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Numerically modelling groundwater in an arid area with ANN-generated dynamic boundary conditions

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Abstract:

Groundwater is sensitive to the climate change and agricultural activities in arid and semi-arid areas. Over the past several decades, human activities, such as groundwater extraction for irrigation, have resulted in aquifer overdraft and disrupted the natural equilibrium in these areas. Regional groundwater simulation is important to determine appropriate groundwater management policies, and numerical simulation has become the most popular method. However, most groundwater models were developed with static boundary conditions. In this research, the Minqin oasis, an arid region located in northwest China, was selected as the study area. An artificial neural network (ANN) was developed to simulate effects of weather conditions, agricultural activities and surface water on groundwater level in a dynamic boundary of the domain. Subsequently, a groundwater numerical model, named ANN-FEFLOW model, was developed, with a dynamic boundary condition defined by the ANN model. The verifying results showed that the model has higher precision, with a root mean square error (RMSE) of 0·71 m, relative error (RE) of 17·96% and R^2 of 0·84 relative to the great groundwater change. Furthermore, the groundwater model has higher precision than the conventional groundwater model with static boundary condition, particularly in the area near the dynamic boundary. This study demonstrated that dynamic boundaries can improve the precision of the regional groundwater model in an arid area and that ANN can provide higher accuracy prediction capability for groundwater levels with dynamic boundary. Copyright © 2010 John Wiley & Sons, Ltd.

KEY WORDS groundwater; numerical modelling; neural network; boundary condition

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INTRODUCTION

Groundwater plays an important role in the economic development and ecological balance in arid and semi-arid areas, particularly in northwest China (Cui *et al.*, 2005). Over the past several decades, human activities, such as groundwater extraction for irrigation, have resulted in aquifer overdraft in these areas, disrupting the natural equilibrium of these systems (Hu *et al.*, 2002). Excessive groundwater level declines have produced serious ecological problems, such as land desertification and soil salinization, displacing inhabitants from their ancestral homeland (New York Times, 2006). Consequently, it has become extremely important to accurately simulate and predict potential groundwater level changes in these regions so that appropriate water resources management and environmental protection policies can be developed and implemented.

Numerical simulation models had been used successfully for simulating and predicting groundwater levels for many years (Zhao *et al.*, 2005; Matej *et al.*, 2007). It is well known that groundwater flow in the aquifer is governed by the boundary condition of the regional system and the determination of boundary conditions is important for regional groundwater numerical modelling. Generally, the boundary conditions (groundwater levels or flux) of groundwater numerical models are defined as constant values with time, named static boundaries, which can be ascertained before the models are used (Wen *et al.*, 2007). Or, they are empirically determined time-variant water head or flux boundaries. In arid regions, however, the groundwater levels or flux in boundaries of the domain are sensitive to weather conditions, surface water and agricultural activities such as pumping groundwater and irrigation and will change with time. As a result, some boundaries of the domain in arid regions can be defined as dynamic boundaries. Therefore, it is important to describe the non-linear relationship between the dynamic groundwater levels or flux in boundaries of the domain and various factors which can be measured feasibly.

Artificial neural network (ANN) is one promising method which can be used to represent more generalized relationships. Among the most important features of ANN models is their ability to adapt to recurrent changes and detect patterns in complex natural systems. In hydrology, ANNs have been largely applied to rainfall-runoff modelling, precipitation forecasting and water quality modelling (Coulibaly *et al.*, 1999; ASCE, 2000a, 2000b; Maier *et al.*, 2000). ANNs have also been applied successfully to groundwater level prediction under variable weather conditions (Coulibaly *et al.*, 2001) and under pumping conditions (Coppola *et al.*, 2005a, 2005b; Daliakopoulos *et al.*, 2005; Lallahem *et al.*, 2005; Huo *et al.*,

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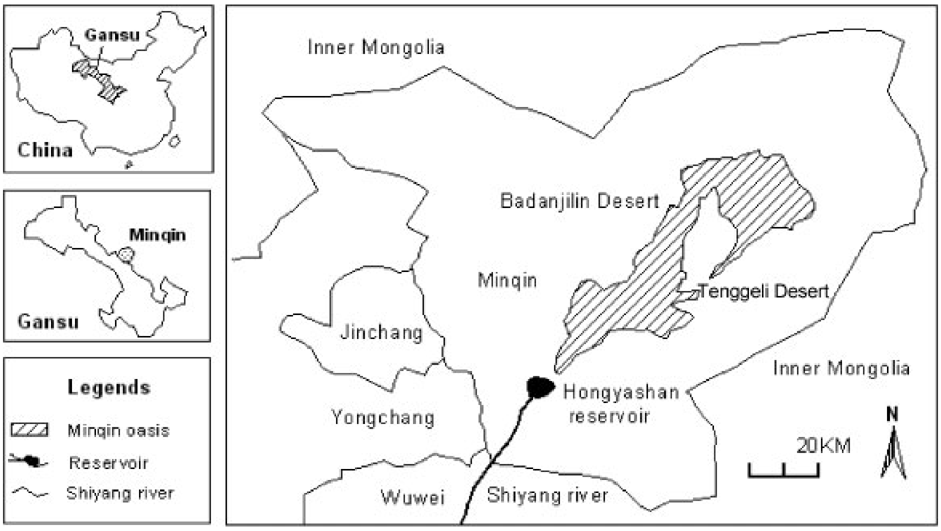

Figure 1. Location of the study area

2008). All of these researches have proved that ANN can accurately simulate the effects of weather and pumping conditions on groundwater. Feng *et al.* (2008) developed ANN models for groundwater levels in arid regions and successfully modelled groundwater levels under different irrigation and surface water scenarios. In an effort to combine the relative advantages of numerical models and ANNs, Szidarovszky *et al.* (2007) presented a new modelling paradigm of coupling ANN and numerical models. In their study, the ANN models generated accurate predictions for a limited number of field locations. Predicted groundwater levels were then used to develop a groundwater numerical model which potentially yielded more accurate numerical predictions. This research supplies a feasible procedure which combines the relative advantages of numerical models and ANNs to simulate a regional groundwater model. However, ANN has not been used to simulate groundwater levels or flux in the boundaries of the experimental area and to couple with groundwater numerical models.

The objectives of this study were (1) to develop an ANN model with weather factors, surface water and irrigation as inputs for groundwater level in the boundary of the domain; (2) to develop a regional groundwater model (named ANN-FEFLOW model) with the ANN-predicted boundaries and (3) to compare the performance of the ANN-FEFLOW model and the FEFLOW model with static boundary conditions.

THE STUDY AREA

In this research, an arid area of northwest China, named Minqin oasis, was selected as the study area. The Minqin oasis, encompassing an area of 160 000 km^2, is surrounded by the Badanjilin and the Tengeli Deserts, and is located within the lower reach of the Shiyang River basin in the Hexi Corridor of Gansu province (Figure 1), supporting a population of about 307 000. The Minqin oasis has an arid climate, with average annual precipitation and evaporation values of 109·5 and 2646·2 mm/year, respectively, over the last 50 years.

The groundwater system of the Minqin oasis is a highly complex multi-layered system consisting of 10–15 layers or zones, with thickness ranging from 2 to 20 m. The upper unconfined aquifer consists predominantly of sand and gravel, and the lower aquifers exist under semi-confined to confined conditions with vertical interconnections. Except for the unconfined aquifer, there are no continuous aquifers or hydrogeologic units within this system. The groundwater systems are mainly influenced by the source and sink terms in vertical direction with relatively minor lateral fluxes into the system. A more detailed description of the hydrogeologic system can be found in Ma *et al.* (2005).

The agricultural sector is by far the major user of water resources, and makes up 93·3% of total water consumed in this region. The size of the irrigation area in the study region has increased from 56 kha in 1980 to 63 kha in 1997. In the 2000s, there were about 9000 known pumping wells in the Minqin oasis, with the estimated quantity of extraction $6{\cdot}57 \times 10^8$ m^3, substantially exceeding that of natural replenishment, estimated to be $1{\cdot}0 \times 10^8$ m^3 (Huo *et al.*, 2007a). Because the groundwater usage is not sustainable, groundwater levels in the oasis have declined significantly.

In the Minqin oasis, land-use patterns include irrigation field, forest land, shrub land, desert, unused land and so on. Irrigation field is the main land-using type which affects groundwater change. In the Minqin oasis, groundwater depth has declined to 10–20 m except for the area near Hongyashan reservoir and therefore the effect of precipitation, condensed water and evaporation on groundwater can be neglected. So, the land-use patterns affecting groundwater flow include irrigation fields, forests and shrub.

Irrigation has the biggest effect on the groundwater in the Minqin oasis and is the dominant source/sink factor of groundwater. The source terms in irrigation fields include the recharge volume by deep percolation

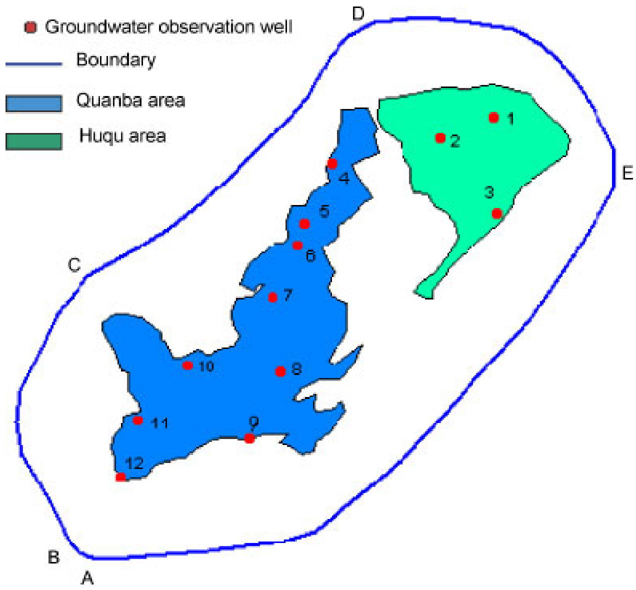

Figure 2. Boundaries, observation well of groundwater levels and two sub-areas of the study area

from the canals and fields. The sink term in irrigation field is mainly the groundwater pump. The irrigation schedule and its surface distribution are different between the upper reaches and the lower reach of the Minqin oasis. The study area was therefore divided into two sub-regions, i.e., Quanba area and Huqu area for determining the source/sink terms in irrigation field (Figure 2). The irrigation year in the Minqin oasis starts from the winter irrigation using water from the reservoir in mid-October to the next October. The volumes of well water and reservoir water for irrigation in the whole sub-region are calculated according to the growing areas of crops, irrigation schedule of crops and the irrigation systems. Then the pumped groundwater volume is calculated on the basis of the utilization coefficients of the canal systems. The detailed calculating flow chart for this source/sink terms can be found in Huo *et al.* (2007b).

According to the climate condition in the Minqin oasis, the main growing period of plants covers 8 months from March to October, and so the evapotranspiration is significant during this period and the seasonal difference is dramatic. Accordingly, the groundwater losses caused by the evapotranspiration occur in the 8 months. The average annual groundwater losses caused by evapotranspiration from the forest and shrub lands are 270 and 38 mm, respectively. The seasonal evapotranspiration from the forest and shrub lands are listed in Table I.

METHODOLOGY

The method can be summarized as follows:

1. Development of ANN model to predict dynamic head boundary. The groundwater dynamics and the influencing factors in the dynamic boundaries were analysed and inputs for ANNs were selected. An ANN model was developed with real data to predict groundwater levels in the dynamic boundaries of the domain.
2. Development of regional groundwater model (named ANN-FEFLOW model) with the ANN-predicted boundary. The predicted groundwater levels or flux were set as boundary conditions of the numerical model that the model can start. Hydrogeological parameters were calibrated by matching simulated and measured groundwater levels within the domain.

GROUNDWATER MODEL

Governing equation

According to the characteristics of the aquifer formation and groundwater flow in the Minqin oasis, the hydrogeologic models were developed. Considering the non-obvious changes of the media in the phreatic aquifer changes in the alluvial plains, it can be assumed that the local media are homogeneous. The following assumptions can be made for the two-dimensional phreatic flow on the plane of the horizontal impervious layers: (1) the change of head values at all the points of any section with z can be neglected and (2) the horizontal current velocity does not change with z. On the basis of these assumptions, the equations governing the horizontal two-dimensional phreatic flow in a homogeneous anisotropic medium are given as (Bear, 1977)

$$\begin{cases} \frac{\partial}{\partial x}\left(Kh\frac{\partial H}{\partial x}\right) + \frac{\partial}{\partial y}\left(Kh\frac{\partial H}{\partial y}\right) + w(x, y, t) = \mu\frac{\partial H}{\partial t} \\ H(x, y, t)|_{t=t_0} = H_0(x, y), \quad (x, y) \in \Omega \\ H(x, y, t)|\Gamma_1 = h_1(x, y, t), \quad (x, y) \in \Gamma \\ h\frac{\partial H}{\partial n}|_{\Gamma_2} = q(x, y, t), \quad (x, y) \in \Gamma_2 \end{cases} \tag{1}$$

where Ω is the domain of the simulation area, Γ_1 and Γ_2 are the Dirichlet and Neumann boundaries, n is the direction of the outer normal line of the second boundary and $H_0(x, y)$ are the initial conditions, i.e. the initial head distribution (m), $h_1(x, y, t)$ is the water head along the Dirichlet boundary (m), q (x, y, t) is the flux along the Neumann boundary with outflow positive (m^3/d), H is the groundwater level (m), h is the distance between the bottom elevation of the phreatic aquifer (z) and the phreatic free surface (m), K is the permeability coefficient of the aquifer (m/day), μ is the water yield and w (x, y, t) denotes the source/sink terms of groundwater, i.e. the intensities of the vertical water pumping and of the percolation recharge per unit area (m/day).

Equation (1) can be solved numerically using the finite element method by FEFLOW (Diersch and Kolditz, 1998). According to the hydrogeologic features in the study region, it is determined that the study area of 3198 km^2 in the generalized area from the southern boundary of the Hongyashan reservoir to the northern boundary of the desert zone. The domain was divided into 5895 triangular meshes and 3006 total nodes.

Boundary conditions

Groundwater flow in the aquifer is governed by the boundary condition of the regional system. Boundary

Table I. The seasonal evapotranspiration of the forest and shrub lands in the Minqin oasis

Months	4	5	6	7	8	9	10
Shrub (mm)	0·54	12·96	50·22	110·97	49·41	42·39	3·78
Forest (mm)	0·076	1·824	7·068	15·618	6·954	5·966	0·532

of the domain for groundwater numerical model was shown in Figure 2. A no-flow boundary was defined between points B and C and C and D in the basin, because a groundwater divide is present at this boundary. According to local hydrogeology investigations, constant flux cells of 0·0038 m/day were defined between points D and E where groundwater flows outside. The boundary EA is in the desert and the groundwater level varies slightly. Groundwater flows from the desert into the oasis along this boundary. Consequently, constant flux cells of 0·0059 m/day were also defined between points E and A. The boundary A–B is near the Hongyashan reservoir and surface water recharge is via the Hongyashan reservoir. High inflows into the reservoir occur in spring, but relatively little flow in summer and autumn seasons reaches the reservoir because of upriver diversions by Wuwei City. Because groundwater storage in the Minqin oasis is strongly influenced by surface water conditions, the Hongyashan reservoir plays an important role on transient groundwater levels.

Hydrogeology investigations showed that groundwater flows through boundary A–B into the Minqin oasis. In past simulations, a constant flux boundary of 0·0148 m/day is defined in this boundary (Ma *et al.*, 2005). In this study, groundwater models for the Minqin oasis with the dynamic A–B boundary condition obtained from an ANN model will be established and calibrated. Similar to the other groundwater models, a groundwater model with static boundary condition was also established at the same time to compare the performance between the two models. The constant flux of 0·0148 m/day is defined in the boundary A–B and the other boundary conditions are similar to the groundwater model with the dynamic A–B boundary.

STATISTICAL INDICES USED TO EVALUATE THE GOODNESS OF FITTING

In this study, statistical indices were used to provide quantitative evaluation of the modelling performance. The R^2 measures the degree to which two variables were linearly related. Root mean square error (RMSE) and relative error (RE) provided different types of information about the predictive capabilities of the model. The RMSE measured the goodness of fit relevant to high groundwater levels, whereas the RE yielded a more balanced perspective of the goodness of fit at moderate groundwater levels. The RMSE, RE and R^2 were defined as follows:

1. The RMSE:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(y_i - O_i)^2}{m}} \tag{2}$$

where m is the number of observations, and O_i and y_i are the ith observed and predicted data (using the ANN procedures).
2. The RE:

$$RE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|y_i - O_i|}{\max(O_i) - \min(O_i)}\right) \times 100\% \tag{3}$$

where $\overline{O}$ is the average value for O_i with $i = 1, 2, \ldots,$ m.
3. The coefficient of determination, R^2:

$$R^2 = \frac{\left[\sum(y_i - \overline{y})(Oi - \overline{O}\right]^2}{\sum(y_i - \overline{y})\sum(O_i - \overline{O})} \tag{4}$$

where $\overline{y}$ and $\overline{O}$ are the averages of the data arrays of y_i and O_i.
4. The error at the end of the year, R_{12}

$$R_{12} = |\overline{y}_{12} - \overline{O}_{12}| \tag{5}$$

where $\overline{y}_{12}$ and $\overline{O}_{12}$ are the average groundwater levels at the end of 1 year.

ANN MODEL FOR GROUNDWATER LEVEL DYNAMICS IN THE BOUNDARY

Development of ANN model

There are many types of ANN structures and training algorithms, and different ANN structures are used for different purposes. For most problems involving continuous mapping functions (as required for this study), a structure known as a multi-layer perception network can represent a function to any specified degree of accuracy. An important part of the approach is to define the learning paradigm and algorithm. The ANN most commonly used for hydrological applications is a multi-layer feedforward network structure with a back-propagation training algorithm.

In this study, a three-layer feedforward ANN (BP-ANN) was developed to simulate effects of weather conditions, irrigation and surface water on groundwater in the domain boundary. The following five variables were used as ANN model inputs: initial groundwater level, monthly total precipitation, monthly total water surface evaporation (E_0), water volume in the reservoir and monthly synthesis irrigation ratio. The synthesis irrigation ratio is the average monthly irrigation quantity per unit area, defined by the proportions and irrigation ratio of specific crop planting, computed in accordance with Equation (10):

$$W = \sum_{k=1}^{K} (q_k \times w_k) \tag{6}$$

where W is the synthesis irrigation ratio, q_k is the planting percentage of the kth crop, K is the number of crop types and w_k is the irrigation water volume per unit area for the kth crop.

The data used to develop the ANN model were within the period from 1990 to 1999. Altogether, 120 input and output samples were randomly divided into two groups and one including 80 samples was used for training the ANN, the other samples including 40 were for validating the ANN. A combination of back-propagation and conjugate gradient learning algorithms was used for training. Intermittent verification during ANN training was performed to avoid overtraining. That is, during training, network learning was verified periodically with the verification data set, and this process was repeated until the verification error began to increase. The number of hidden nodes was determined using a trial and error method and the final number is seven (Table II). Consequently, the structure of ANN for the groundwater levels in the boundary is 5 : 7 : 1.

The testing results showed that the ANN model has higher precision, with RMSE of 0·12 m and RE of 8·3%. The simulated *versus* observed groundwater levels in the boundary A–B have consistent change in trends (Figure 3), illustrating high predictive performance. Furthermore, the analysis for variance of error shows that the variation in error for both ANN models is small. Therefore, we can conclude that groundwater levels in the boundary A–B are influenced by precipitation, evaporation, water volume in the reservoir and irrigation and the developed ANN model can simulate the groundwater levels well.

Sensitivity analysis of the ANN model

For gaining a better understanding of the factors influencing groundwater levels in the boundary, a sensitivity analysis was conducted to semi-quantify the relative importance of each input variable for accurately predicting groundwater levels. In this analysis, comparison ANN models that excluded a single input variable were developed and validated. To assess the relative importance of the excluded variable, the prediction accuracy of the 'reduced' ANN model (i.e. one excluded input variable) was compared against the prediction accuracy attained by the 'complete' ANN model (i.e. using all seven input variables).

Similar to Coppola *et al*. (2005a), the ratio for each ANN input variable was computed as

$$\text{Ratio} = \frac{\text{RMSE without simulator variable}}{\text{RMSE with ANN simulator variable}} \tag{7}$$

The results of the sensitivity analysis indicate that all five input variables improve ANN predictive capability, though their relative importance varied, from nominally to extremely important (Table III). The initial groundwater level is the most important input variable for determining the next month's water level. Agricultural activities, namely, groundwater irrigation, as represented by monthly synthesis irrigation ratio in the ANN model, is the next important prediction variable, which is consistent with groundwater storage changes in this system. As the depth of the groundwater table is small, precipitation and evaporation also have significant influence on monthly groundwater level prediction in the boundary

Table II. The error change of ANN with different network structures for the groundwater levels in boundary A–B

Network structure (input–hidden–output)	Maximal error (m)	Average error (m)
5–5–1	0·45	0·22
5–6–1	0·32	0·16
5–7–1	0·3	0·12
5–8–1	0·39	0·13
5–9–1	0·36	0·14
5–10–1	0·46	0·18
5–11–1	0·51	0·29
5–12–1	0·7	0·42

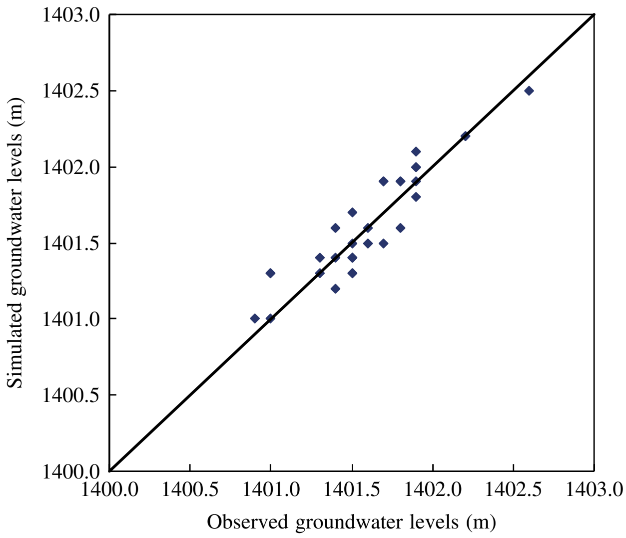

Figure 3. Comparison between ANN simulated and observed groundwater levels in the boundary of the study area

Table III. Sensitivity analysis result for ANN of groundwater level in boundary A–B models during validation

	AF	LG	WR	PR	EV	SI
Mean absolute error(m)	0·12	0·62	0·13	0·26	0·23	0·29
Maximum absolute error (m)	0·30	4·16	0·47	0·78	0·85	0·90
Ratio	—	5·14	1·12	2·17	1·95	2·41
Rank	—	1	5	3	4	2

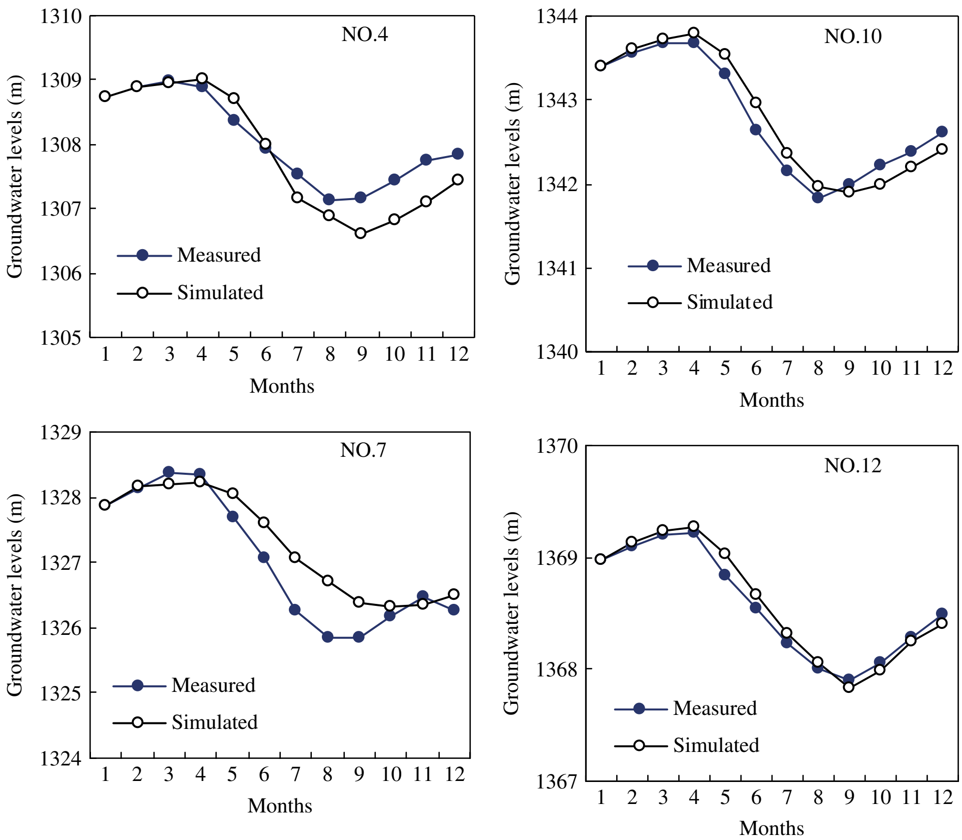

Figure 4. Comparison between ANN-FEFLOW model simulated and observed groundwater levels for four monitoring wells

A–B, which is different from the ANN model for groundwater levels in the Minqin oasis (Feng *et al*., 2008). The results indicate that surface water inflow into the reservoir is the last most important variable relative to the other factors. This can be attributed to the decreasing inflow into the reservoir.

The sensitivity analysis was useful for confirming and even slightly refining the conceptual framework of the system, as well as providing insights for improving ANN prediction performance. Because the full range of values for the other input variables is considered in the analysis, the average importance of each input variable for accurately predicting groundwater levels with the particular ANN model is quantified. The results demonstrate a high degree of consistency with physical conditions both within each region and between regions, which increases confidence in the validity of the results. Furthermore, the results are partially supported by the simulations described in the next section.

CALIBRATION AND EVALUATION OF ANN–NUMERICAL MODEL

After the ANN model was developed, groundwater levels in the boundary of the domain in the interested period of time can be simulated using some input data including the weather, irrigation and water volume in the reservoir. Then the dynamic head predicted by ANN can be set as the regional groundwater levels can be set as a boundary. Groundwater levels can be simulated using the numerical model with the dynamic boundary-defined ANN model. Therefore, the groundwater simulating method of combining ANN and the numerical model is named ANN-FEFLOW model. Before the model was used to predict groundwater levels, calibration was carried out using historical data. The calibrated parameters in this groundwater model are hydrogeological parameters including permeability coefficient (K) and water yield (μ) which are calibrated according to the four fitting criterions above and the models are modified by using the land-use maps and the measured data of groundwater levels. A transient simulation was undertaken for a 1-year period from January 1998 to December 1998 with 1-day per time step. The calibration makes the calculated results of the models match the measured data of the groundwater level as much as possible within the 1-year period. The comparison between the simulated and the measured groundwater levels from 12 monitoring wells shows a similar groundwater level trend with the hydrogeologic situation in the Minqin oasis, which indicates that the generalized models of the hydrogeologic conditions mentioned above are reasonable. The results show that the change in trend of the simulated groundwater levels matches basically with that of the measured values.

The models are verified using the measured data of groundwater level in 1999. Figure 4 shows the comparison between the simulated values and the measured ones of the groundwater levels from four monitoring wells in 1999. Overall, the groundwater models have higher precision with RMSE of 0·71 m, RE of 17·96% and R^2 of 0·84

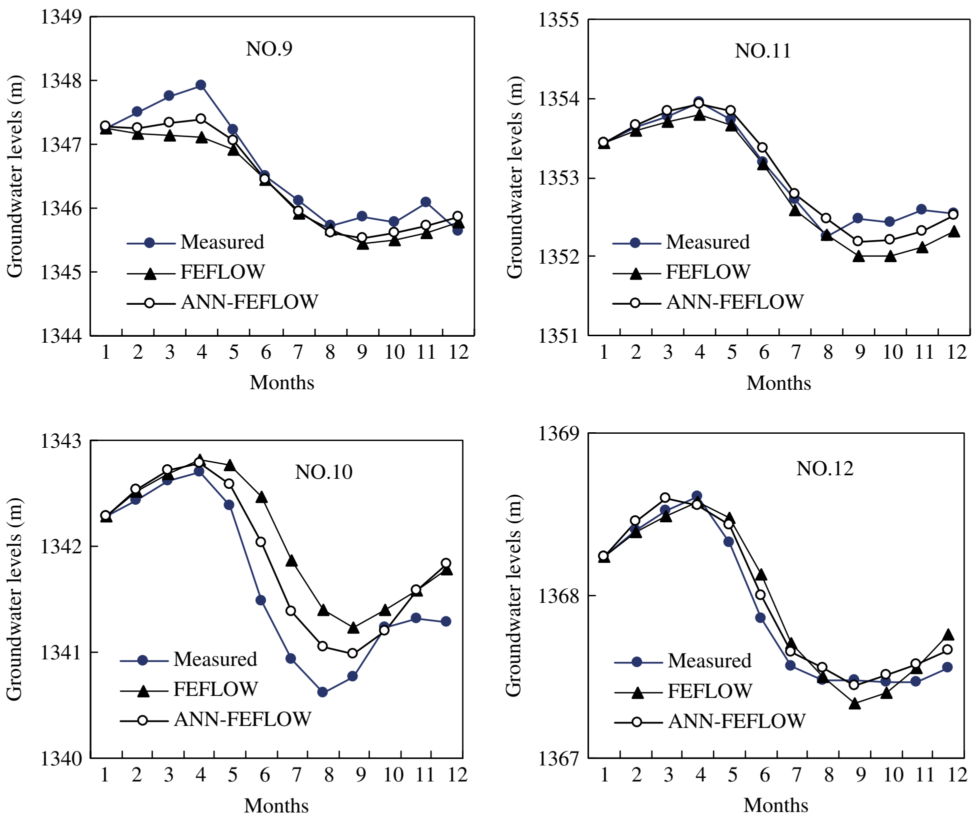

Figure 5. Comparison of groundwater levels simulated by the ANN-FEFLOW model and the numerical model

Table IV. Error statistics for ANN-FEFLOW model in the Minqin oasis (1999)

	RMSE (m)	RE (%)	R^2	E_{12} (m)
Up-basin (wells 1–6)	0·32	12·47	0·94	0·53
Down-basin (wells 7–12)	1·05	21·7	0·76	0·21
Average	0·71	17·96	0·84	0·39

(Table IV). However, the difference between the errors of groundwater levels between upper basin (Quanba area) and down basin (Huqu area) is evident. The RMSE, RE and R^2 between simulated and measured groundwater levels are 0·32 m, 12·7% and 0·94, respectively, in the Quanba area. Comparatively, the groundwater model has higher error with RMSE of 1·05 m, RE of 21·7% and R^2 of 0·76 in the Huqu area. This can be attributed to the strong exploitation of groundwater in the Huqu area where there is almost no surface water to use and the change in scope of groundwater is large, with an average value of 4·13 m. Relative to the change in scope of groundwater levels, the groundwater model has low error and the RE changes between 7·37 and 22·14%.

In addition, the error of groundwater levels at the end of 1 year for the model has been analysed. The results indicate that the model has a small error at the end of 1 year with R_{12} of 0·39 m, which is lower than the average RMSE by 0·32 m. Furthermore, R_{12} are 0·21 and 0·53 m, respectively, for Quanba area and Huqu area and lower than the corresponding RMSE. In winter, the exploitation volume of groundwater is less and change in groundwater levels is little. As a result, the simulated groundwater levels are more near to the observed value. So, the groundwater model is more applicable to simulate groundwater at the end of 1 year.

COMPARISON OF GROUNDWATER MODELS BETWEEN DYNAMIC AND STATIC BOUNDARIES

In this study, a groundwater numerical model with static A–B boundary conditions was also calibrated and verified independently to compare with the result of the groundwater model with the ANN–numerical model. According to the hydrogeology survey, a constant flux was defined at the A–B boundary. Overall, the groundwater model with dynamic boundary has higher precision than the groundwater model with static boundary, with constant water flux with time (Table V). Especially, simulation average error for ANN–numerical model in part regions including wells 9, 10, 11, 12 near boundary A–B is significantly lower than groundwater model with static boundary (Figure 5). The average groundwater simulation RMSE, RE and R^2 for these four wells enhance to 0·24 m, 10·5% and 0·97, respectively, for the ANN–numerical model from 0·37 m, 14·2% and 0·93 for the numerical model. Similarly, the E_{12} also decreases from 0·14 m for numerical model to 0·12 for the ANN–numerical model. Comparative results indicating dynamic groundwater levels or flux in boundaries of the study area instead of static value in regional

Table V. Comparison of results from ANN-FEFLOW model and FEFLOW models in the Minqin oasis (1999)

Wells	FEFLOW					ANN-FEFLOW				
	9	10	11	12	Average	9	10	11	12	Average
RMSE (m)	0·39	0·52	0·25	0·13	0·37	0·36	0·32	0·17	0·12	0·24
RE (%)	13·34	21·44	10·40	7·37	14·22	12·43	13·49	8·61	7·46	10·50
R^2	0·95	0·90	0·97	0·97	0·93	0·96	0·97	0·98	0·98	0·97
E_{12} (m)	0·14	0·51	0·21	0·21	0·25	0·09	0·55	0·02	0·17	0·21

groundwater model can improve the precision, particularly in the area near the dynamic boundary.

Furthermore, the groundwater budget from the two models has significant difference for the study area, particularly for the Quanba area (Table VI). On the basis of the groundwater model with dynamic boundary condition, groundwater budget in the Quanba area is $-2·254 \times 10^8$ m^3 and $-2·263 \times 10^8$ m^3, respectively, in 1998 and 1999, which is lower than the values simulated with groundwater model with static boundary condition. Furthermore, groundwater budget based on the numerical model with dynamic boundary is close to the calculated value based on water balance. This can be attributed to the groundwater level or flux changed with many factors including weather conditions, agricultural activities and surface water. So, for the groundwater numerical simulation, the boundary conditions of the domain can change the groundwater simulation results and ANN model can describe dynamic characters of groundwater levels or flux in boundaries.

GROUNDWATER LEVEL CHANGE UNDER PRESENT CONDITIONS

To understand the trend of groundwater changes under current agricultural activities, groundwater levels within the period from 2000 to 2020 had been simulated by the ANN-FEFLOW model. The groundwater levels in the A–B boundary were predicted with ANN model before the ANN-FEFLOW was used. In details, the inputs of the ANN, i.e. monthly total precipitation, monthly total water surface evaporation (E_0), are average values from the recent 10 years and the water volume in the reservoir, monthly synthesis irrigation ratio are values in 2000. The results indicate that groundwater levels have a significant decline trend in the Minqin oasis (Figure 6). This can be attributed to excessive groundwater pumping. According to the measured data by the local water management department, the groundwater exploitation has increased from $3·73 \times 10^8$ m^3 in 1980s to $4·57 \times 10^8$ m^3 in 2000. The calculated groundwater overexploitation based on the simulated results of groundwater is $3·029 \times 10^8$ m^3 (Table VII). As a result, the groundwater levels in the Minqin oasis will have a decreasing trend. At the same time, the simulated results show that the declined speed is different between Quanba area and Huqu area. In Huqu area, the groundwater level will decline with a velocity of 1·8 m/year and groundwater depth in the centres of sub-areas will drop to 48 m in 2020. Because near the Honyashan reservoir, some fields in the Quanba area can be irrigated with surface water and relatively the groundwater level will decline at a rate of 1·1 m/year and groundwater depth will drop to 35 m in 2020. Therefore, it is necessary to determine the rational exploitation volume of groundwater and the distribution scheme of surface water in the Minqin oasis.

Table VI. Groundwater budget simulated with FEFLOW and ANN-FEFLOW models in the Minqin oasis (10^8 m^3/yr)

	Models	Quanba area	Huqu area	Study area
1998	FEFLOW	−2·237	−0·738	−3·000
—	ANN-FEFLOW	−2·254	−0·740	−3·019
1999	FEFLOW	−2·242	−0·747	−3·011
—	ANN-FEFLOW	−2·263	−0·749	−3·029

CONCLUSIONS

For groundwater numerical simulation in arid regions, usually groundwater level or flux in the boundaries of the domain will change with weather conditions and human

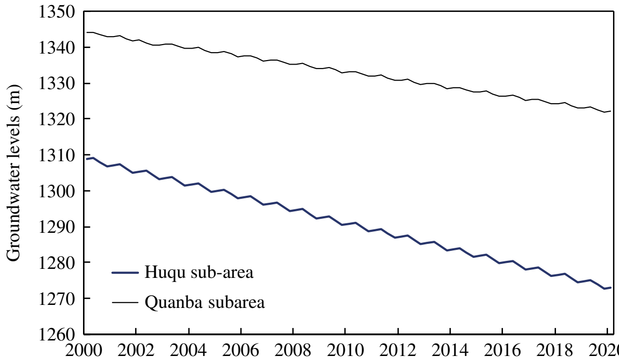

Figure 6. Groundwater dynamics simulated by ANN-numerical model under the current conditions in the Quanba and Huqu areas

Table VII. Composition of groundwater in the Minqin oasis under present condition (10^8 m^3/yr)

Item	The Minqin oasis	Quanba area	Huqu area
Lateral recharge	0·472	0·39	0·052
Lateral discharge	0·306	0·14	0·158
Vertical recharge	0·016	0·089	0·013
Vertical discharge	3·791	2·704	0·946
Budget volume	−3·029	−2·263	−0·749

activities. A groundwater numerical model with dynamic boundary defined by ANN (ANN-FEFLOW model) has been developed to assess the impacts of agricultural activities on groundwater in the arid regions. In the model, an ANN was employed to simulate the effects of weather conditions, agricultural activities and surface on groundwater levels in a boundary. As the ANN model captured the non-linear relationship between the changes in the groundwater levels and impact factors and duplicated the changes in the groundwater levels well, the models have higher precision than conventional groundwater model with static boundary condition, particularly in the area near the dynamic boundary. However, the accuracy of the ANN can vary with the study area. Although dynamic boundary with ANN predicted improved precision of groundwater simulation near the boundary in this study, the performance of groundwater model depends on the accuracy of dynamic boundary with ANN predicted. This study only supplies a method to improve the performance of the regional groundwater numerical model by dynamic boundary with ANN predicted.

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REFERENCES

ASCE Task Committee on Application of artificial neural networks in hydrology. 2000a. Artificial neural networks in hydrology. I: preliminary concepts. *Hydrological Engineering* **5**(2): 115–123.

ASCE Task Committee on Application of artificial neural networks in hydrology. 2000b. Artificial neural networks in hydrology. II: hydrologic applications. *Hydrological Engineering* **5**(2): 124–137.

Bear J. 1977. On the aquifer integrated balance equations. *Advances in Water Resources* **1**(1): 15–23.

Coppola E, Rana A, Poulton M, Szidarovszky F, Uhl V. 2005a. A neural network model for predicting water table elevations. *Ground Water* **43**(2): 231–241.

Coppola E, McLane C, Poulton M, Szidarovszky F, Magelky R. 2005b. Predicting conductance due to upconing using neural networks. *Ground Water* **43**(6): 827–836.

Coulibaly P, Anctil F, Bobee B. 1999. Hydrological forecasting using artificial neural networks: the state of the art (in French). *Canadian Journal Of Civil Engineering* **26**(3): 293–304.

Coulibaly P, Anctil F, Aravena R, Bobee B. 2001. Artificial neural network modeling of water table depth fluctuation. *Water Resources Research* **37**(4): 885–896.

Cui Y, Shao J. 2005. The role of groundwater in arid/semiarid ecosystems, northwest china. *Ground Water* **43**(4): 471–477.

Daliakopoulos I, Coulibaly P, Tsanis I. 2005. Ground water level forecasting using artificial neural networks. *Journal of Hydrology* **309**: 229–240.

Diersch HJG, Kolditz O. 1998. Coupled groundwater flow and transport: 2. Thermohaline and 3D convection systems. *Advances in Water Resources* **21**(5): 401–425.

Feng SY, Kang SZ, Huo ZL, Chen SJ, Mao XM. 2008. Neural Network to simulate regional ground water levels affected by human activities. *Ground Water* **46**(1): 80–90.

Huo ZL, Feng SY, Kang SZ, Dai XQ, Li WC, Chen SJ. 2007a. The response of water-land environment to human activities in arid Minqin oasis, northwest China. *Arid Land Research and Management* **21**: 21–36.

Huo ZL, Feng SY, Kang SZ, Chen SJ, Ma Y. 2007b. Simulation of effects of agricultural activities on groundwater level by combining FEFLOW and GIS. *New Zealand Journal of Agricultural Research* **50**: 839–846.

Huo ZL, Feng SY, Kang SZ. 2008. *ANN Models for groundwater dynamics in the lower reach of Shiyang River basin in Northwest China*, *Redbook of IAHS*, vol. 319, Chen X, Chen YD, Xia J, Zhang H. (eds). IAHS Publ. 319: Guangzhou, China; 17–24.

Hu RJ, Fan ZL, Wang YJ. 2002. Ground water resources and their characteristics in arid lands of Northwestern China. *Journal of Natural Resources* **17**(3): 321–326.

Lallahem S, Maniaa J, Hani A. 2005. On the use of neural networks to evaluate ground water levels in fractured media. *Journal of Hydrology* **307**: 92–111.

Ma JZ, Wang XS, Edmunds WM. 2005. The characteristics of groundwater resources and their changes under the impacts of human activity in the arid northwest China-a case study of the Shiyang River Basin. *Journal of Arid Environments* **61**: 227–295.

Maier HR, Dandy GC. 2000. Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications. *Environmental Modelling & Software* **15**: 101–124.

Matej G, Isabelle W, Jan M. 2007. Regional groundwater model of northeast Belgium. *Journal of Hydrology* **335**: 133–139.

New York Times. 2006. *A Sea of Sand is Threatening China's Heart*. June 8, Late Edition- Final, Section A, Page 1, Column 2.

Szidarovszky F, Coppola E, Long JJ, Hall AD, Poulton MM. 2007. A hybrid artificial neural network-numerical model for ground water problems. *Ground Water* **45**: 590–600.

Wen XH, Wu YQ, Lee LJE, Su JP. 2007. Groundwater flow modeling in the Zhangye basin, Northwestern China. *Environmental Geology* **53**: 77–84.

Zhao CY, Wang YC, Chen Xi., Li BG. 2005. Simulation of the effects of groundwater level on vegetation change by combining FEFLOW software. *Ecological Modelling* **187**: 341–351.

