton classification, the Kashan Plain and its southern mountainous regions are classified as arid and semi-arid, respectively. The plain itself resembles a narrow valley extending from northwest to southeast, with a width of approximately 20 kilometers. The maximum and minimum elevations are 1,300 meters and 800 meters above sea level, respectively, located at the western (foothills) and eastern (desert) margins of the valley. The mean annual precipitation and temperature in the area are 150 mm and 19°C, respectively. The geographical location of the study area, along with the distribution of rivers and piezometers, is illustrated in Fig. 1.

Using data from the piezometric wells and water level measurements, groundwater contour lines were generated. These equipotential lines also help illustrate the direction of groundwater flow. Groundwater contours range from 780 m in the northern and northwestern slopes to 1,260 meters in the southern slopes. Fig. 2 displays the groundwater depth contour lines.

To achieve the objectives of this study, the GMS package, in conjunction with the three-dimensional numerical model Modflow, was utilized to simulate the actual behavior of the groundwater system in the Kashan Plain aquifer. Subsequently, a combination of simulation model with the ant colony optimization algorithm, implemented in MATLAB, was used to develop and analyze a decision-making model applicable for the aquifer.

1.2 Groundwater conceptual model

In the MODFLOW model, the finite difference method is used to solve the differential equations. The governing equation for three-dimensional groundwater flow in an unconfined aquifer is derived from Equation (1).

$$\frac{\partial}{\partial x}\left(-K_x\frac{\partial h}{\partial x}\right)+\frac{\partial}{\partial y}\left(-K_y\frac{\partial h}{\partial y}\right)+\frac{\partial}{\partial z}\left(-K_z\frac{\partial h}{\partial z}\right)=$$
$$S_s\frac{\partial h}{\partial t}+S_y\frac{\partial h}{\partial t}\mp q(xyz) \tag{1}$$

Where: h is groundwater level, q represents the rate of recharge or discharge from the aquifer, k is the hydraulic conductivity (HK), and t is time. In practice, the specific storage coefficient (S_s) in an unconfined aquifer is much smaller than the specific yield (S_y), and therefore it is often neglected.

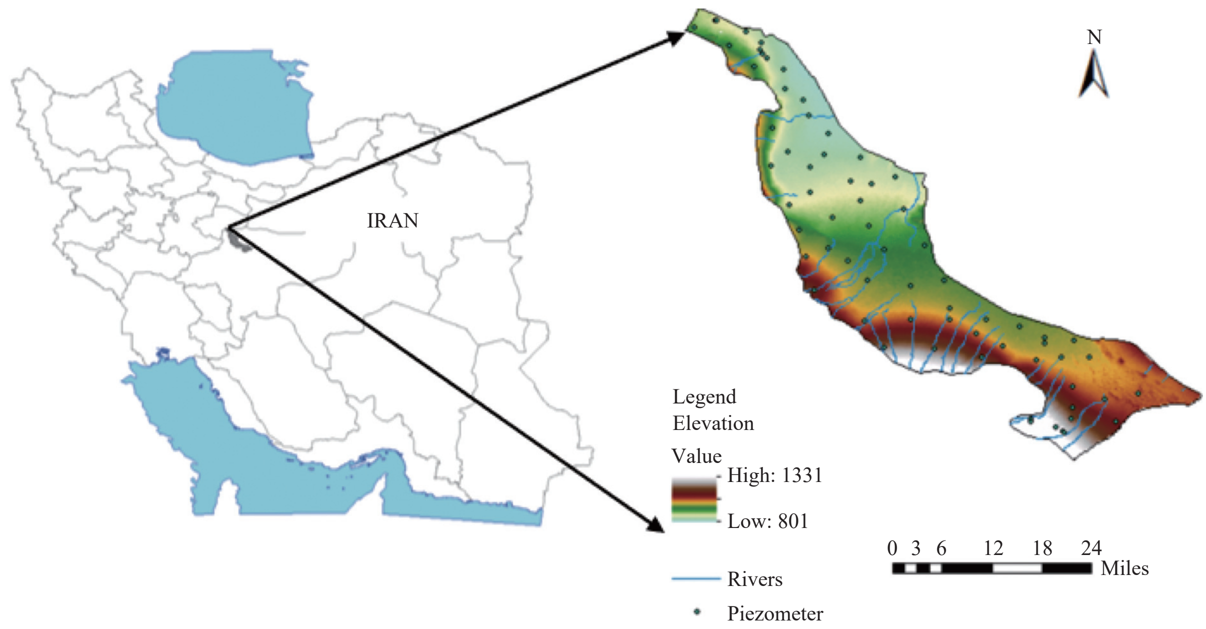

Fig. 1 Location of the study area in Iran

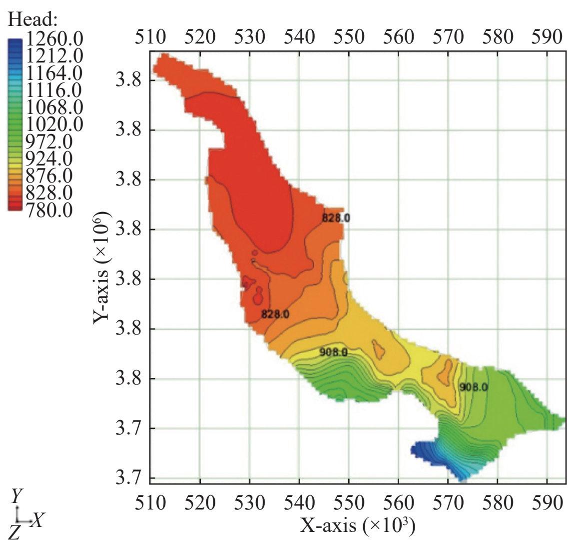

Fig. 2 Contour lines of groundwater level

The conceptual model of the Kashan aquifer was developed considering factors such as groundwater recharge and discharge, boundary conditions, and recharge areas. This model was implemented in MODFLOW using a 500×500 meter grid, applied to both steady-state and transient conditions over a period of 10 years, from October 2008 to February 2019. The model includes 125 stress periods with a monthly time step.

The total number of cells created in the model, based on a 115-row by 120-column grid, is 13,800, with 11,076 cells being inactive and 2,724 cells active. Water level measurement in Kashan started in 1965 with 100 piezometers, and as of the latest data, there are 56 active piezometers in the area. The only source of surface recharge considered in the model is return water from urban and agricultural uses, at rates of 80% and 15%, respectively. The groundwater extraction resources in the study area include 1,958 wells, 268 springs, and 540 qanats. The contribution of each resource, from various locations and elevations within the plain, along with the extraction rate for each source, is detailed in Table (1). The total water consumption in this area is 399 million cubic meters (mcm), including 95.361 mcm per year from groundwater (wells and qanats) and 68.37 mcm per year from surface water flows and springs. Table (2) presents the information on water consumption in Kashan Plain.

After developing the simulation model, its accuracy was assessed and evaluated using criteria such as Mean Error (ME), Modified Regression Coefficient (bR^2), and Root Mean Square Error (RMSE). The formulas for these criteria are given in Equations (2), (3), and (4).

$$\mathrm{ME} = \frac{\sum_{i=1}^{n} (h_o - h_s)_i}{n} \tag{2}$$

$$bR^2 = \frac{n\left(\sum h_o \times h_s\right) - \left(\sum h_o\right)\left(\sum h_s\right)}{\sqrt{\left[n\sum h_o^{\,2} - \left(\sum h_o\right)^2\right]\left[n\sum h_s^{\,2} - \left(\sum h_s\right)^2\right]}} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (h_o - h_s)_i^{\,2}}{n}} \tag{4}$$

Table 1 The number and discharge of groundwater resources (mcm)

Alluvial aquifer		Total range		Heights		Plain		Resource
Discharge	Number	Discharge	Number	Discharge	Number	Discharge	Number	
239.42	961	267.36	1958	25.86	987	241.5	971	**Well**
0	0	27.90	268	27.90	268	0	0	**Spring**
6.46	33	97.37	540	88	504	250.9	36	**qanat**

Table 2 Water consumption and its resources by plain and heights areas (mcm)

Surface water and spring				Groundwater (well and qanat)			
Total	agriculture	Industry	Urban	Agriculture	Industry	Urban	
261.13	1.85	0	8.50	268.29	5.37	27.11	**Plain**
88.50	26.61	0.21	0.51	51.11	1.16	8.90	**Heights**

Where: h_o is the observed groundwater level; h_s the calculated groundwater level obtained from the simulator; b denotes the regression coefficient.

Considering the simplifications, data limitations, uncertainties in reconstructing missing data, and other inherent model limitations, the mathematical model required calibration. After several iteration in both steady state and transient stress periods (94 months), using over a dozen variables in pilot point form and the computational engine PCGN, two parameters, specific discharge and hydraulic conductivity, were calibrated.

To evaluate the optimal parameter values during the calibration period, a validation period was conducted with 31 monthly stress periods. After completing the calibration and validation processes and confirming the model's performance accuracy, groundwater level simulation for the study period (2008–2019) was carried out.

1.3 Optimization algorithm

Optimizing groundwater extraction does not necessarily mean finding the best solution, as model simplifications and uncertainties in problem-solving make it impossible to determine a truly optimal solution (Nguyen et al. 2014).

In recent years, meta heuristic algorithms have been widely used to solve optimization problems, particularly in the filed of water resources management (Ketabchi and Ataie-Ashtiani, 2015a). According to studies by Ataie-Ashtiani and Ketabchi (2015b), the Ant Colony Optimization (ACO) algorithm is one of the most effective optimization method in this field. The ACO algorithm operates by finding potential solutions based on pheromones. In this study, the GMS simulation model was combined with the ACO algorithm, implemented using MATLAB programming. In the next step, decision variables, constraints, limitations, and objective functions were introduced into the optimization model. This approach enhances accuracy, as the simulation model rerun each time the decision variables are adjusted. Fig. 3 provides a brief overview of the study process.

1.4 Hedging rules

In this study, the hedging rules that have been applied to reservoir operation are employed to manage the operation of aquifers. These rules were first conceptually introduced by Hashimoto and colleagues in 1982 and have evolved over time. The rules are derived from the Standard Operation Policy (SOP) curve, which adjusts the release from the reservoir in such a way that a certain storage volume is preserved for future drought periods. This modification aims to replace severe scarcity during the operation period with smaller, but more prolonged scarcities. Various hedging rules have been developed, which can be classified into the following categories:

1. One-point hedging rule: In this rule, the release starts from zero and increases linearly until it reaches the desired release amount, similar to the SOP curve.
2. Two-point hedging rule: This rule starts from the first point and increases linearly until it reaches the second point. The slope of the line is less than one, and it intersects with the target release amount at the second point.
3. Three-point hedging rule: In this rule, an additional point is added between the two points of the two-point hedging rule. This creates two linear segments with different slopes.
4. Continuous hedging rule: In this rule, the slope of the hedging segment can change continuously.

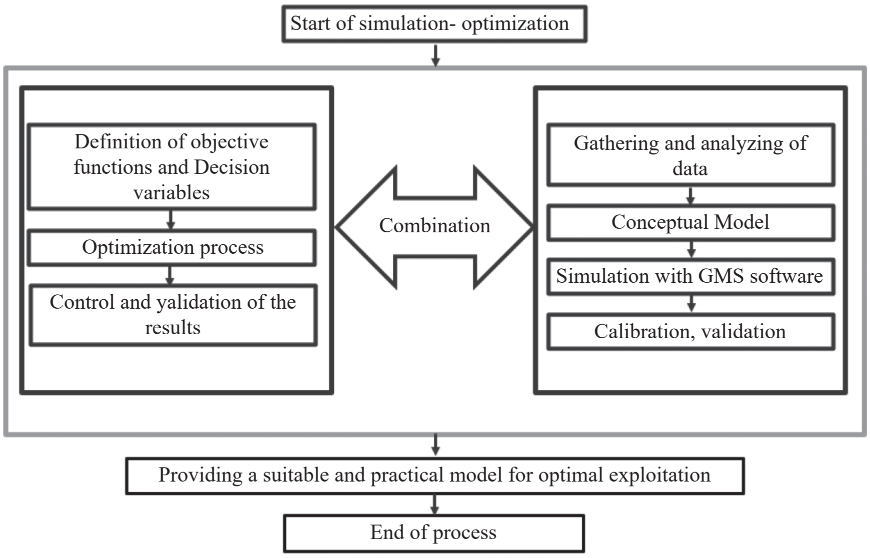

Fig. 3 Overview of integrated simulation-optimization model

5. Zone Based hedging rule: In this rule, releases are defined as ratios of target requirements, which vary in each different zone.

Fig. 4 shows the Types of hedging rule.

In this study, a modified two-point hedging rule (Fig. 5), proposed by Srinivasan and Philipose in 1998, was used to manage the operation of groundwater resources. The start and end points of the two-point hedging policy are represented by the Start Water Available (SWA) or (End Water Available) (EWA) respectively. When the available water drops below the SWA, all available water is released to meet demand. If the available water exceeds the EWA, the hedging stops, and normal operation resumes. When the available water falls between the SWA and EWA, hedging is applied, and a portion of the demand is provided to increase storage. In the modified two-point hedging approach, in addition to defining the decision variables of SWA and EWA, the value of the Hedging Factor (HF) is specified. This factor addresses the question, "*How much water should be hedged?*" in addition to the start and the end periods of the hedging process (Bhatia et al. 2018).

1.5 Modified two-point hedging rule for the operation of aquifer

Given that the Modified two-point hedging rule has been used for the management of surface water resources, specifically dam reservoirs of, it is necessary to make proportional changes to these

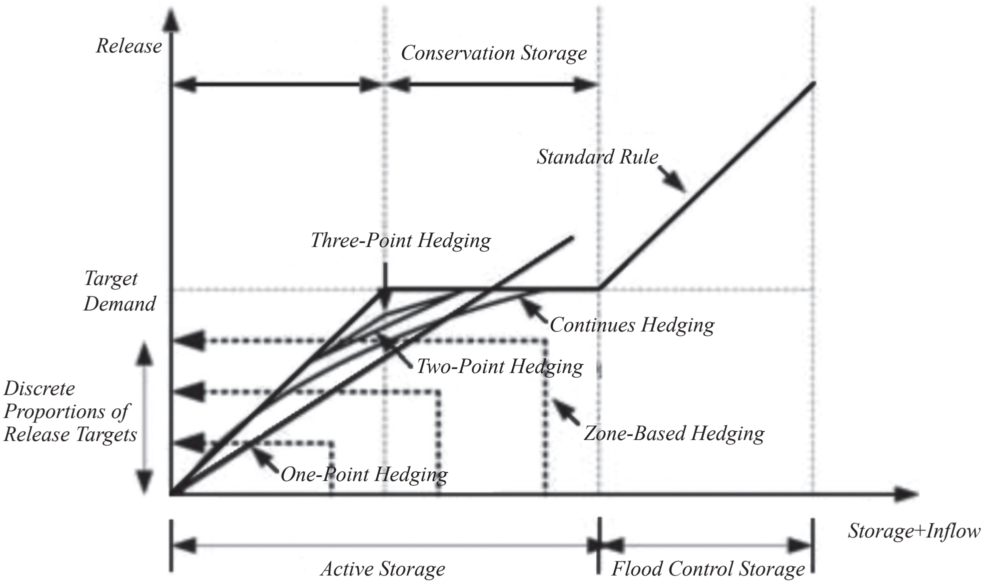

Fig. 4 Types of hedging rule (Shourian and Jamshidi. 2022)

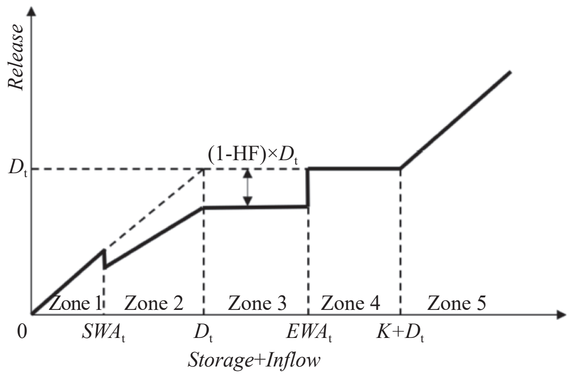

Fig. 5 Modified two-point hedging rule

rules for the operation of groundwater resources, considering the constraints of aquifers. In groundwater management, these resources are treated as reservoirs; however, they differ from dam reservoirs due to their nature. In dam reservoirs, the water level can be determined through volume-height curves based on water release; but in groundwater resources, the soil properties also play a role, making the process more complex. The equations used in the modified hedging rule for groundwater operation management are as follows:

$$GE_t = 0.7 \times GS_t + I_t \ \ if\ (0.7 \times GS_t + I_t) \leqslant SWA_t \quad (5)$$

$$GE_t = (0.7 \times GS_t + I_t) * (1 - HF) \ \ if\ SWA_t \leqslant (0.7 \times GS_t + I_t) \leqslant D_t \quad (6)$$

$$GE_t = D_t * (1 - HF) \ \ if\ D_t \leqslant (0.7 \times GS_t + I_t) \leqslant EWA_t \quad (7)$$

$$GE_t = D \ \ if\ (0.7 \times GS_{max} + D_t) \leqslant (0.7 \times GS_t + I_t) \quad (8)$$

The constraint conditions of the proposed optimization model are given by Equations (9)-(10).

$$0 \leqslant HF \leqslant 1 \quad (9)$$

$$GS_{min} < GS_t \leqslant GS_{max} \quad (10)$$

In Equations (5)-(10), GE_t represents the groundwater extraction volume at time t, GS_t denotes the groundwater storage at time t, and It refers to the infiltration of precipitation and return water into the aquifer at time t. The coefficient 0.7 is the allowable extraction volume of the aquifer, determined based on its characteristics. D represents the projected groundwater demand, SWA_t denotes the start water availability at time t, varying from 0 to D. EWA_t is the ending water availability at time t, which can vary from D to D+ 0.7 × GS_{max}. GS_{max} is maximum storage of groundwater, and HF represents the hedging factor. If either SWA or EWA equals D, the hedging mechanism does not apply, and the operation follows the normal operation policy.

1.6 Decision variables and objective functions in multiobjective optimization model

The parameters SWA and EWA act as thresholds for the start and end of hedging, respectively, and can take various values within the specified range, leading to different hedging rules. In this study, these two parameters, along with hedging factor, are considered as decision variables, and their optimal values are determined through optimization. The objective functions of this model aim to minimize the drop in the water table and the Modified Shortage Index, as follows.

$$minimize\ DrawDown = \overline{H}_0 - \overline{H}_{end} \quad (11)$$

$$minimize\ MSI = \frac{100}{T} \sum_{t=1}^{n} \left(\frac{GE_t - D_t}{D_t} \right)^2$$
$$t = 1, 2, 3, \cdots\cdots, T \quad (12)$$

Where: $\overline{H}_0$ and $\overline{H}_{end}$ denote the groundwater level at the beginning and ending of the simulation period, respectively, and D_t represents the monthly average water demand from the aquifer during period t. As seen from Equations (11) and (12), these two objective functions are contradictory: An increase in one leads to a decrease in the other.

1.7 Indicators used in groundwater

Groundwater sustainability indicators evaluate the status of groundwater resources based on monitoring programs. These indicators offer insights into both the current and future state of the groundwater system. They analyze both the temporal and spatial dimensions of human activities and the natural processes impacting the groundwater system. The use of these indicators helps in achieving meaningful results and enhances the connection and effectiveness between policy-making and planning (UNESCO, 2007). Equations (13)-(16) represent the vulnerability, reliability, resilience, and sustainability indexes used in this study, respectively.

$$Vul = \frac{\sum_{t=1}^{T} (D_t - GE_t | GE_t < D_t)}{[N_{t=1}^{T} (GE_t < D_t)] \sum_{t=1}^{T} D_t} \quad (13)$$

$$Rel = \frac{\sum_{t=1}^{T}(GE_t > D_t)}{T} \tag{14}$$

$$Res = \frac{N_{t=1}^{T}(D_{t+1} \leqslant GE_{t+1}|GE_t < D_t)}{N_{t=1}^{T}(GE_t < D_t)} \tag{15}$$

$$SI = \sqrt[3]{(1-Vul)*Res*Rel} \tag{16}$$

2 Results and discussion

After developing the groundwater behavior simulation model and incoporating all necessary data, boundary conditions, and initial conditions into the GMS model, a simulation was conducted with 125 monthly stress periods: 94 months for calibration and 31 months for validation of the hydrodynamic parameters. This process was performed to ensure the accuracy of the simulation model. The automated calibration method (Parameter ESTimator, or PEST) was used for parameter calibration. Table (3) summarizes the values obtained during the transient calibration stage for the hydraulic conductivity (HK) and specific yield (Sy) parameters. It is noteworthy that while the maximum value of hydraulic conductivity may initially appear high (in the calibration stage), it should be noted that in the MODFLOW model, hydraulic conductivity refers to horizontal hydraulic conductivity, which can be several times greater than total or vertical hydraulic conductivity.

Fig. 6 illustrates the correlation between observed and calculated values during the calibration (first month) and validation (last month) stress periods. For the parameters of hydraulic conductivity and specific yield, the Inverse Distance Weighting (IDW) interpolation of pilot points is used to generate their distribution, as showed in Fig. 7.

To evaluate the model's accuracy in simulating groundwater levels, a comparison between calculated and observed data was performed using evaluation criteria. The results of this assessment are presented in Table (4).

Based on these results and the small difference between the observed and calculated water table, it can be concluded that the model accurately simulates groundwater flow in the aquifer. After confirming the simulator model's reliability, groundwater levels were simulated for the study period of 2008–2019. The groundwater level in October 2008 was recorded at 887.683 m, decreasing to 883.260 m by February 2019, indicating a 4.4 m drawdown over the 10-year period. This corresponds to an average annual decline of 0.44 m due to the current extraction practices.

Subsequent simulations were conducted to analyze variations in the water table until the year 2028 under three scenarios: The current extraction trend, a 15% increase, and a 15% decrease in groundwater extraction. Fig. 8 illustrates the changes in groundwater levels under these scenarios, while Table (5) summarizes the simulation results of the aquifer behavior. According to the GMS model outputs, the water table will decrease by 11.8 meters (6.9 meters) over a 20-year period (2008–2028) under a 15% increase (decrease) in extraction. With minimal effective rainfall in the region and limited groundwater recharge, if the current extraction trend continues, the water table will drop by 9.8 meters by the end of 2028.

Completing the above steps, the ant colony algorithm for optimizing the modified two-point hedging rule was integrated with the groundwater level simulator model in MATLAB. For the integrated model, two objective functions were defined: Minimizing the water table dropdown and minimizing the Modified Shortage Index (MSI). These two objectives are inherently conflicting, as reducing one typically results in an increase in the other. In such cases, a single optimal solution is rarely available. Instead, a set of optimal solutions known as the Pareto front is generated. Fig. 9 shows the set of optimal solutions obtained from 3,000 iterations of the integrated model. As shown in the figure, when groundwater depletion is at 0.44 m, all demands are met without any shortage. However, over time, with the implementation of the hedging policy, although the depletion gradually decreases, which is desirable, a supply scarcity emerges, which is undesirable. As the Kashan plain relies solely on its aquifer for water supply, with no alternative source available, managing groundwater resources becomes crucial. The relative optimal solution selected from the Pareto front are in Fig. 9 using three distinct colors: the yellow dot (solution A), red dot (solution B), and orange dot (solution C). Each solution represents a trade-off between groundwater drawdown and demand shortages.

The selection of points A and C is based on their alignment with the optimization objectives. The yellow point (A) corresponds to minimizing the Modified Shortage Index (MSI), while the orange point (C) prioritizes minimizing the groundwater drawdown. A more balanced solution, optimizing both objectives relatively, is considered ideal. The red point (Solution B) represents this optimal balance. It was selected as the ideal scenario because, beyond this point, the unmet demand

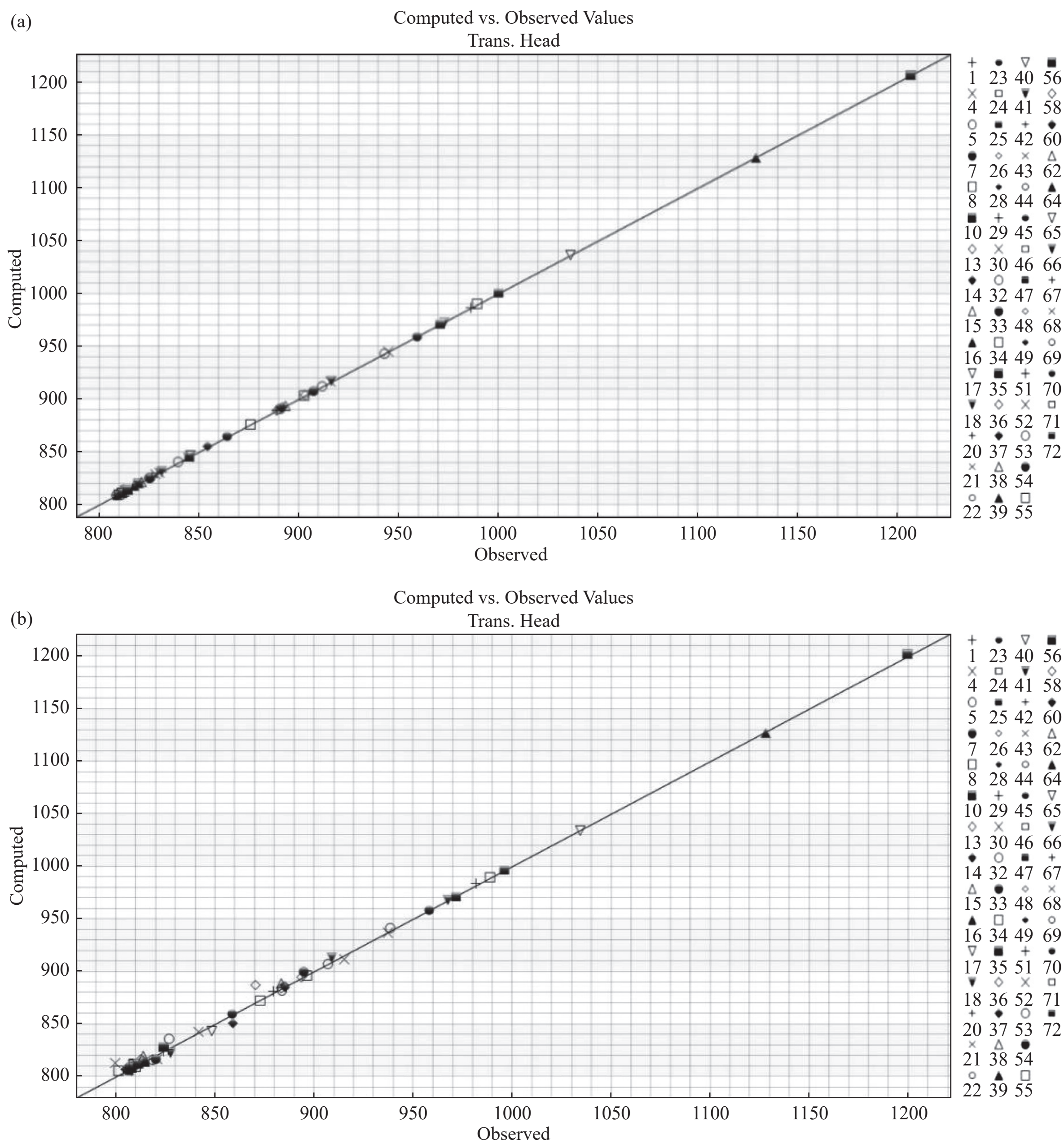

Fig. 6 Correlation between observed and calculated groundwater levels: (a) calibration (first month) (b) validation (last month) for the piezometers located in the area

increases significantly, making hedging management impractical.

After identifying Solution B as the relative optimal choice, the decision variables, HF, SWA, and EWA, were determined using the ant colony optimization algorithm, as shown in Table 6. The table reveals that the hedging factors peak during the hot months, indicating that the most significant demand shortage occur during these months. In contrast, hedging factors decrease during the colder months of the year.

By considering two conflicting objective functions, the model moderates the increasing trend of hedging factor during warm months and the decreasing trend during the cold months, achieving a balanced approach to groundwater management.

To evaluate the performance of the aquifer system under the modified two-point hedging policy, reliability, resilience, vulnerability, and sustainability indices were employed throughout the study period. Each indicator was addressed as a separate optimization problem. The results of the evaluation indicators are presented in Table 7. As shown in the table, while reliability decreases under the modified two-point hedging policy, the severity of scarcity during the study period is reduced. This reduction mitigates the damages

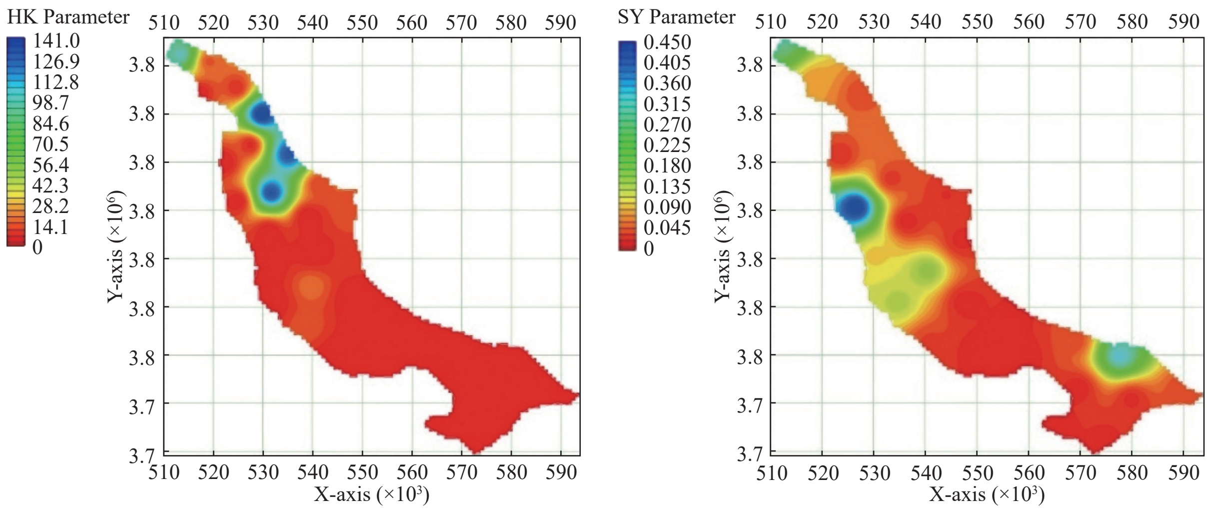

Fig. 7 Interpolation of calibrated hydraulic conductivity and specific yield

Table 3 Parameter statistics obtained from transient calibration

Standard deviation	Mean	Min	Max	Parameter
0.081	0.072	0.0026	0.45	**Sy**
29.5	15.73	0.003	139.5	**HK (m/d)**

Table 4 Error evaluation criteria for the simulation model

ME (m)	RMSE (m)	bR2	Stage
0.64	0.34	0.95	**Calibration**
0.82	0.41	0.89	**Validation**

associated with unmet demand.

Table 8 presents a comparison of various extraction scenarios. The implementation of the rationing scenario results in an annual decline of 0.31 meters in groundwater levels, whereas a 15% reduction in extraction leads to an annual decline of 0.35 meters. These findings suggest that the rationing scenario outperforms the 15% reduction scenario in terms ofgroundwater level preservation.

3 Conclusion

This study utilized the MODFLOW model, with user-friendly interface GMS (version 10.4), to

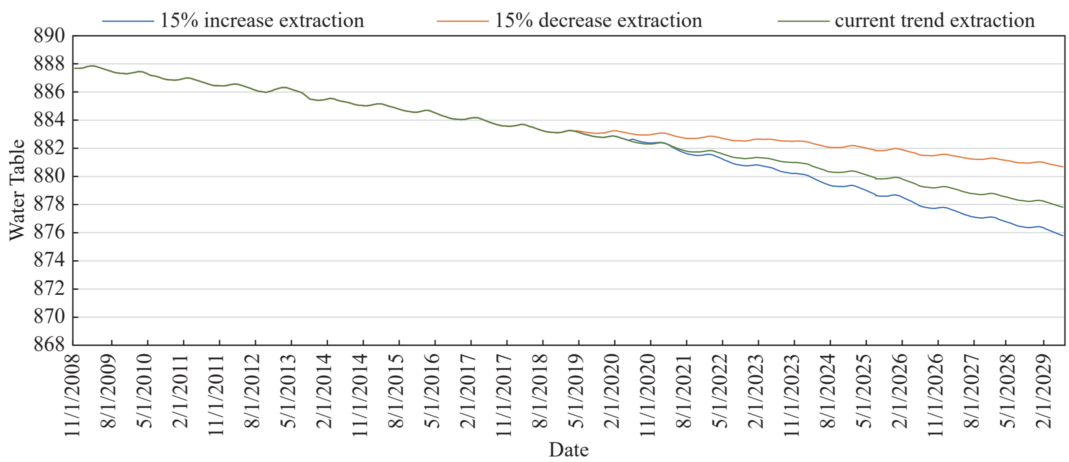

Fig. 8 Trend of groundwater level changes under different aquifer extraction scenarios

Table 5 Results of the three groundwater extraction scenarios

15% decrease in extraction	15% increase in extraction	Current extraction trend	
887.6	887.6	887.6	**Water table of the first month (2008)**
880.6	875.78	877/81	**Water table of the last month (2029)**
−6.9	−11.9	−9.8	**Groundwater drop**

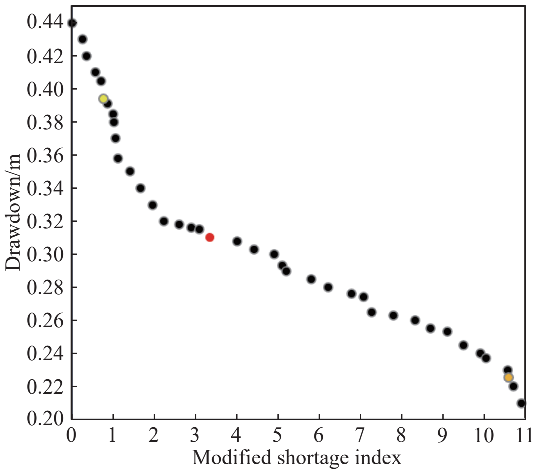

Fig. 9 Pareto fronts for the objective functions obtained using the ant colony optimization algorithm

Table 6 Decision variables of the modified two-point Hedging

EWA(MCM)	SWA(MCM)	HF	Month
207.65	21.2	0.36	October
180.02	13.06	0.22	November
134.89	11.32	0.35	December
101.35	7.89	0.22	January
95.65	10.94	0.26	February
104.87	10.97	0.35	March
115.36	10.69	0.38	April
139.12	14.08	0.48	May
150.23	24.56	0.51	June
208.84	30.21	0.55	July
211.54	33.47	0.64	August
133.62	25.76	0.49	September

Table 7 Performance criteria for supply-demand management using the modified two-point hedging policy

Sustainability	Vulnerability	Resilience	Reliability	Selected Optimal solution	
				MSI	Drawdown
51	62	46.06	77.46	3.35	**0.31**

Table 8 Comparison between extraction scenarios

MTPHP(Modify Two Point Hedging Policy)	15% decrease extraction	Current trend extraction	Extraction scenario
0/31	0/35	0/45	**Groundwater depletion (m/a)**

simulate groundwater behavior in the Kashan plain aquifer over 125 monthly stress periods (2008–2019). The model was calibrated and validated in both steady state and transient condition using 94 monthly stress periods, with the remaining 31 monthly stress periods reserved for validation.

To evaluate the calibration and validation accuracy, the criteria of Mean Error (ME), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were used. The results demonstrated that the model accurately estimates the aquifer parameters. The simulation results indicated a 4.4-meter drop in groundwater levels over a 10-year study period. Further simulations, extending to 2029, revealed a significant decline in groundwater levels in the Kashan Plain under three scenarios: the current withdrawal trend, a 15% increase in withdrawal, and a 15% decrease in withdrawal. The western areas are projected to experience the greatedest decline due to a higher concentration of operation wells.

Given the declining trend of the aquifer's volume, an effective solution for groundwater recharge and aquifer management is optimal withdrawal regulation using the modified two-point hedging policy. To achieve this, the Ant Colony Optimization (ACO) algorithm was integrated with the simulation model in MATLAB, including all objective functions and constraints. The implementation of this policy resulted in a reduction in the average annual groundwater level drop from 0.44 m to 0.31 m, which corresponds to a conservation of 225 million cubic meters of water annually in the aquifer.

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