



Optimization of groundwater artificial recharge systems using a genetic algorithm: a case study in Beijing, China

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Abstract

An optimization approach is used for the operation of groundwater artificial recharge systems in an alluvial fan in Beijing, China. The optimization model incorporates a transient groundwater flow model, which allows for simulation of the groundwater response to artificial recharge. The facilities' operation with regard to recharge rates is formulated as a nonlinear programming problem to maximize the volume of surface water recharged into the aquifers under specific constraints. This optimization problem is solved by the parallel genetic algorithm (PGA) based on OpenMP, which could substantially reduce the computation time. To solve the PGA with constraints, the multiplicative penalty method is applied. In addition, the facilities' locations are implicitly determined on the basis of the results of the recharge-rate optimizations. Two scenarios are optimized and the optimal results indicate that the amount of water recharged into the aquifers will increase without exceeding the upper limits of the groundwater levels. Optimal operation of this artificial recharge system can also contribute to the more effective recovery of the groundwater storage capacity.

Keywords Artificial recharge · Optimization model · Genetic algorithm · Numerical modeling · China

Introduction

Artificial recharge plays a vital role in the sustainable management of groundwater resources. More storage of water in aquifers via artificial recharge is necessary to save water in times of water surplus for use in times of water shortage (Oki and Kanai 2006). Particularly in some arid or semi-arid areas, it is necessary to develop effective and efficient artificial recharge systems to supplement aquifers. Many artificial recharge systems have been implemented around the world in the last few decades (Al-Assa'd and Abdulla 2010; Babcock and Cusing 1942; Peters and Ji 2010; Wright and du Toit 1996).

Beijing in eastern China, with a population of over 19 million (BSB 2011), has been exploring groundwater as the major water supply source for decades. Persistent overexploitation of groundwater has resulted in alarming water level decline and some large regional groundwater depression cones have developed. Recovery from overexploitation is expected to be very slow. For this reason, China initiated the Middle Route Project (MRP) for the South-to-North Water Transfer Project (CCSNWD 2008), which will provide more water for the recovery and efficient management of groundwater resources (Li et al. 2017) such as artificial recharge of groundwater.

However, designing the feasible and efficient operation of an artificial recharge system is far from simple because human activities have placed various constraints on land use, and the aquifers' characteristics are usually complex and the response of water levels to recharge is nonlinear. Nevertheless, determining the optimized operation of an artificial recharge system is preferred over constructing too many recharge facilities that may be used inefficiently. Moreover, implementing optimized operation of an artificial recharge scheme is important for increasing groundwater storage as much as possible and avoiding undue water level rises under the recharge and the adjacent areas.

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Before an artificial recharge system is developed, it is necessary to assess the potential of the recharge facilities. Pilot testing is suggested as the most reliable way to evaluate the infiltration rate of a recharge facility (Bouwer 2002), but full-scale field testing is expensive, and the results do not assist in determining how many facilities should be installed. Numerical simulation is a widely used method to assess the potential and the efficiency of an artificial recharge system (Flint et al. 2012; Izbicki et al. 2008; Sayit and Yazicigil 2012; Singh et al. 1996). However, it cannot automatically calculate the facilities' optimal recharge rates under given constraints. By combining a groundwater simulation model with an optimization model, it is possible to solve the problem effectively. This technique is known as simulation optimization (S/O), and it is a powerful tool in groundwater resources management.

Optimization of groundwater systems has been the subject of many studies (Gorelick 1983). Many optimization studies have been conducted in the field, addressing, for example, remediation design (Mantoglou and Kourakos 2007; Zheng and Wang 1999), identification of pollution sources (Aral et al. 2001; Singh et al. 2004) and saltwater intrusion prevention (Abarca et al. 2006; Cheng et al. 2000). However, the actual operation of a groundwater artificial recharge system has been attempted in only a few studies.

The focus of the presented paper is on optimization of an artificial groundwater recharge system in Beijing. The operating objective is to maximize the volume of water recharged into the aquifers, while satisfying hydraulic constraints. An optimization model is proposed, which directly incorporates the groundwater flow model. In this study, a parallel genetic algorithm (PGA), with application of the multiplicative penalty method (MPM) and the relative fitness scaling function, is developed using the FORTRAN language to solve this optimization problem. The MPM method is used to penalize these individual violated constraints, to ensure that the proper individuals could be selected, while the relative fitness function is employed to deal with population stagnation and premature convergence. In addition, the effect of parameter uncertainty on optimization results is analyzed using the scenario modeling method. Lastly, the optimization results are compared with those of previous studies.

Study area

The study area, the Yongding River alluvial fan, is part of the Beijing Plain (Fig. 1). Beijing has a temperate continental climate that is cold and dry in the winter, hot and humid in the summer, and moderate temperatures prevail during spring and autumn. The long-term (1958–2006) average annual precipitation is around 590 mm, while the long-term (1979–2006) average annual pan evaporation in the Beijing plain is

around 1,725 mm. The pan water evaporation is almost three times as much as the precipitation (Hu 2017).

Yongding River is the largest river flowing through Beijing Municipality, at 650 km in length, and it drains an area of 47,016 m². It is dammed by Guanting Reservoir, the biggest reservoir serving Beijing; however, river inflows have drastically decreased since the 1970s. In addition, the consecutive droughts since 1999 have contributed significantly to the further reduction of river inflows.

The study area consists of Quaternary deposits covering a series of Paleozoic to Mesozoic geological formations, which comprise the impermeable base of the aquifers. The Quaternary aquifer system is complex with variable sediment thickness and lithology (Fig. 2; Gu et al. 2017). From northwest to southeast, the sediment thickness increases, whereas grain size decreases with land surface topography gradually sloping south-eastwards, while the aquifer systems change from a single gravel aquifer to multiple aquifer systems of sand layers separated by silt and clay layers (Hao et al. 2012; Yang et al. 2012).

The western and north-western aquifers are impermeable boundaries composed of sandy shale and lava. The eastern aquifers' boundary is a natural aquifer boundary composed of relatively less permeable sediments, including multiple layers of silt sand and clay. These boundary conditions mean that the aquifers become a relatively independent hydrogeological unit. Considering the rapid decline of groundwater levels caused by human overexploitation, an ideal groundwater-level depression has been formed, which could act as a reservoir, covering approximately 333 km² in area (Cui et al. 2009).

Methodology

Figure 3 illustrates the framework of the optimization model developed to perform the optimal solution search. The optimization model mainly includes the following three components: (1) a groundwater flow model for simulating the groundwater response of the aquifer under different artificial recharge schemes; (2) a recognizer (a program to calculate fitness and penalty points) to evaluate the fitness of each scheme and then give penalty points both to the fitness of the scheme, which violated the constraints, and to the corresponding variables; and (3) a parallel genetic algorithm (PGA) technique for searching for a global optimal solution.

Groundwater-flow-simulation model

A transient regional groundwater flow model was developed consisting of three aquifers: the top aquifer is phreatic and the other two aquifers are confined. The surface and the bottom of each aquifer was delineated based on digital elevation model

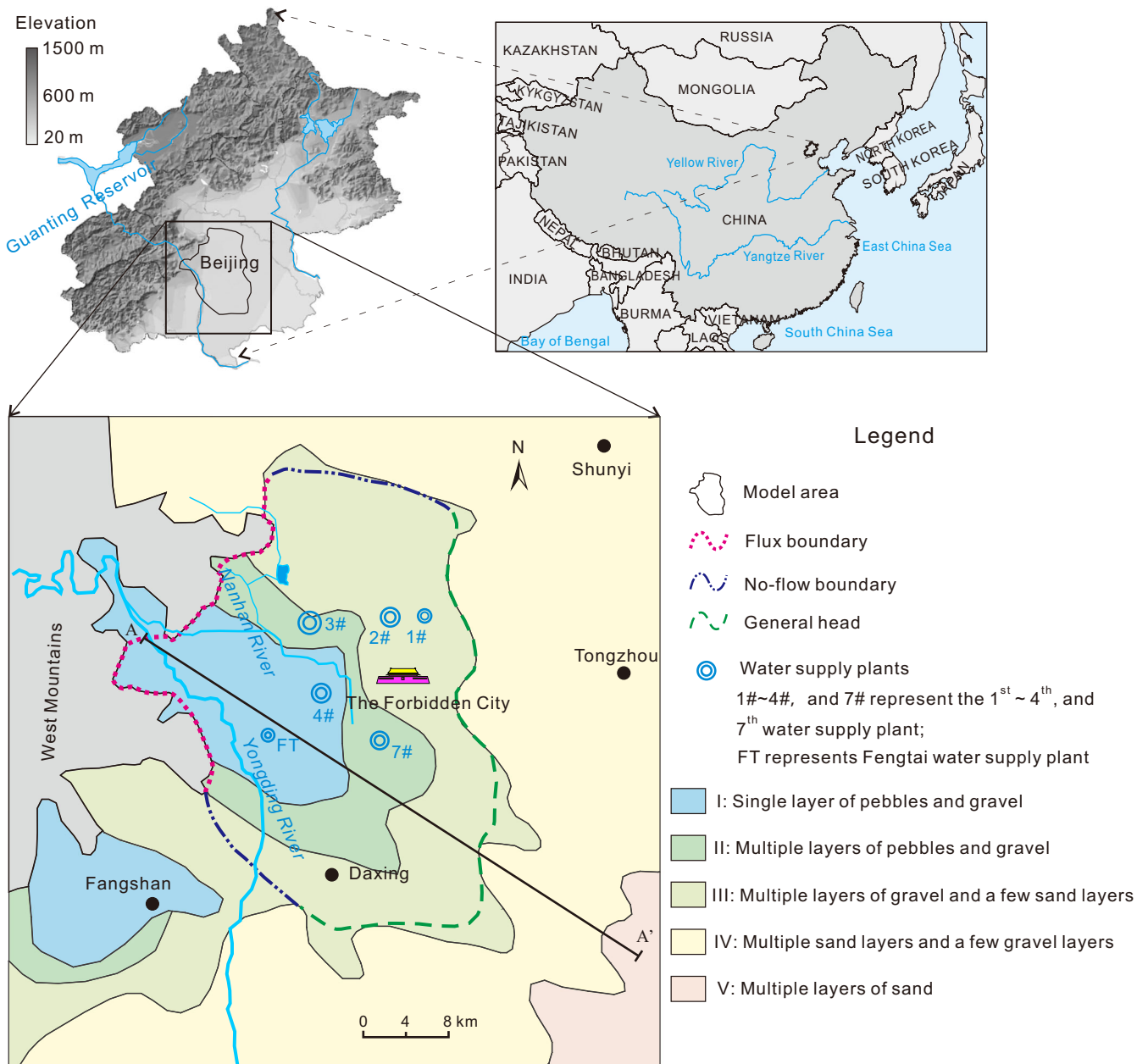


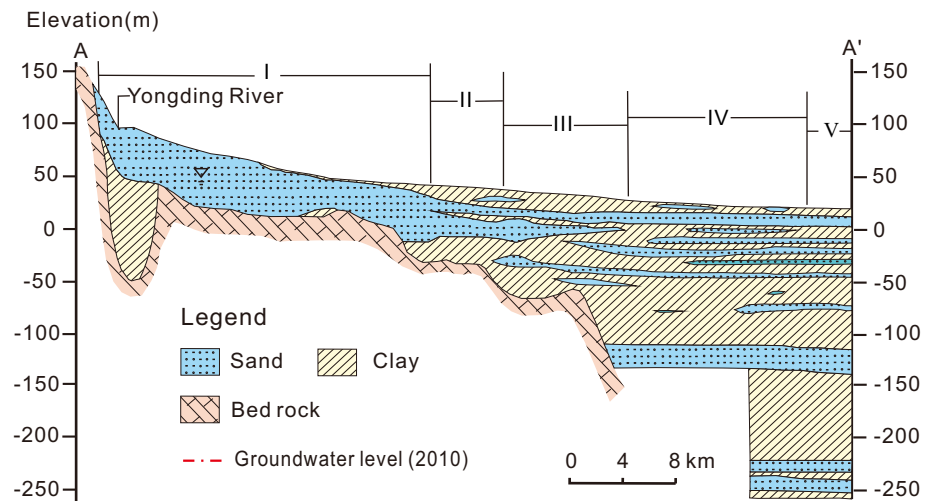
Fig. 1 Location and lithology of the study area

(DEM) data and the data of 49 boreholes using Kriging interpolation, generating aquifer contour lines.

The modeling domain was discretized into a rectangular grid, varying from 10×10 m to 200×200 m, with MODFLOW 2005 (Harbaugh 2005). At the recharge site proposed, the minimum grid size is 10×10 m, while the grid size becomes larger gradually from the recharge sites to the other place away from the recharge sites. The modular structure of MODFLOW is beneficial when it is coupled with an optimization model. The 11-year simulation period is from 16 June 2000 to 15 June 2011, and it is divided into 132 stress periods, with a stress period of a month. For each stress period, the average hydrologic conditions are assumed constant.

The mountain front in the west was defined as an inflow boundary and the flux rate from the western boundary was determined according to a previous study (HEGTB 2008). The northern and southern boundaries were defined as no-flow boundaries because the flow lines are generally parallel to them under present conditions; however, the northern and the southern boundaries were changed to general head boundaries in the prediction model to cope with the influence of artificial recharge on the flux rate out of the boundaries (Fig. 1). The eastern boundary was also defined as a general head boundary and the groundwater heads were obtained from measured data.

Fig. 2 Hydrogeology profile of the study area



The initial aquifer parameter values that pertain to groundwater flow were zoned and assigned based on the sediment features and the results from the previous investigation (BHEGS 1982). The distribution of hydraulic conductivity values varied from 15 to 300 m/day. The recharge and discharge volumes of aquifers were also collected from the previous studies and investigations (Zhai and Wang 2012; Zheng et al. 2009). Aquifer parameters were adjusted during the calibration process using long-term groundwater level data obtained from 15 observation wells.

Optimization model

Objective function and decision variables

The purpose of the groundwater recharge system considered here is to replenish the aquifers with surface water through several recharge facilities. Therefore, the objective of this optimization problem is to maximize the total volume of water recharged into the aquifers. The objective function can be expressed as follows:

$$\text{Maximize } Q_{\text{opt}} = \sum_{i=1}^M \sum_{j=1}^T Q_{ij} \Delta t_j \quad (1)$$

where the decision variable Q_{ij} represents the recharge rates in each of the M facilities in the time period j ; M includes recharge basins, injection wells, and dry rivers; Δt_j is the length of the time period j . The value of Q_{ij} in each facility can be adjusted during the recharge period in order to satisfy the constraints, particularly under a long continuous recharge condition.

The location of each recharge site is another implicit variable. A number of promising recharge sites are initially selected as potential recharge locations. However, after optimization, the optimal recharge rates of some of these facilities may be relatively small, due to locality-specific constraints in groundwater levels or the influence of other recharge

facilities; thus, in practice, these locations are not suitable for artificial recharge and should be excluded during the artificial recharge system's design.

Constraint conditions

Optimization of artificial recharge must come under some constraints. Firstly, the optimized recharge volume of a facility cannot exceed its potential recharge ability. Secondly, the groundwater levels after recharge cannot exceed the upper-limit water levels, otherwise groundwater may leach from the landfills in the study area and then cause contamination of water. Thus, two constraints are taken into consideration in the optimization problem: the infiltration rates of the recharge facilities and the groundwater levels. Therefore, the objective function (Eq. 2) is subject to:

$$0 < Q_{ij} \leq Q_{\text{max},i} \quad i = 1, \dots, M \quad (2)$$

$$H_{j,t} \leq H_j^{\text{limit}} \quad j = 1, \dots, N \quad (3)$$

where $Q_{\text{max},i}$ is the maximum infiltration rate of each M facilities, which can be obtained by field testing and the analogy method; $H_{j,t}$ is the groundwater head at point j at time step t predicted by the simulation model and H_j^{limit} denotes the upper limit of groundwater levels due to land use and/or environmental constraints.

Parallel genetic algorithm

The genetic algorithm (GA), the most widely used evolutionary algorithm method, is a stochastic global search procedure based on the mechanics of natural selection and genetics (Goldberg 1989; Holland 1992). In the GA, the solution is obtained with a random search process based on the 'survival of the fittest' concept. Moreover, the GA can be directly

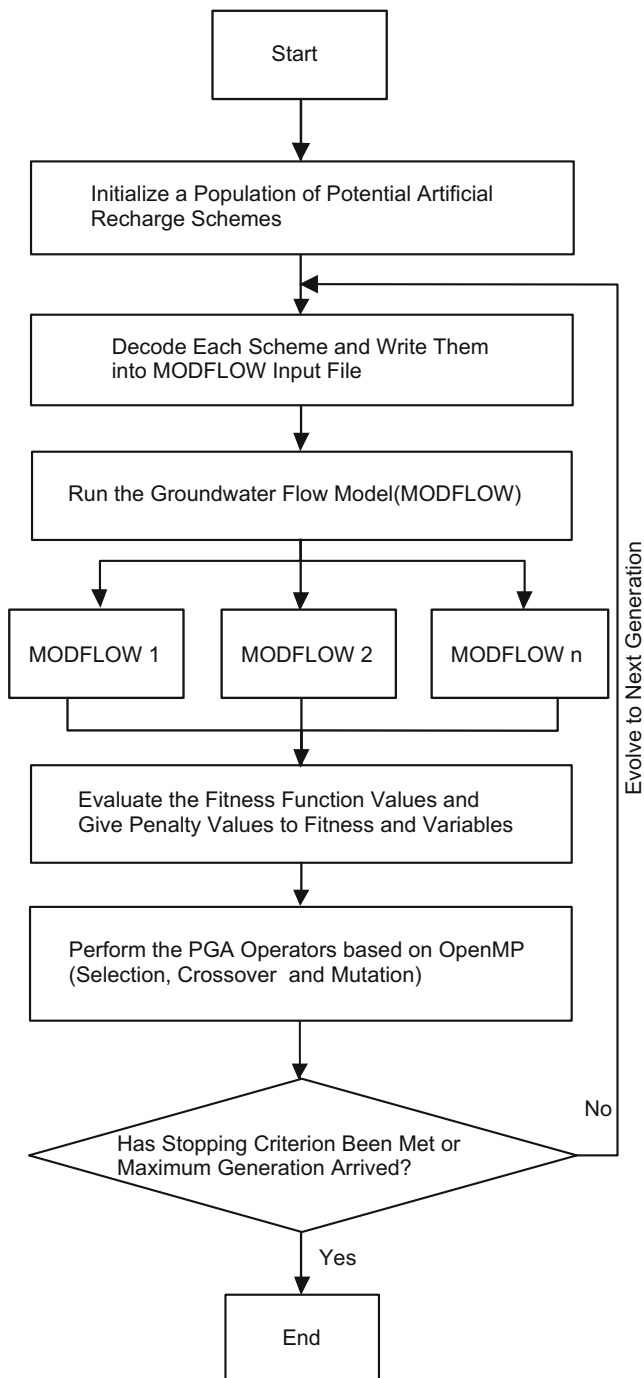


Fig. 3 The flowchart of the PGA-based optimization model used in the study for identifying the optimal operation of artificial recharge of groundwater

applied to parallelization in high-performance computing, in order to search for the optimal solution efficiently.

In the present study, an OpenMP-based PGA is developed on a shared-memory computer for parallel computations of this optimization problem. The OpenMP supports multiprocessing programming in FORTRAN and gives a simple and flexible interface for developing parallel multi-physics applications efficiently, especially for groundwater systems

(Amritkar et al. 2012; Dong et al. 2010). In the PGA, one of the processors is used to control the operation of the GA (selection, crossover, mutation, reproduction), and then all the other processors simultaneously calculate the results of a large number of simulation models (MODFLOW), which represent the responses of the groundwater system to different levels of stress.

Selection method and the relative fitness scaling function

In the optimization model, the fitness function gives individual scores based on how well they perform under the given condition. The fitness in this study is equal to the volume of water recharged to an aquifer, and each individual has a corresponding fitness score. The higher the score an individual has, the higher the chance the individual is selected by the selection method. Here the commonly used roulette wheel selection is applied in the GA, whereby the probability of an individual being selected for reproduction is proportional to its fitness. However, it faces two main challenges: population stagnation and premature convergence. In order to solve these problems, a fitness scaling technique is used, which is known as relative fitness (RF) for roulette-wheel-parent selection (Gupta 2009). Relative fitness scaling gives most individuals a small or average score and very high score to a few individuals with high fitness; thus, these individuals with high fitness would be selected efficiently. The RF scaling function can be described as follows:

$$f(x) = x \left(\frac{1}{\sqrt{1 - \frac{x^2}{c^2}}} \right) \quad (4)$$

where x is the fitness of an individual, i.e., the volume of water recharged to the aquifer, which is calculated when an individual (a recharge scheme) was created; c is the ceiling fitness, which can take on values greater than or equal to the maximum possible fitness. It can be maintained as a constant or vary with the number of generations. In the present study, the ceiling fitness is equal to the maximum volume of water that could be recharged to the aquifer without considering the constraint of limited water level, i.e., the sum of all potential recharge facilities' infiltration ability.

Penalty function method

The GA is directly applicable only to unconstrained optimization. It is necessary to use some additional methods to deal with constraints when the GA is used (Yeniay 2005). The penalty function is mostly used to deal with constraint conditions (Nanakorn and Meesomklin 2001). The method

transforms a constrained problem to an unconstrained one with the penalty function added into the fitness function; thus, the fitness of individuals violating the constraints decreases greatly, and their possibility of producing offspring is reduced. In the present study, the multiplicative penalty method (MPM) is used to incorporate constraints into the objective function (Carlson 1995; Hilton and Culver 2000). In general, this method is the more robust method for constraint handling, because it can find feasible solutions over a broad range of weight values. The new objective function is then determined by the following:

$$Q_{opt} = \alpha_{i,j} \sum_{i=1}^M \sum_{j=1}^T Q_{ij} \Delta t_j \tag{5}$$

where $\alpha_{i,j}$ is the multiplier that penalizes an infeasible string. It is given by the function:

$$\alpha_{i,j} = \frac{1}{1.0 + \sum_{i=1}^M \sum_{j=1}^T \omega V_{i,j}} \tag{6}$$

where the constraint violation $V_{i,j}$ is defined as follows:

$$V_{i,j} = \max[0, H_{j,t} - H_j^{limit}] \tag{7}$$

and ω = weight applied to the violation on constraint $V_{i,j}$. The constraint weight ω can also be kept constant or vary as the GA generations proceed.

Implementation of the optimization problem

Infiltration rates of facilities

Figure 4 shows the potential surface facilities of the artificial recharge system in the study area. It consists of four gravel pits (XHC, LGZ, BW and LS), one dry river known as Nan han River (NH River) and a number of recharge wells, which may be installed at sites relatively close to the rivers, where no building is located. The recharge water from the Middle Route Project (MRP) can be transferred from Kunming Lake to these recharge facilities mentioned previously.

In most previous studies, the infiltration rates of these facilities were kept constant in numerical simulations. The recharge period was manually reduced to prevent simulated groundwater levels from exceeding the upper limits; however, this is not the most efficient way to manage artificial recharge facilities. In optimization works, one needs to make the infiltration rates vary with time; therefore, the facilities' infiltration rates should be expressed as follows:

$$Q_i^t = \alpha_i^t Q_{max,i} \tag{8}$$

where Q_i^t is the infiltration rate for facility i at time t , $Q_{max,i}$ is the maximum infiltration rate for facility i and α_i^t is the

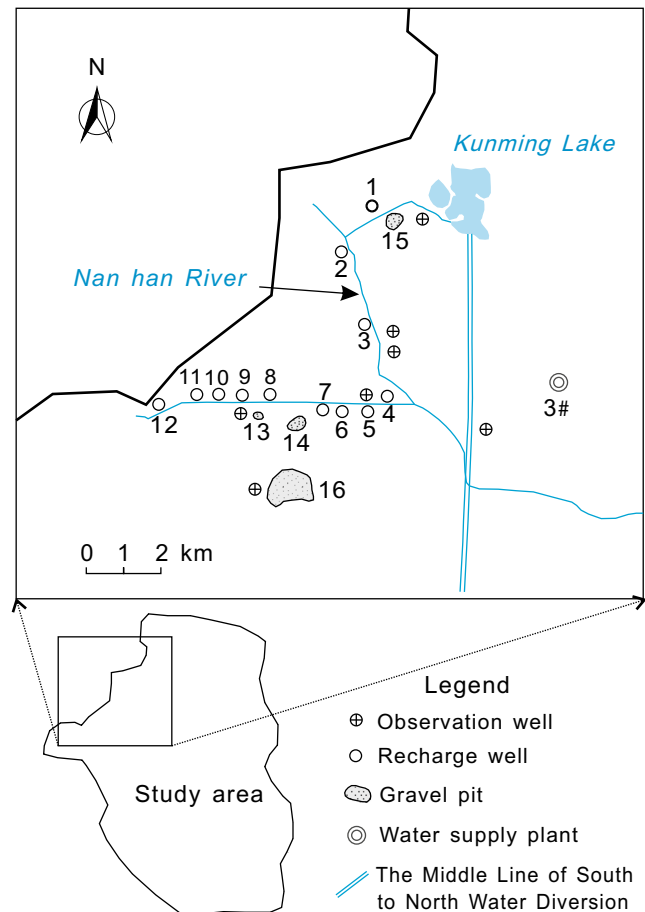


Fig. 4 The locations of the potential surface infiltration facilities and observation wells. 1–12 represent recharge well fields. 13–16 represent XHC gravel pit, LGZ gravel pit, BW gravel pit and LS gravel pit, respectively. Observation wells are not only installed in the location shown in the figure, but also in the location where infiltration facilities are located. These observation wells have the same name as the associated facilities

coefficient automatically searched by the optimization model.

Table 1 shows the maximum infiltration rates ($Q_{max,i}$) of the infiltration facilities cited from the previous study (Hao et al. 2014). In that study, the analogy method was used

Table 1 Maximum infiltration rates of the infiltration facilities

Infiltration facility name	Area (m ²)/length × width (m ²) / diameter × depth (m·m)	Max infiltration rate (m ³ /d)
Gravel pits:		
XHC	26,000	69,120
LGZ	68,000	181,440
BW	52,000	69,120
LS	163,000	432,000
Nan han River	7,040 × 6.4	86,400
Recharge well	0.5 × 60	4320

to determine the maximum infiltration rates of these recharge facilities. Liu et al. (1988) once conducted a field experiment of artificial recharge in this area. The recharge facilities they used included: (1) an average 5.5 m wide, about 1,150-m-long dry river which had a steady recharge rate of 26,784 m³/d; (2) a gravel pit with an area of 26,000 m², which had a steady infiltration rate of approximately 86,400 m³/d; (3) a 25-m-deep large-diameter hole (8 m) with steady infiltration rate of 25,920 m³/d; (4) and a 42-m-deep well with diameter of 0.5 m with an infiltration rate of 7,776 m³/d.

Since the infiltration facilities proposed in this study are located in the same hydrogeological unit as Liu's study, they have a similar hydrogeological setting. Therefore, it is feasible to determine the infiltration rate herein by analogue analysis. As the artificial recharge process normally lasts for a long time, the vertical hydraulic gradient could be assumed to be close to one. Thus, the maximum infiltration rates of the surface infiltration facilities (the gravel pits and the river) were determined to linearly correlate to their infiltration areas and the hydraulic conductivity of the aquifers. On this assumption, the derived maximum infiltration rate of the surface facilities varies from 69,120 to 432,000 m³/d. According to Liu's infiltration experiment of the recharge wells, and considering the difference in the hydraulic conductivity of the aquifers and the time needed for backwash, 4,320 m³/d was determined as the maximum infiltration rate for a 60-m-deep recharge well with a diameter of 0.5 m.

Artificial recharge scenarios

Two artificial recharge scenarios are proposed in this optimization problem. The first scenario only considers using surface infiltrations facilities, whereas additional recharge wells are installed under the second scenario in order to recharge more water into the aquifers. The recharge rates of the surface infiltration facilities and recharge well fields under water level constraints are optimized using the PGA.

The upper limit of the groundwater level refers to the highest elevation that does not have a negative effect on the environment, such as water percolating through landfills or foundations of buildings. The elevation of the upper limit is calculated according to the suitable groundwater level required by environmental geology and engineering geology investigations in Beijing (Cui et al. 2009).

Groundwater levels in 2015 are simulated with the groundwater flow model MODFLOW and used as the initial condition of the optimization model. The recharge period is set as 6 months, from May until October, because that period includes the flood season, so that there is possibly some surface water surplus.

Results and discussion

Model calibration

The model was manually calibrated by trial and error. Preliminary analysis indicated that rainfall and artificial exploitation had the greatest influence on the groundwater-level fluctuations of the model. Therefore, to minimize the difference between the simulated and the observed groundwater levels, the rainfall recharge and artificial exploitation rates had to be adjusted; additionally, the hydraulic conductivity values of different subareas were adjusted to further reduce the difference between them. Finally, the storage coefficient was adjusted so that the simulated groundwater levels were closer to the observed. These steps were repeated until the difference between the simulated and the measured heads of each observation well were within 1 m. The average difference of all stress periods is referred to as the mean residual. Table 2 shows the mean residual of the 15 observation wells in the study area. In general, the mean residual values range from -0.71 to 0.97 m.

To assess the accuracy and reliability of the calibrated model, the Nash-Sutcliffe efficiency (NSE) was used as shown in Eq. (7):

$$NSE = 1 - \frac{\sum_{i=1}^n (Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^n (Y_i^{obs} - Y_i^{mean})^2} \quad (9)$$

where Y_i^{obs} is the i th observed groundwater head of one observation well, Y_i^{sim} is the i th simulated level of this observation well, Y_i^{mean} is the mean observed level of the observation well, and n is the total number of observation wells.

Table 2 Calibration error of observation wells

Observation well code	Mean residual (m)	NSE
46	-0.64	0.912
98	0.97	0.898
667	0.37	0.939
45	-0.54	0.936
17	-0.66	0.933
DJ4	-0.03	0.939
173	0.13	0.944
522	0.41	0.937
DJ35-1	-0.58	0.941
22	0.23	0.942
150	-0.71	0.924
DJ35-3	0.48	0.902
DJ41	0.75	0.935
473	-0.25	0.947
D6	-0.49	0.933

There are 15 observation wells used for calibration for the period of June 2000 to June 2011. All the values of NSE except one are higher than 0.9 as shown in Table 2, indicating that simulated results get good agreement with the observed groundwater levels. Through the calibration process, the model adequately reproduced the observed water level variation throughout the aquifers.

Analysis of the RF scaling function and penalty function

The proposed PGA with the RF scaling function can be used to determine the optimal solution; however, the convergence rate is significantly affected by the ceiling value (c) in the RF scaling function, as shown in Fig. 5. Without applying the RF scaling function method, the optimization model fails to reach the optimal fitness. This is because the difference among all the individuals is not large enough that the ordinary roulette-wheel selection method is able to choose the fittest ones. Setting the value of c to 1.30 or 1.05 times that of the maximum possible fitness (F_{max}) of the optimization problem, the average fitness value increases rapidly at the beginning, but it also cannot achieve the optimal solution within 200 generations owing to the drastic decline of the convergence rate from approximately the 30-th and the 50-th generation, respectively. However, one can obtain higher fitness values by setting c to 1.05 times of the F_{max} rather than 1.30 times, which suggests that the lower the value of c , the higher the fitness can become within the same generation. When c is equal to F_{max} , which is the lowest value of c that satisfies the RF scaling function, one can rapidly achieve the optimal solution within about 100 generations. This is because the most suitable individuals are valued more under this situation. Considering its fast convergence rate, the optimal solution sometimes may be just the local-optimal solution; therefore, a varying c is necessary in the RF scaling function. As shown in Fig. 5, with c exponentially dropping from 1.05 of the F_{max} to a value very

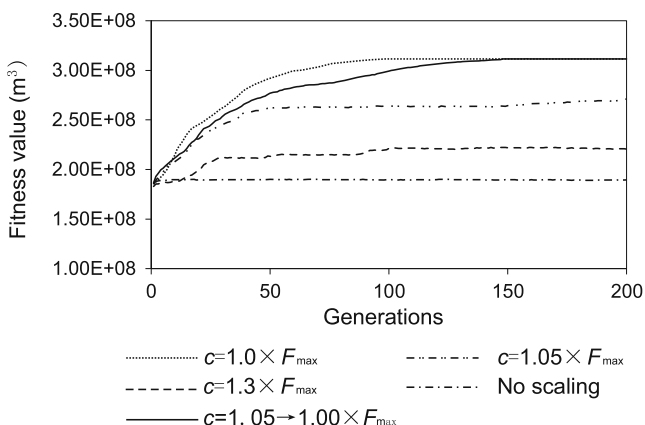


Fig. 5 Effect of the ceiling value (c) in the RF scaling function on the convergence rate. The solution does not consider any constraints of the optimization problem

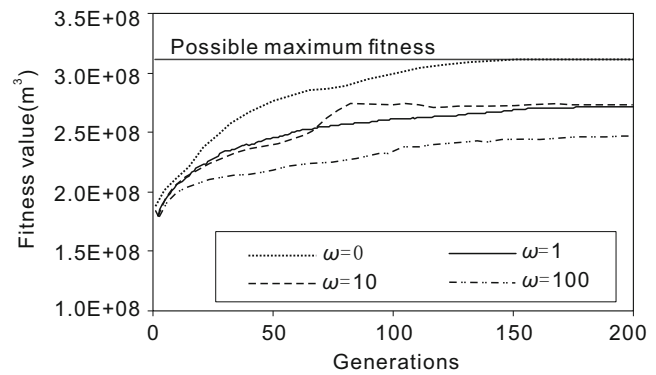


Fig. 6 Effect of the penalty weight (ω) on the convergence

close to F_{max} , the convergence rate of the optimization model is relatively much slower and more reliable than that when c is equal to F_{max} . In this study, c is used as a variable.

Penalty functions are commonly used to handle constraints in the GA. In this study, the MPM is used because of its robustness; however, the value of w (penalty weight) also affects the GA convergence rate, as shown in Fig. 6. As this parameter is related to the specific optimization problem and there is no recommended default value, the value of w should be determined first.

$\omega = 0$ means that it does not penalize any individuals that violate constraints. Under this situation, the fitness value would finally reach the maximum fitness, which obviously is not the optimal solution as expected. When ω is set to 1 or 10, the same fitness value is achieved at the last generation, which is the true optimal solution, indicating that the MPM is able to play its role in penalizing constraint violations. In addition, the MPM with $\omega = 1$ is more efficient and stable than that when $\omega = 10$; thus, the optimal solution can be reached after much fewer generations. However, if ω is set too large, such as 100, the convergence rate becomes very slow, because the MPM with $\omega = 100$ would penalize the individuals with violation too much; thus, more time would be required to find the optimal solution. Consequently, for the present study, the MPM with $\omega = 1$ is the most stable and efficient penalty function and is selected for the PGA.

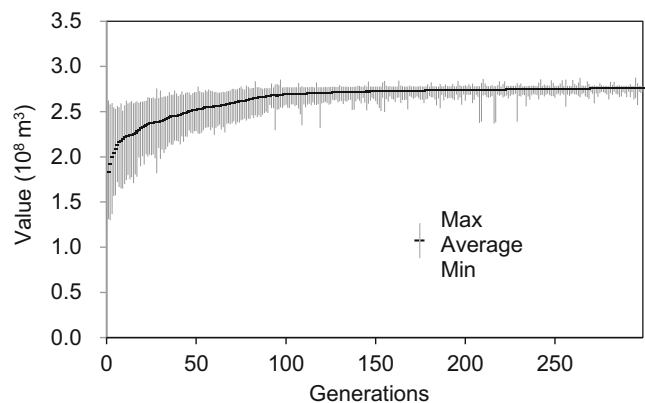


Fig. 7 The objective function values versus generations for scenario 2

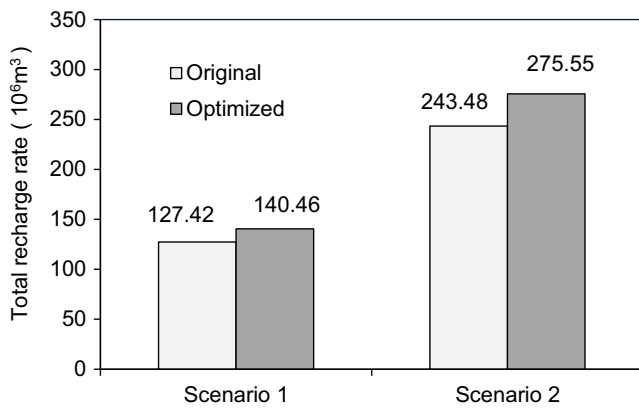


Fig. 8 Comparison of the optimized recharge rates and original recharge rates for scenarios 1 and 2

Optimal volume of recharge water and uncertainty

In the optimization problem for the Beijing case, the initial generation is randomly produced. The population size *M* is 200 with the crossover probability *P_c* = 0.80 and the mutation probability *P_m* = 0.05. Each run is performed for 300 generations. Figure 7 shows that the optimization model for scenario 2 reaches a steady value of the average fitness within 300 generations. The same results can be found for scenario 1 (not shown here).

The improvements over the trial-and-error results of the previous model can be clearly seen in Fig. 8. The total recharge rates increase from 127.42 × 10⁶ m³ and 243.48 × 10⁶ m³ to 140.46 × 10⁶ m³ and 275.55 × 10⁶ m³ for scenario 1 and scenario 2, respectively. Scenario 2 has a relative larger increase than scenario 1, because additional recharge wells are taken into consideration under scenario 2. The more recharge facilities are analyzed in the study area, the more complex the problem is. Moreover, it is much more difficult to find an optimized solution by the trail-and-error method; therefore, the optimization solution is more effective under scenario 2 than under scenario 1.

The groundwater model sensitivity to parameters in the study area has been illustrated in the literature (Fang et al. 2015). It was found that hydraulic conductivity is the most sensitive factor affecting the groundwater model uncertainty. Therefore, this study mainly presented the uncertainty

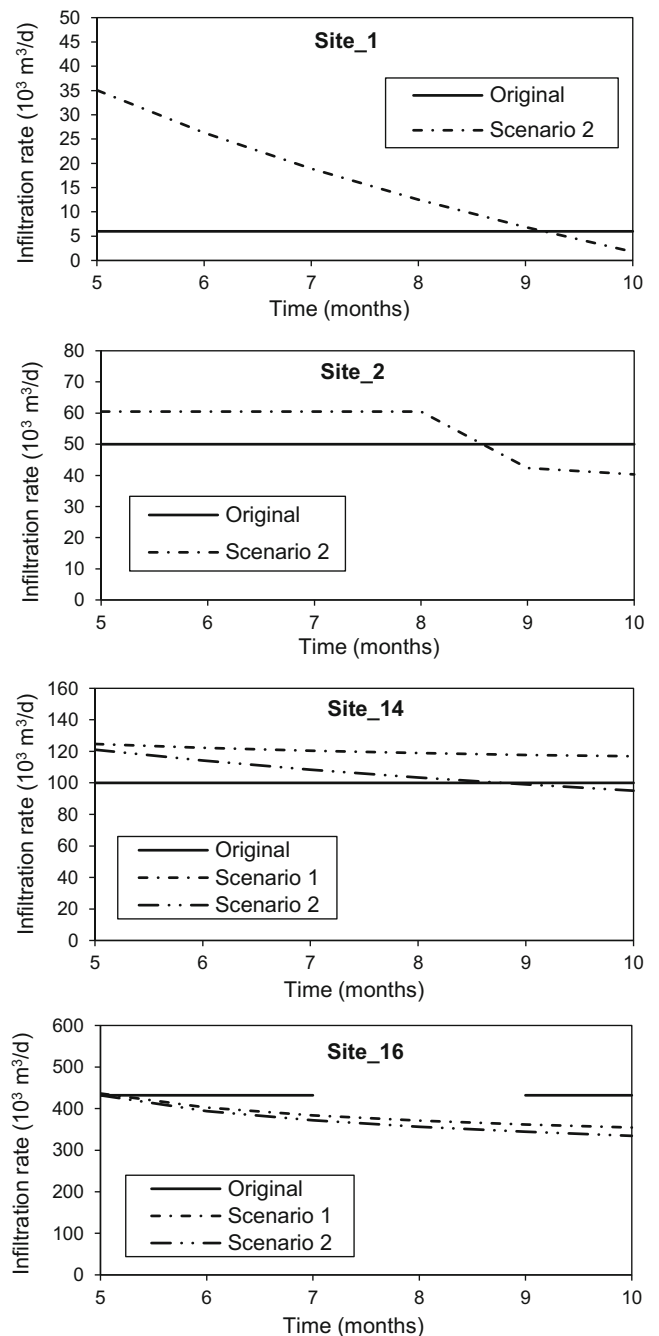


Fig. 9 Optimized recharge rates for some of the recharge facilities and well fields

Table 3 Optimization uncertainty related to hydraulic conductivity

Optimization model	Hydraulic conductivity variation	Optimal total volume of recharged water (10 ⁶ m ³)	Change ratio of the volume
Model I	+20%	281.28	2.08%
Model II	+10%	279.11	1.29%
Model III	0%	275.55	0.00%
Model IV	-10%	271.35	-1.52%
Model V	-20%	269.02	-2.37%

analysis of the optimization resulting from the hydraulic conductivity. The uncertainty analysis was addressed by employing the scenario modeling method (Anderson et al. 2015), and scenario 2 was selected to assess the uncertainty. Five optimization models with different values of hydraulic conductivity in scenario 2 were run as shown in Table 3. Model III is the base model with calibrated hydraulic conductivity. The hydraulic conductivity in model I and model II is set larger than that of the base model with 20 and 10%, respectively. In contrast, the hydraulic conductivity in model IV and model V is less than that of the base model with 10 and 20%, respectively. Optimization results show that the optimal total volume of the recharged water varies when hydraulic conductivity changes, but the variation range is much smaller. When the hydraulic conductivity decreases by 10%, the optimal total volume of the recharged water just decreases by

1.52%. A similar trend can be found when the hydraulic conductivity increases. These results indicate that the uncertainty of hydraulic conductivity will have little impact on the optimization problem. A reliable solution can be achieved through the optimization model even if the parameters of the groundwater model have some uncertainty.

Optimal recharge rate and groundwater level variation

Optimization reduces the recharge rates of some facilities or recharge well fields. Figure 9 shows that recharge rates of sites 1, 2, 14 (LGZ gravel pit) and 16 (LS gravel pit) would decrease; only in that way would the calculated water levels of observation wells beside recharge facilities not exceed the upper limits.

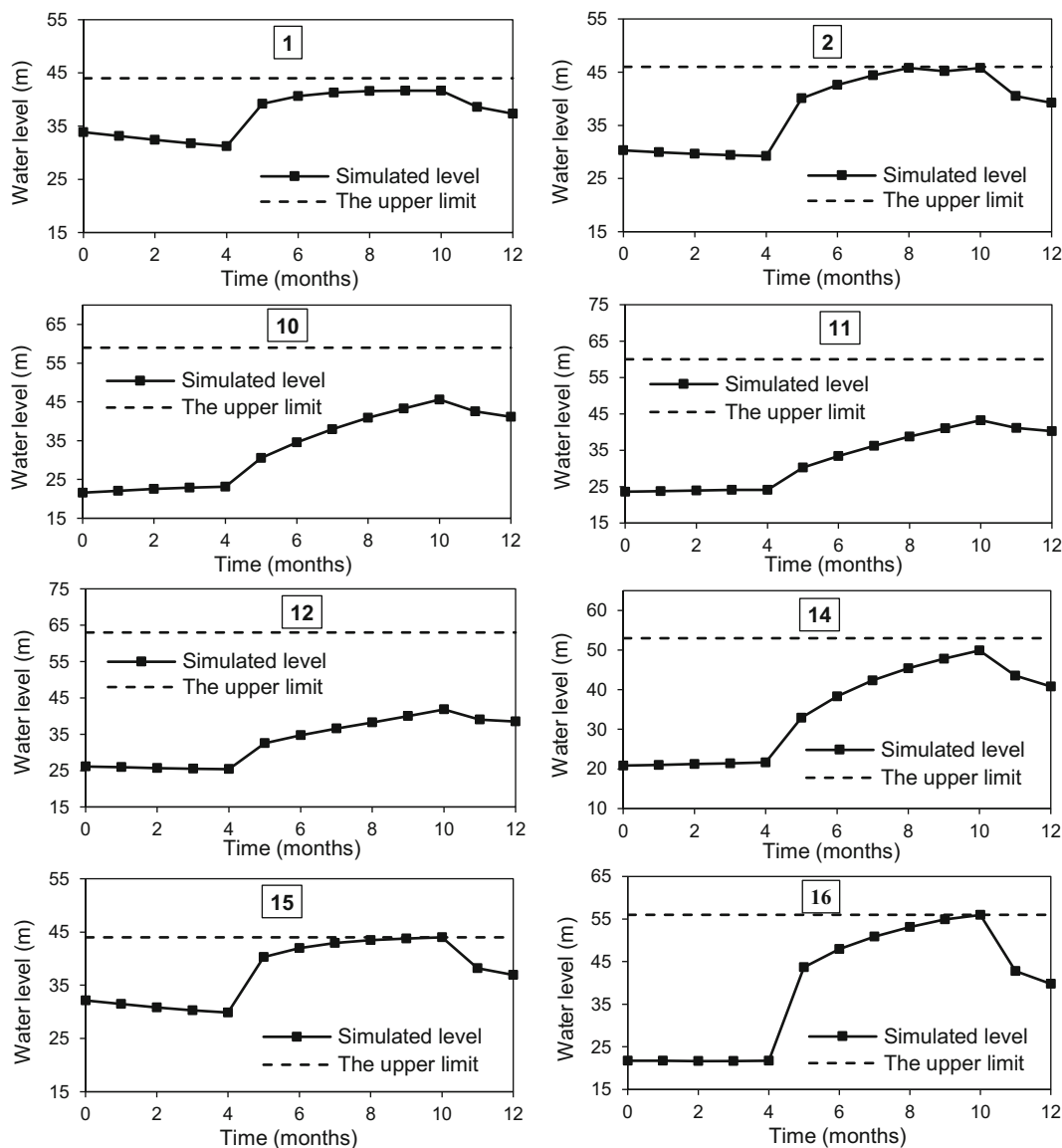


Fig. 10 Groundwater-level variation under optimized scenario 2

The recharge rates of big facilities or recharge well fields with large areas are prone to decrease in the optimization model. The LS gravel pit has a large infiltration capacity of 432,000 m³/d because it has a very large area for artificial recharge. However, the groundwater level does exceed the upper limit if such an amount of water is put into the aquifers at a given time. After optimization, the recharge rate of the LS gravel pit gradually decreases from 432,000 to 334,405 m³/d. Only in this way does the groundwater level of obs-16 increase dramatically without exceeding the upper limit of the groundwater levels.

Recharge facilities or recharge well fields also affect each other if the distance between them is very small. As shown in Fig. 4, the distance between the recharge site 1 and site 15 (BW gravel pit) is only 110 m. Under the influence of the BW gravel pit, the optimal recharge rate of site 1 decreases dramatically from 35,058 to 1,783 m³/d. At a certain level, it is unwise to consider it as a recharge site for the installation of recharge wells, because the optimal solution is much less than that for other facilities or recharge well fields.

However, the upper limit of groundwater levels sometimes does not seriously affect the artificial recharge operations at some recharge sites. As shown in Fig. 10, in the groundwater levels of Obs-10, Obs-11 and Obs-12, after artificial recharge, there is a large distance between the water levels and the upper limits, up to 20 m. Under these circumstances, other constraints, such as land use and capacity of recharge facilities, may be the main constraints for artificial recharge, rather than the upper limit of the groundwater levels.

Figure 11 shows the changes in groundwater levels when the optimal artificial recharge stops for the two examined

scenarios. The maximum water-level increase, compared with no artificial recharge, is 26 m for both scenarios. To illustrate this point, it was considered that the water-level rise is represented by the 0.5 m isoline. When the process of artificial recharge stops, the area over which groundwater level increased covers 127.56 and 163.12 km², respectively for scenarios 1 and 2, and will include the third water-supply plant. Then, coverage will gradually increase, and more groundwater source fields will be usable due to the groundwater level rise.

Groundwater budget change

Table 4 shows the changes in the groundwater budget under the two optimal recharge scenarios and under the condition of no artificial recharge. By calculation, the deficit in the groundwater balance changes under both scenarios with the balance, increasing from -94.35×10^6 m³ to 43.21×10^6 m³ and to 174.00×10^6 m³, respectively. This indicates that the optimized artificial groundwater recharge under both scenarios can effectively improve the groundwater storage of the aquifers.

Under scenario 1, precipitation infiltration remains the main recharge source in the study area, accounting for 34.37% of the total recharge. Nevertheless, under scenario 2, artificial recharge water is the main recharge source, contributing 41.55% of the total recharge, followed by rainfall infiltration, which accounts for 26.37% of the total recharge. Therefore, artificial recharge is an efficient way to store water in aquifers in the study area.

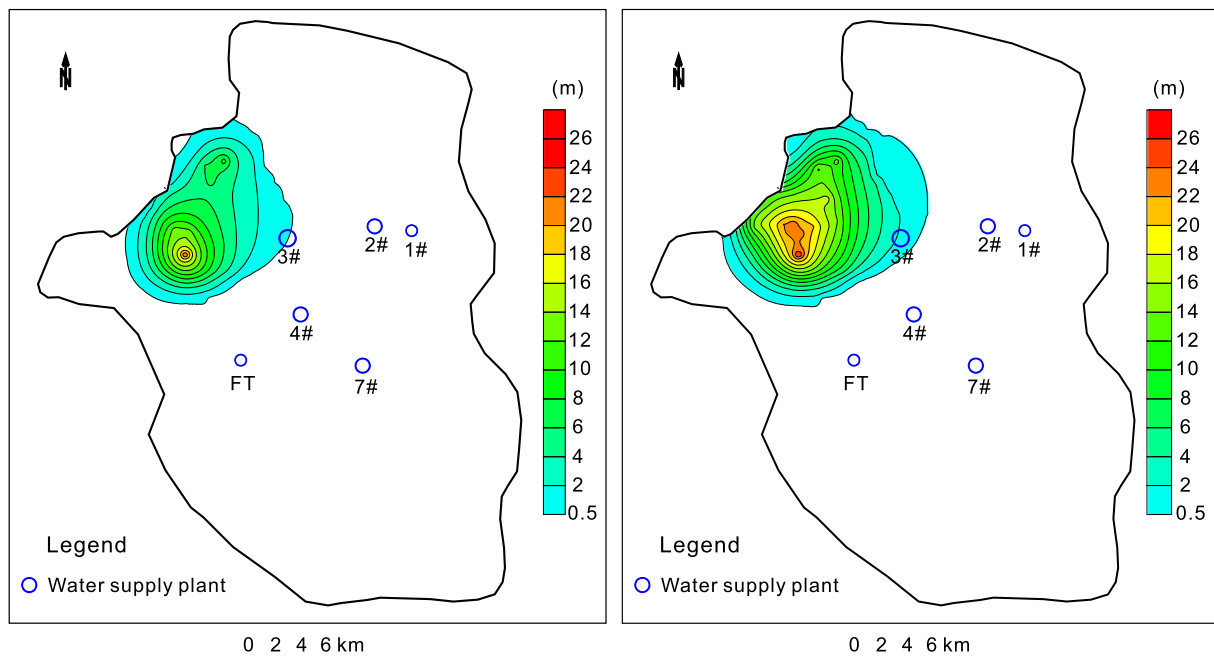


Fig. 11 Groundwater-level-rise contours under a scenario 1 and b scenario 2 compared with the ‘no artificial recharge’ scenario

Table 4 Changes in groundwater budget under optimized artificial recharge scenarios in the first hydrological year

Budget components		No artificial recharge		Scenario 1		Scenario 2	
		(10 ⁶ m ³)	(%)	(10 ⁶ m ³)	(%)	(10 ⁶ m ³)	(%)
In	Precipitation	181.53	46.83	181.53	34.37	181.53	27.37
	Irrigation infiltration	15.56	4.02	15.56	2.95	15.56	2.35
	Pipe leakage	62.23	16.05	62.23	11.78	62.23	9.38
	Lateral inflow	67.00	17.28	67.00	12.69	67.00	10.10
	Valley subsurface flow	61.31	15.82	61.31	11.61	61.31	9.24
	Artificial recharge	<i>0.00</i>	0.00	<i>140.46</i>	26.60	<i>275.55</i>	41.55
	Total in	387.63	100.00	528.09	100.00	663.18	100.00
Out	Exploitation	405.81	84.20	405.81	83.69	405.81	82.96
	Lateral outflow	76.16	15.80	79.07	16.31	83.36	17.04
	Groundwater evaporation	0.00	0.00	0.00	0.00	0.00	0.00
	Total out	481.98	100.00	484.88	100.00	489.18	100.00
In-out	–	–	43.21	–	174.00	–	

Values in italic are the amount of water recharged in the aquifers

Discharge mostly occurs through exploitation, accounting for 83.69 and 82.96% of the total discharge, respectively for scenarios 1 and 2. Even though a large amount of water is artificially recharged into the aquifers, lateral outflow increases marginally at the first hydrological year, from $76.16 \times 10^6 \text{ m}^3/\text{year}$ to $79.07 \times 10^6 \text{ m}^3/\text{year}$ and $83.36 \times 10^6 \text{ m}^3/\text{year}$, respectively. Evaporation in the study area remains zero, as neither scenario results in increased evaporation. Because the groundwater level is quite deep in the study area, it is lower than the extreme evaporation depth even after artificial recharge. That is, within a short time, the artificially recharged water could be almost stored in the aquifers, and the storage of groundwater could be efficiently increased in the study area.

Conclusions

This study emphasizes the importance and necessity of the optimal operation of artificial recharge systems, to supplement aquifers in areas where groundwater has been overexploited. An optimization model has been developed for an artificial recharge system in Beijing, which integrates the three-dimensional groundwater flow model MODFLOW and the genetic algorithm. The facilities' recharge rates in the optimization model are formulated as a nonlinear programming problem to maximize the amount of surface water recharged into the aquifers. In addition, the optimum locations for recharge facilities are determined from the results.

The optimal solution to this problem is obtained using a parallel genetic algorithm method, and the parallel genetic algorithm can largely reduce the computation time for this kind of problem, because MODFLOW models employed by the optimization model can run simultaneously in different cores rather than only one MODFLOW model running at a given time.

The presented results of the optimization problem greatly improve the original model. The amount of water recharged into the aquifers increases from 127.42×10^6 to $140.46 \times 10^6 \text{ m}^3$ and from 243.48×10^6 to $275.55 \times 10^6 \text{ m}^3$ for scenario 1 and scenario 2, respectively, without exceeding the upper limits of groundwater. Therefore, the proposed optimization method improves the efficiency of the recharge system.

It is predicted that groundwater levels will rise under the optimal recharge scenarios, and the water levels recovery area would eventually cover some important well fields, especially the third water-supply plant. It is also expected that it will efficiently augment the groundwater storage without inducing much discharge from the aquifers in the short term, like lateral outflow or phreatic water evaporation.

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