

Neural Networks to Simulate Regional Ground Water Levels Affected by Human Activities

by Shaoyuan Feng¹, Shaozhong Kang¹, Zailin Huo², Shaojun Chen¹, and Xiaomin Mao¹

Abstract

In arid regions, human activities like agriculture and industry often require large ground water extractions. Under these circumstances, appropriate ground water management policies are essential for preventing aquifer overdraft, and thereby protecting critical ecologic and economic objectives. Identification of such policies requires accurate simulation capability of the ground water system in response to hydrological, meteorological, and human factors. In this research, artificial neural networks (ANNs) were developed and applied to investigate the effects of these factors on ground water levels in the Minqin oasis, located in the lower reach of Shiyang River Basin, in Northwest China. Using data spanning 1980 through 1997, two ANNs were developed to model and simulate dynamic ground water levels for the two subregions of Xinhe and Xiqu. The ANN models achieved high predictive accuracy, validating to 0.37 m or less mean absolute error. Sensitivity analyses were conducted with the models demonstrating that agricultural ground water extraction for irrigation is the predominant factor responsible for declining ground water levels exacerbated by a reduction in regional surface water inflows. ANN simulations indicate that it is necessary to reduce the size of the irrigation area to mitigate ground water level declines in the oasis. Unlike previous research, this study demonstrates that ANN modeling can capture important temporally and spatially distributed human factors like agricultural practices and water extraction patterns on a regional basin (or subbasin) scale, providing both high-accuracy prediction capability and enhanced understanding of the critical factors influencing regional ground water conditions.

Introduction

In China, a huge country with a population of more than 1.3 billion, half of its land is situated within arid or semiarid regions of which 26.6% has an average precipitation of less than 200 mm/year (Tang and Zhang 2001). Ground water plays an important role in the economic development and ecological balance in these arid and semiarid areas, particularly in Northwest China (Cui and Shao 2005). Over the past several decades, human activities such as ground water extraction for irrigation have resulted in aquifer overdraft in these areas,

disrupting the natural equilibrium of these systems (Hu et al. 2002). Excessive ground water level declines have produced serious ecological problems such as land desertification and soil salinization, displacing inhabitants from their ancestral homeland (New York Times 2006).

Currently in China, there is 150×10^3 km² of desert area, which is increasing at an annual rate of approximately 2000 to 3000 km²/year. The saline areas produced by irrigation with the highly mineralized deep ground water encompass roughly 2 million hectares, which occupy approximately one-third of the country's total saline area (Qiu et al. 1998). Because of these severe consequences and recognizing China's growing reliance on increasingly scarce ground water resources, it has become extremely important to accurately simulate and predict potential ground water level changes in these regions so that appropriate water resources management and environmental protection policies can be developed and implemented.

A number of previous researchers focused on the impact of human activities on ground water systems in

¹Centre for Agricultural Water Research in China, China Agricultural University, Beijing 100083, People's Republic of China.

²Corresponding author: Centre for Agricultural Water Research in China, China Agricultural University, No. 17 Qinghua East Road, Haidian, Beijing 100083, P.R. China; +86-10-62736762; fax +86-10-62736860; huozailin@yahoo.com.cn

Received January 2007, accepted July 2007.

Copyright © 2007 The Author(s)

Journal compilation © 2007 National Ground Water Association.
doi: 10.1111/j.1745-6584.2007.00366.x

arid and semiarid areas, leading them to conclude that overexploitation of these systems has produced excessive ground water level declines (IAHS 2001; Fan et al. 2001; Horton 2001; Kang et al. 2004; Cui and Shao 2005; Ma et al. 2005; Wang et al. 2002). However, these studies have analyzed only the relationships between ground water levels and human activities on a qualitative level. Others have used advanced numerical models to simulate and quantify the impact of human activities (e.g., ground water extraction) on ground water conditions (Ma et al. 2002, 2003).

Numerical simulation models had been used successfully for simulating and predicting ground water levels for many years, extending back into the 1960s. As noted by Coppola et al. (2003b), "The power of these models is they can capture high spatial and temporal variability of aquifer properties and conditions inherent to natural hydrogeologic systems. However, this capability renders numerical models data intensive, and to achieve acceptable simulation and prediction performance, the properties and conditions of the ground water system must be accurately represented within the model's space and time domains. The unavoidable discrepancies between the model and the real world system inevitably produce simulation and prediction error." Because the properties and conditions of the ground water system can never be ascertained with absolute accuracy, empirical models may provide an appropriate alternative method and can provide useful results without costly calibration time (Daliakopoulos et al. 2005).

The artificial neural network (ANN) methodology is an alternative modeling and simulation tool, especially for dynamic nonlinear systems. One of the most important features of ANN models is their ability to adapt to recurrent changes and detect patterns in a complex natural system. As Coppola et al. (2003b) discussed, unlike traditional physical-based numerical models, ANNs often do not require explicit characterization and quantification of physical properties and conditions and are not based upon simplifying mathematical and physical assumptions (e.g., porous media). Rather, ANNs learn the system behavior of interest from representative data that often consist of easily measurable variables.

The advantages and disadvantages of ANNs over conventional simulation methods have been discussed in detail by French et al. (1992). In hydrology, ANNs have been largely applied to the rainfall-runoff modeling, precipitation forecasting, and water quality modeling (ASCE Task Committee on Application of Artificial Neural Networks in Hydrology 2000a, 2000b; Coulibaly et al. 1999; Govindaraju and Ramachandra Rao 2000; Maier and Dandy 2000). ANNs have also been applied successfully to ground water level prediction under variable weather conditions (Coulibaly et al. 2001; Mao et al. 2002) and under pumping conditions without explicitly accounting for this variable (Daliakopoulos et al. 2005; Lallahem et al. 2005). Coppola et al. (2003a, 2003b, 2005b) developed ANN models that accurately predicted transient ground water levels in response to variable weather and pumping conditions and extended this work to water quality for an upcoming problem in a coastal aquifer (Coppola

et al. 2005a). Some ANN ground water prediction models have been used for ground water management, where the models are combined with formal optimization methodology (Rao et al. 2003; Coppola et al. 2003a, 2007). This body of research collectively demonstrates that ANN models may serve as efficient and accurate models for simulating ground water systems and can be used for developing effective management and protection strategies.

In this study, ANNs were developed to predict average ground water levels in a semiarid region using monthly stress periods, with predictor input variables addressing meteorological, hydrological, population, and agricultural ground water extractions. Therefore, unlike previous studies by others like Coulibaly et al. (2001) and Coppola et al. (2003a, 2003b, 2005b), this article demonstrates that important and numerous ground water extractions that are temporally and spatially distributed over a large regional-scale system can be accounted for by an ANN, with their corresponding effect on the system accurately predicted by the model. The ANN models were used to perform valuable sensitivity analyses, identifying the relative importance of different factors on the regional ground water system. In addition, the models were used to perform extended simulations over hypothetical 1-year periods, using different sets of input values, to assess the impacts of agricultural activities on the ground water system. This modeling simulation and analysis helped quantify average expected ground water level responses to different levels of agricultural activities, which can be used to help develop appropriate long-term strategies to promote the long-termed sustainability of the resource and the surrounding environment.

Study Area Description

The Minqin oasis, encompassing an area of 160,000 km², is surrounded by the Badanjilin and Tenggeli Deserts (Figure 1); it is located within the lower reach of the Shiyang River basin in the Hexi Corridor of northwest China, supporting a population of about 307,000. The ground water system of the Minqin oasis is a highly complex multilayered system consisting of 10 to 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 semiconfined to confined conditions with vertical interconnections. Except for the unconfined aquifer, there are no continuous aquifers or hydrogeologic units within this system. Furthermore, the system is further complicated by two hidden faults that transect the Minqin oasis aquifer. The ground water system is mainly influenced by the source and sinks 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).

In the study area, the Shiyang River is the only source of surface water and has been used for irrigation in the Minqin oasis, with the Hongyashan reservoir established within the lower reach in 1958. Unfortunately,

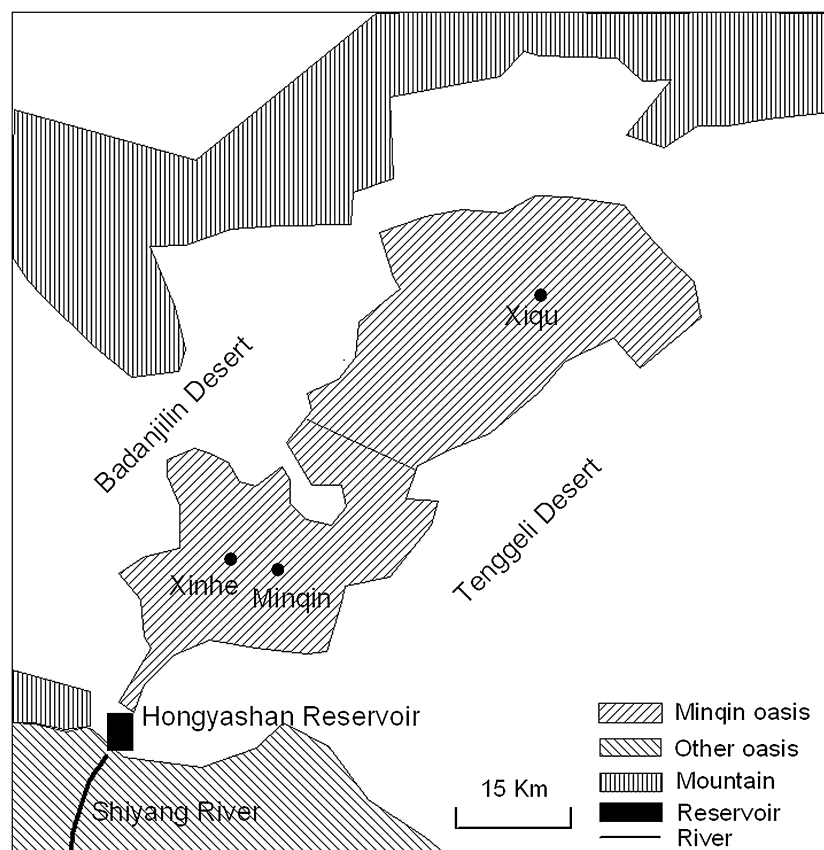


Figure 1. Map depicting the Minqin oasis, the lower reach of Shiyang River, and the Hongyashan reservoir.

with the development of industry and agriculture in the neighboring city of Wuwei, large diversions from the Shiyang River have significantly reduced inflows into the Hongyashan reservoir from $5.4 \times 10^8 \text{ m}^3$ in 1950s to $1.2 \times 10^8 \text{ m}^3$ in 1990s with a decrease of $1.2 \times 10^8 \text{ m}^3$ occurring from 1980 to 2000 (Huo et al. 2007). 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 ground water storage in the Minqin oasis is strongly influenced by surface water conditions, the Hongyashan reservoir plays an important role on transient ground water levels.

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 past 50 year. The agricultural sector is by far the major user of water resources and makes up 93.3% of total water consumed in this region. Because the size of the irrigation area in the study region has increased from 56 kha in 1980 to 63 kha in 1997, ground water extractions have increased. In the year 2000, there were 9140 known extraction wells in the Minqin oasis, with the estimated quantity of extracted ground water via these wells, $6.57 \times 10^8 \text{ m}^3$, substantially exceeding that of natural replenishment, estimated to be $1.0 \times 10^8 \text{ m}^3$ (Huo et al. 2007). Because the ground water usage is not sustainable, ground water levels in the oasis have declined significantly.

Last, there is a seasonal component to ground water level changes, coinciding with both human activities and

weather. Ground water levels decline in the summer and autumn agricultural seasons in response to higher irrigation extractions and evapotranspiration (ET) losses, with partial ground water level recovery in winter and spring. The combination of increased ground water extraction and reduced surface water recharge via the Hongyashan reservoir, however, has produced a long-term trend of ground water level declines in the study area that has accelerated in recent years.

ANN Methodology

The ANN methodology is an alternative to physical-based ground water modeling approaches. Coppola et al. (2005b) provide an overview of basic ANN concepts related to architecture, transfer functions, learning algorithm, development heuristics, and issues related to ground water modeling. Among the ANN architectures and algorithms, the back propagation (BP) ANN has been applied successfully to solve many different types of problems. Figure 2 shows a representative feed forward neural network, which was also used in this study, consisting of three distinct layers: an input, hidden, and output layer.

The training of the network consists of a forward propagation of the inputs and a backward propagation of the error. In the forward procedure, the effect of an applied activity pattern at the input layer is propagated through the network layer by layer. The activation value

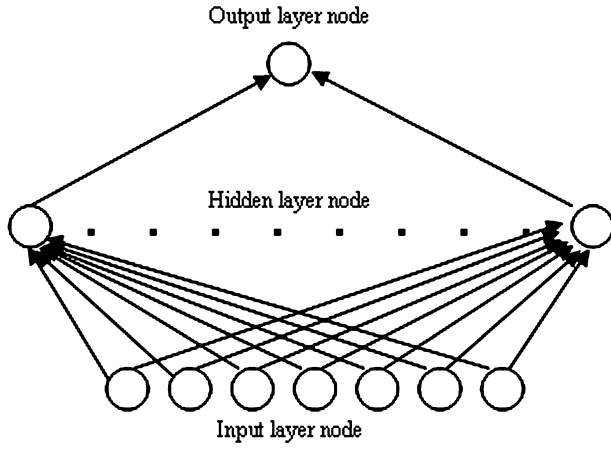


Figure 2. Architecture of a three-layered BP-ANN used in study.

at i th neuron in n th layer a_i^n is given by the following equation:

$$a_i^n = \sum_{j=1}^m W_{ji}^n O_j^{n-1} + b_i^n \quad (1)$$

where W_{ji}^n is the weight of the link between i th neuron in the n th layer and j th neuron in the $(n - 1)$ th layer; O_j^{n-1} is the output of the j th neuron in the $(n - 1)$ th layer; b_i^n is the bias of the i th neuron in the n th layer; and m is the number of neurons in j layer. The activation value of a neuron is used to obtain the output value of that neuron through the transfer function. The general functional form of the sigmoidal logistic transfer function, which was used in this study and is the most commonly used non-linear transfer function, is given by:

$$f(t) = 1/(1 + \exp(-t)) \quad (2)$$

where t represents the weighted sum for a node in the hidden layer and \exp denotes the natural exponential function. The function value of each neuron in the output layer is obtained by propagating the effect of input through layers. The goal of ANN is to establish a relation of the form as follows:

$$Y^m = f(X^n) \quad (3)$$

where X^n is an n -dimensional input predictor vector consisting of x_1, x_2, \dots, x_n ; and Y^m is an m -dimensional output or target vector consisting of prediction variables of interest y_1, y_2, \dots, y_m . Normally, the network is trained by a BP algorithm, which adjusts the weights and biases so as to minimize the error function given by:

$$E = \sum_P \sum_m (y_i - \bar{h}_i)^2 \quad (4)$$

In this case, y_i is the ANN computed output of sample i , \bar{h}_i is the observed output of sample i , and P is the number of training patterns or data sets.

In this study, the data were divided into three distinct data sets for the purpose of ANN training, verification,

and validation. During network learning, the training samples are processed through the ANN, and the connection weights are adjusted adaptively until a minimum acceptable error is achieved between the predicted and the observed output. Intermittently, during training, the verification data set is processed through the ANN to ensure that it is not overfitting the training set. Following training, the ANN is tested with the validation data set to assess how well it has learned to generalize system behavior.

In designing a robust and accurate ANN model, the modeler must address a number of important factors, including the type and structure of the neural network, the input prediction variables used, and data preprocessing. This is generally accomplished through a combination of best professional judgment, heuristic rules, and trial and error.

ANN Models for Ground Water Level Variations

Model Variables

Perhaps the single most important step in ANN model development is selecting the set of input variables necessary for predicting the output variables (i.e., system behavior) of interest. Ideally, selection of the inputs is predicated on a basic conceptual if not theoretical understanding of the system dynamics (Coppola et al. 2003b). In this application, to predict a regional average ground water level at the conclusion of a monthly stress period, important source and sink terms, which govern ground water level responses via aquifer storage changes, were represented either explicitly or implicitly by ANN model inputs.

For this modeling problem, there are a number of important causal variables that are difficult to explicitly represent because they are difficult to accurately quantify either by their nature or as a practical matter. For example, in the oasis, where agriculture is the dominant ground water user, irrigation extraction is the variable that most strongly influences monthly ground water level changes. However, with more than 9000 wells within the oasis for which limited well withdrawal information exists, it is difficult to accurately estimate monthly ground water extractions. Consequently, total irrigation area and synthesis irrigation area, which largely determine the total agricultural water demand that must be met by irrigation, were used as surrogate input variables for ground water extraction.

In this study, the following seven variables were used as ANN model inputs: initial ground water level, monthly total precipitation, monthly total water surface evaporation (E_0), monthly total surface water reservoir inflow, population, monthly synthesis irrigation ratio, and irrigation area.

The initial monthly ground water level is a fundamental input for stepwise prediction of this variable at the conclusion of the monthly stress period. That is, the initial state of a system is a fundamental variable for predicting a system's future state.

E_0 is correlative with meteorologic factors that determine the evapotranspiration for specific plants. For the Minqin oasis, changes in crop types cultivated and their relative proportions vary little over time. Consequently, evapotranspiration was principally determined by climate factors, with E_0 serving as a surrogate variable for evapotranspiration. The E_0 values were estimated with an evaporation dish located in the center of study area. Precipitation data were collected from a single weather station located within the oasis.

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 5:

$$W = \sum_{k=1}^K (q_k \times w_k) \quad (5)$$

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

Because total irrigation water volume always exceeds the total surface water inflow volume, the total annual surface water volume is usually exploited for irrigation. Any irrigation water shortage is made up by ground water exploitation. Surface water inflows not only reflect ground water recharge via reservoir leakage but also help determine ground water irrigation extraction. Consequently, surface water inflow in combination with the two agricultural factors aforementioned serve as surrogate variables for irrigation ground water extraction. This demonstrates how the ANN approach can use surrogate variables for implicitly representing important causal factors that are extremely difficult to quantify, particularly over a large regional area.

The monthly surface water inflow was calculated using Equation 6:

$$Q = v \times d \times 24 \times 3600 \quad (6)$$

where Q is the total monthly surface inflow (m^3), v is the flow velocity measured at the reservoir (m^3/s), and d is the sum number of days in 1 month. The constants 24 and 3600 represent seconds and hours, respectively, and are conversion factors.

Last, population was included to represent potable and industrial water extraction as well as other potential human impacts on ground water (e.g., impervious surface creation).

There are 70 ground water-monitoring wells that are relatively uniformly distributed across the Minqin oasis, with levels monitored weekly. In general, as shown in Figure 3, there is a long-term declining trend in water levels from 1980 to 1997, but with a consistent interannual seasonal cycle, characterized by lower levels during the summer and autumn agricultural season followed by partial ground water level recoveries in spring and winter. In this study, the monthly average ground water level represents the target ANN prediction variable and was calculated using Equation 7:

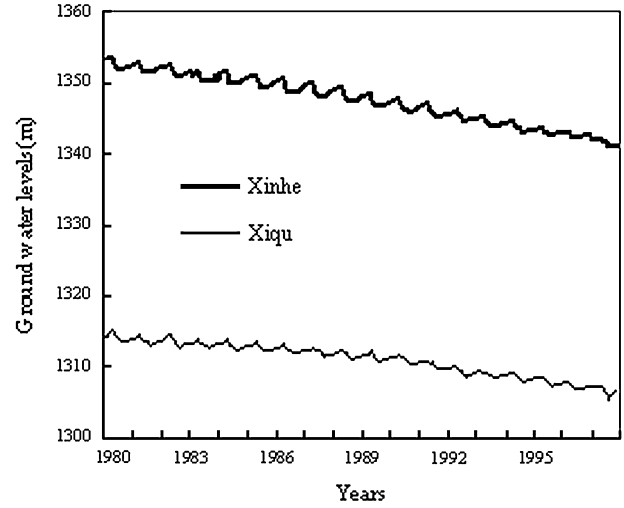


Figure 3. The ground water level dynamics from 1980 to 1997 in typical wells in Xinhe and Xiqu.

$$\bar{h} = \left[\sum_{l=1}^q \left(\sum_{s=1}^r h_{ls} \right) \right] / (q \times r) \quad (7)$$

where h_{ls} is the observation data in well l at s time, q is the total number of wells, and r is the total times for observation of ground water level within 1 month.

It should be noted that while the ANN models developed in this study used only seven input variables to capture overall regional factors, many of the variables could be further spatially disaggregated as necessary and could easily be represented with additional ANN input nodes. This may be warranted, for example, if predicting ground water levels at multiple specific locations within the region, where slightly different meteorologic, hydrologic, and agricultural irrigation patterns may exist over space. An alternative approach is to develop a separate ANN model for each prediction location using inputs specific and unique to the area, but it is still possible that spatial disaggregation of the inputs may improve model performance.

Development and Testing of ANN Models

Recognizing that the impact of inflow into the Hongyashan reservoir on ground water is different in the various regions, two separate ANN models were developed for the Minqin oasis; one for the Xinhe subregion located in near proximity to the Hongyashan reservoir, and the other for the Xiqu subregion located relatively far from the reservoir (Figure 1). The two subregions, Xinhe and Xiqu, are monitored by 34 and 36 monitoring wells, respectively, with monthly average ground water levels calculated for each using Equation 7.

To take advantage of the generalization ability, samples of 216 monthly input-output data from 1980 to 1997 were randomly divided into three equal sets of 72 records for the purpose of training, verification, and validation. ANN development was performed with Matlab 6.5, with final models consisting of a three-layered perception

architecture, with 7 input (i.e., predictor) variable nodes, 10 hidden layer nodes, and 1 output (i.e., prediction) node.

A combination of BP 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 is verified periodically with the verification data set, and this process was repeated until the verification error begins to increase. At this point, approximately after 5000 epochs, training was terminated, with the corresponding set of nodal connection weight values saved. Following this development phase, the ANN model is validated with the third unique data set to evaluate ANN prediction capability.

The mean absolute error (MAE) and relative errors achieved with the training, verification, and validation data sets were calculated using Equations 8 and 9, with values presented in Table 1.

$$E_a = \left(\sum_{i=1}^{72} |h_i - h'_i| \right) / 72 \quad (8)$$

where E_a is the MAEs for training, verification, and validation data sets; h_i is the measured ground water level; and h'_i is the corresponding ANN predicted ground water level.

$$E_r = E_a / \Delta h \quad (9)$$

where E_r is the relative error with respect to the monthly range of fluctuation and Δh is the average monthly range of ground water fluctuation, defined by the average difference between maximum and minimum of ground water level within 1 year. In addition, the variance of absolute error was used to quantify the changes of error.

For both models, the errors for the three data sets (i.e., training, verification, and validation) are low, with the MAE less than 0.5 m. The simulated vs. observed ground water levels in the two subregions are all have consistent change trends (Figure 4) with mean absolute validation errors for the Xinhe and Xiqu models of 0.29 and 0.37 m, respectively, illustrating high predictive performance. The relative validation error with respect to average monthly range of ground water fluctuation for the Xinhe and Xiqu models is 8.3% and 9.3%, respectively. Furthermore, the analysis for variance of error shows that the variation in error for both ANN models is small.

By comparison, a calibrated numerical ground water model for the Minqin oasis was developed (Ma et al. 2002) and achieved a mean absolute validation prediction error of about 0.5 m. Consequently, the ANN models with comparatively much less developmental requirements, time, and effort provided superior predictive accuracy of the mean monthly regional ground water responses. Of course, the numerical model can provide many predictions over space, but for simulating and analyzing general ground water level responses in the oasis, the ANN models used in this study serve as an acceptable surrogate.

Sensitivity Analysis for ANN Models

An important objective in modeling the oasis with ANNs was to gain a better understanding of the factors influencing ground water levels. Systematically varying the values of input variables is useful for projecting responses under different conditions. However, in this study, sensitivity analyses were also conducted to semi-quantify the relative importance of each input variable for accurately predicting ground water 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., used all seven input variables). The sensitivity analysis results derived from the validation data for the Xinhe and Xiqu are presented in Table 2.

The rank is the relative importance of each variable with respect to the other variables, quantified in terms of an error ratio. For example, for the Xinhe model, eliminating the monthly evaporation input variable increased the MAE of the ANN model during validation by a factor of 1.96, represented in the table as the ratio. The corresponding rank for this variable is five, indicating it is the fifth most important variable for accurately predicting ground water levels.

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

$$\text{Ratio} = \frac{\text{MAE without simulator variable}}{\text{MAE with ANN simulator variable}} \quad (10)$$

Table 1
Statistics of ANN Training, Verification, and Validation Results for the Xinhe and Xiqu ANN Models

Statistic	Xinhe			Xiqu		
	Training	Verification	Validation	Training	Verification	Validation
Number of samples	72	72	72	72	72	72
MAE (m)	0.09	0.24	0.29	0.06	0.25	0.37
Variance of the error (m)	0.018	0.037	0.039	0.021	0.039	0.044
Relative error (%)	2.6	6.9	8.3	1.5	6.3	9.3

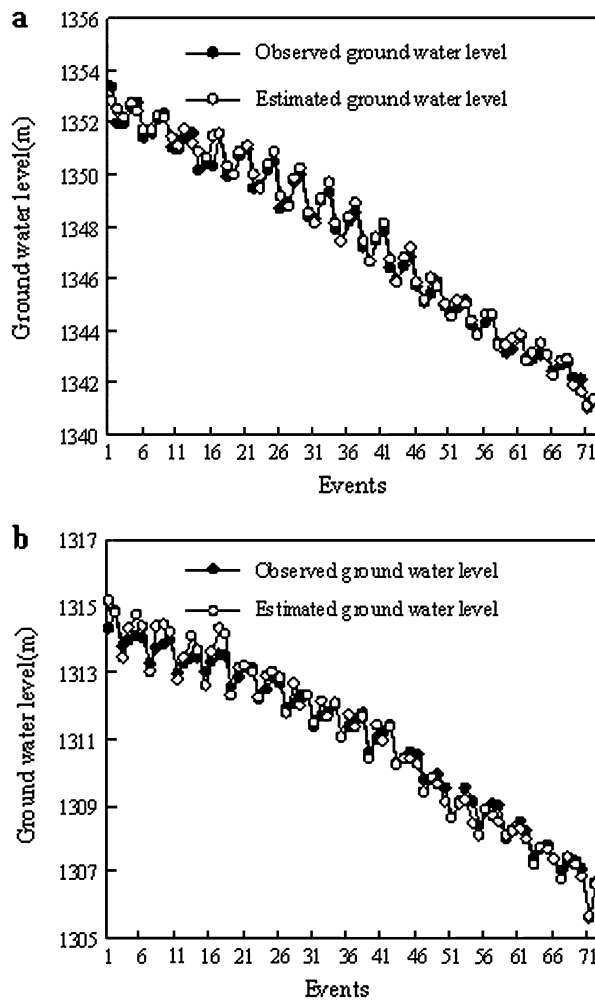


Figure 4. Comparisons of observed vs. ANN predicted ground water levels for validations data using BP network (a, Xinhe and b, Xiqu).

A ratio of less than 1.0 signifies that elimination of the input variable actually increases ANN accuracy, whereas a ratio of more than 1.0 signifies inclusion of the variable

increases predictive accuracy. A ratio = 1 signifies the corresponding variable is neutral and neither increases or decreases ANN performance.

The results of sensitivity analysis for Xinhe and Xiqu indicate that all seven input variables improve ANN predictive capability, though their relative importance varied, from nominally to extremely important. For the two subregions, the initial ground water level is the most important input variable for determining the next month's water level. Agricultural activities, namely ground water irrigation, as represented by irrigation area and monthly synthesis irrigation ratio in the ANN model, are the two next important prediction variables, which is consistent with ground water storage changes in this system.

The results indicate that surface water inflow into the reservoir is the fourth most important variable, and that this variable most strongly influences ground water levels prediction in Xinhe, which is hydrogeologically consistent, as this region is closer to the reservoir than Xiqu. Consequently, Xinhe has more access and hence uses more surface water for irrigation, which simultaneously reduces demand for ground water extractions while artificially increasing areal recharge from irrigation. Also, leakage of water through the unlined reservoir bottom is an added source of ground water recharge in the area.

There is also consistency in the results for the meteorological variables for the two subregions. Generally, precipitation and evaporation have relatively less influence on monthly ground water levels prediction in the Minqin oasis. The impact of these meteorological variables on ground water levels in this region is relatively small over short timescales because of several factors. The relatively deep ground water levels mute temperature effects and delay the arrival time of recharge from precipitation, with the volume of recharge via precipitation in this arid region relatively small. Per unit area, there is only 109.5 mm of annual precipitation vs. 657 mm of irrigation water.

As expected, there were some discrepancies between the two subregions, with evaporation ranking fifth and

Table 2
Sensitivity Analysis Result for Xinhe and Xiqu ANN Models during Validation

Region	Factors	AF	LG	PO	PR	EV	SW	IA	SI
Xinhe	Hidden neuron	10	9	8	8	8	9	9	8
	MAE (m)	0.29	2.07	0.46	0.39	0.57	0.68	0.73	0.75
	Maximum absolute error (m)	1.20	7.58	1.95	1.68	2.34	2.79	3.01	3.21
	Ratio	—	7.15	1.60	1.35	1.96	2.36	2.51	2.60
	Rank	—	1	6	7	5	4	3	2
Xiqu	Hidden neuron	10	9	9	8	8	9	8	8
	MAE (m)	0.37	3.38	0.40	0.41	0.39	0.51	1.21	1.22
	Maximum absolute error (m)	1.20	10.92	1.31	1.36	1.24	1.65	3.94	3.92
	Ratio	—	9.12	1.08	1.12	1.04	1.37	3.26	3.29
	Rank	—	1	6	5	7	4	3	2

Note: AF signifies all seven input variables; LG, PO, PR, EV, SW, IA, and SI mean, respectively, the modes of which last month ground water, population, precipitation, evaporation, surface water inflow, irrigation area, and synthetic irrigation ratio eliminated as ANN input variables.

seventh, respectively, for Xinhe and Xiqu. Because surface water impacts ground water levels via reservoir leakage, high evaporation rates reduce this contribution, which would be most felt in Xinhe, the closer subregion. Similar to meteorological factors and in contrast to agricultural activities, population is a relatively nonimportant variable because of the underdeveloped industry, which is insignificant relative to the extensive agriculture activities in the region.

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 ground water 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.

Simulation of Ground Water Level in the Minqin Oasis

From the sensitivity analysis results aforementioned, irrigation ground water extraction (represented by surrogate agricultural factors) and surface water inflows into the reservoir, both of which constitute human control variables, are the two most influential factors affecting monthly ground water level changes in the Minqin oasis. Monthly synthetic irrigation ratio is mainly correlated with the crop proportion, of which the change is small. In this study, then, ground water levels for Xinhe and Xiqu were simulated using different irrigation areas and inflows into the Hongyashan reservoir.

The objective of these simulations was to investigate ground water levels changes over 1-year horizons in response to variable irrigation area and surface water inflows. For these simulations, initial ground water levels of 1346 and 1309 m, an average condition over the period of interest, for Xinhe and Xiqu, respectively, were selected. Within the Minqin oasis, annual variations between monthly distributions of precipitation, evaporation, and surface inflow are relatively minor. Consequently, average monthly values computed for these variables

from 1980 though 1997 were used for all simulations and are presented in Table 3. In addition, population and irrigation schedule values representing current levels were used. It should be noted that while extreme conditions may also be simulated, the objective of this study was to evaluate operational options for the long-term sustainable use and preservation of the ground water resource.

Figure 5 shows ground water levels simulations over the 1-year horizon for three levels of irrigation areas, 55, 60, and 65 kha, of which 60 kha is near the current irrigation area (58.6 kha), with a fixed surface water inflow value of 1×10^8 m³/yr. The simulation results for Xinhe are consistent with Xiqu, in that ground water level declines are highest in July, August, and September, when the corresponding irrigation quantities are 1050, 1650, and 1050 m³/ha. The ground water levels rise later in the year but do not recover to the initial level because overall there has been a net loss in ground water storage.

The monthly ground water levels change as a function of irrigation areas. Given the same initial conditions, the final monthly ground water levels are lower for larger irrigation areas. The comparative simulations clearly demonstrate a consistent pattern between agricultural and water-use activities and ground water levels. For example, for an assigned irrigation area of 65 kha, the mean ground water levels were predicted to decline to 1342.1 and 1305.5 m above mean sea level (amsl) for Xinhe and Xiqu, respectively, compared with 1344.4 and 1307.2 m amsl for these two subregions when the irrigation area is just 55 kha. Obviously, with larger irrigation areas, ground water levels decline more over the course of the year. Therefore, reducing the irrigation area is an effective measure for reducing the ground water level declines.

Ground water level changes over 1-year periods were also simulated for different surface water inflow values, using an irrigation area of 60 kha, approximately equal to the current level. Figure 6 shows simulation results for the three surface water quantities, 1×10^8 , 2×10^8 , 3×10^8 m³/yr, of which the first constitutes the current level. Similar to irrigation area, surface water inflow influences ground water levels, with larger inflow quantities resulting in higher ground water levels. However, the effect of inflows on ground water levels is different in the two subregions, with more influence exhibited for Xinhe than in Xiqu.

For example, in Xinhe, the mean ground water level declines were predicted to be 0.53 and 0.03 m, with

Table 3
Evaporation, Precipitation, and Irrigation Quantities for Each Month for Simulations

Month	1	2	3	4	5	6	7	8	9	10	11	12
EV (mm)	46.1	71.8	165.7	302.0	389.1	385.3	389.9	339.5	245.2	162.1	91.8	51.8
PR (mm)	0.5	1.1	3.3	4.5	10.1	18.4	23.0	27.4	11.9	5.9	0.6	0.5
SI (m ³ /ha)	900	750	0	1125	1050	1650	1050	450	0	0	0	0
IP (%)	0	4.6	36.1	12.2	7.3	6.6	1.9	1	0.9	15.2	14.2	0

Note: EV, PR, SI, and IP mean, respectively, evaporation, precipitation, synthetic irrigation ratio, and percentage that monthly inflow occupy annual total inflow.

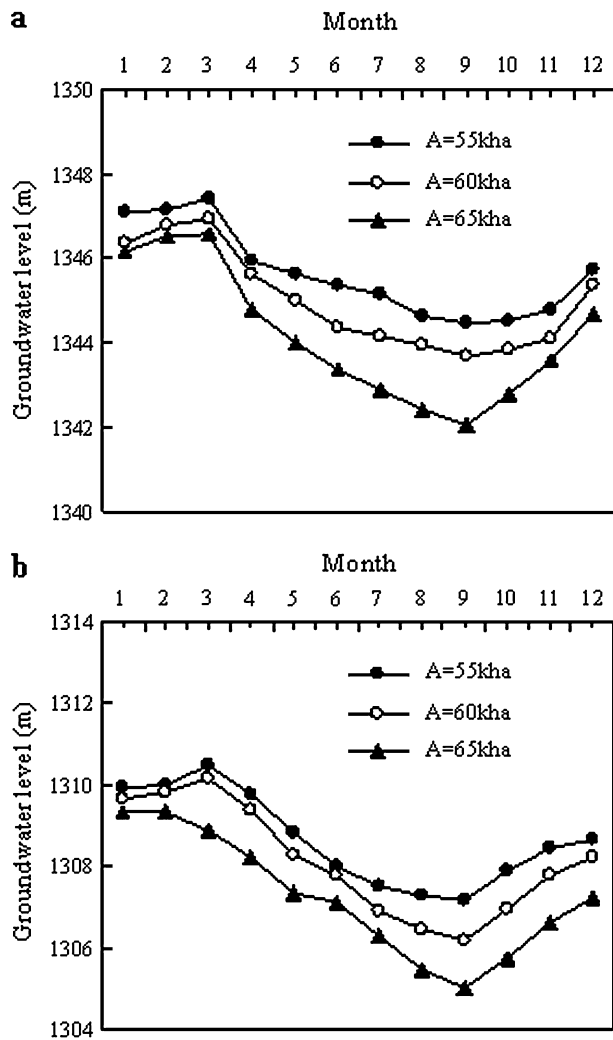


Figure 5. ANN ground water level simulation results for the Minqin region for a 1-year horizon using different irrigation areas (a, Xinhe and b, Xiqu).

surface water inflow values of 1×10^8 and 3×10^8 m³/yr, respectively, for a net difference of 0.5 m over the 1-year period. By comparison, for Xiqu, the difference is only 0.15 m for the same two inflow values. These simulation results are consistent with the sensitivity analysis as well as our conceptual understanding of the system.

Based upon the simulation results, the relationship between declining ground water levels and irrigation area and surface water inflows from the outer region can be extrapolated to linear relationships (Figures 7 and 8). The influence of irrigation area on ground water levels is similar in Xinhe and Xiqu, but the influence of the surface water inflows is different for the two areas. When surface water is 1×10^8 m³/yr and irrigation area less than 53 kha, mean ground water levels in the Minqin oasis are expected to remain at their current levels. Consequently, if surface water inflows cannot be increased, reducing irrigation area is an indispensable method for controlling ground water level declines. Because Xinhe is located near the Hongyashan reservoir, its ground water levels are significantly more affected by surface water inflows into the reservoir. By contrast, Xiqu, located relatively far

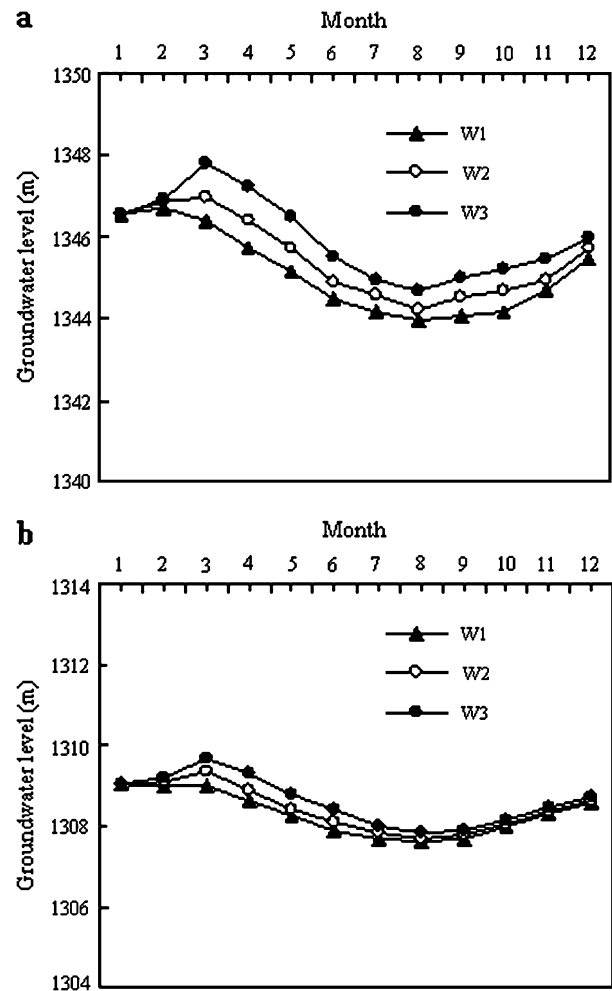


Figure 6. ANN ground water level simulation results for the Minqin region for a 1-year horizon using different surface water inflow from the outer region (surface water inflow W_1 , W_2 , and W_3 , respectively, 1×10^8 , 1×10^8 , 1×10^8 m³/yr; a, Xinhe and b, Xiqu).

from the Hongyashan reservoir, is less affected by surface water inflows.

The simulation results also indicate that when the irrigation area is 60 kha and surface water inflow is 3.2×10^8 m³/yr, ground water levels in Xinhe can be maintained at their present status, whereas ground water levels in Xiqu will continue to drop at 0.3 m/yr. Thus, increasing surface water inflow from outer region can reduce ground water level declines in Xinhe but has relatively little mitigative effect for Xiqu.

Last, it should be emphasized, given the nature of the data and objectives of this study, that one of the inherent advantages of ANNs is their ability to perform well with noisy data (Swingler 1996; Coppola et al. 2003a). This underscores one of the advantages of using ANN in this study, as many of the variables have a high level of impreciseness or uncertainty in their values. The size of the study area and the extreme magnitude of ground water level decline over a relatively long period necessitate that significant changes must be undertaken over a large scale, and, even with imprecise data, the ANN models appear more than capable of providing a sufficiently

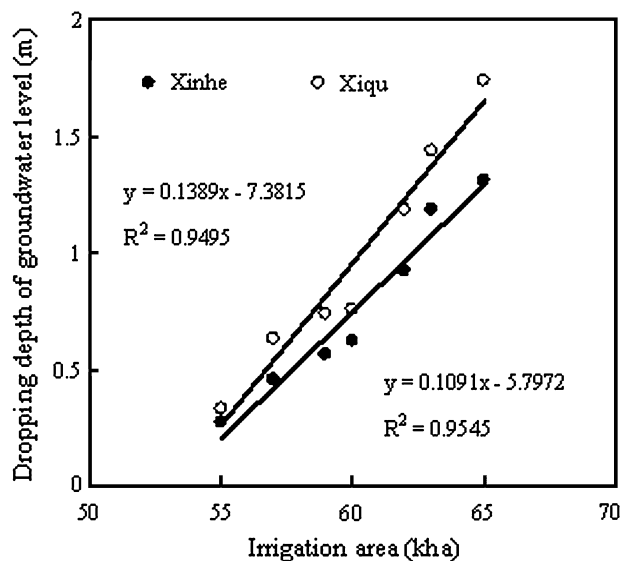


Figure 7. Comparison of ANN simulated ground water level declines for the Xinhe and Xiqu regions under different irrigation areas.

accurate projection of human activities on the ground water system for assisting in developing appropriate policies.

Conclusions

This research demonstrates that ANN modeling can capture important temporally and spatially distributed human factors like agricultural practices and water extraction patterns on a regional basin (or subbasin) scale, and achieve high predictive accuracy, as well as improving understanding of complex ground water systems. The modeling results indicate that human activities and surface water inflows are the most important factors

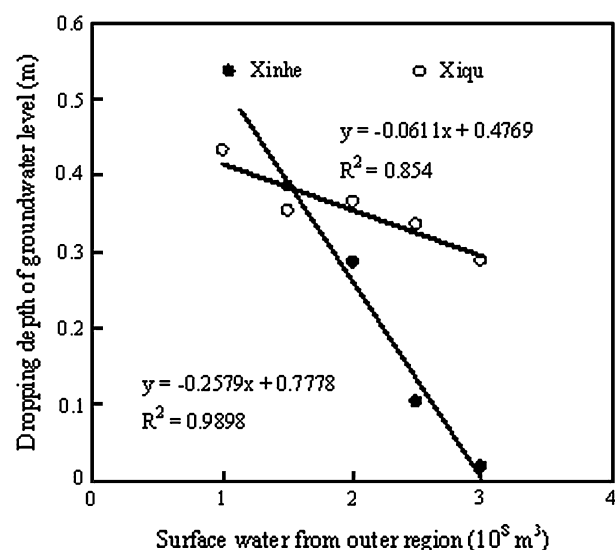


Figure 8. Comparison of ANN simulated ground water level declines for the Xinhe and Xiqu regions under different surface water inflows from outer region.

affecting monthly ground water level changes in the Minqin oasis. As the simulation exercises demonstrate, which is supported by data, the ground water usage has been not sustainable, and if human stresses remain unchecked, ground water levels will continue to decline. The simulation results indicate that reducing irrigation areas and increasing surface water inflows are critical measures for reducing ground water level declines within the Minqin oasis.

For regional-scale ground water basins, water scientists and decision makers need to understand the effect of hydrologic, meteorologic, and human activities on ground water conditions. The sensitivity analysis and simulation capability afforded by ANN models, as shown in this study, can be an extremely effective and efficient tool for ground water analysis and management, and for the Minqin oasis, helped achieve the following objectives: (1) gaining a better understanding of the system by semi-quantifying the relationships between human activities and environmental conditions on ground water levels; (2) identifying the appropriate levels of agricultural activities and surface water reservoir inflows (i.e., upstream diversions) for maintaining ground water levels; (3) revising data collection strategies for improving models and increasing confidence in simulation projections.

The modeling results and analysis will help decision makers understand the influence of human actions on the ground water system, promoting its sustainable use and thereby preserving the long-term economic viability of the region. At the same time, additional work is required. The ANN models developed in this study have limited ability to reveal differences in ground water responses over space in response to variable agricultural practices and environmental conditions. In future work, we will develop ANN models to predict ground water levels at multiple locations to delineate spatial variations of ground water responses across the regional-scale basins, as well as perform multiobjective optimization.

Acknowledgments

The authors are grateful for support from National Key Technology R&D Program of China (2006-BAD111308) and the Program Elitist Program of Chinese Education Ministry (NCET-04-0127). The authors are thankful to Dr. Emery A. Coppola Jr. for his useful suggestions. In addition, the contributions of the three anonymous reviewers whose comments and suggestions significantly improved this article are also appreciated.

References

- ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. 2000a. Artificial neural networks in hydrology. I: Preliminary concepts. *Journal of Hydrologic Engineering* 5, no. 2: 115–123.
- ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. 2000b. Artificial neural networks in hydrology. II: Hydrologic applications. *Journal of Hydrologic Engineering* 5, no. 2: 124–137.
- Coppola, E., F. Szidarovszky, and D. Davis. 2007. Multiobjective analysis of a public wellfield using artificial neural networks. *Ground Water* 45, no. 1: 53–61.

- Coppola, E., C. McLane, M. Poulton, F. Szidarovszky, and R. Magelky. 2005a. Predicting conductance due to upconing using neural networks. *Ground Water* 43, no. 6: 827–836.
- Coppola, E., A. Rana, M. Poulton, F. Szidarovszky, and V. Uhl. 2005b. A neural network model for predicting water table elevations. *Ground Water* 43, no. 2: 231–241.
- Coppola, E., M. Poulton, E. Charles, J. Dustman, and F. Szidarovszky. 2003a. Application of artificial neural networks to complex ground water management problems. *Natural Resources Research* 12, no. 4: 303–320.
- Coppola, E., F. Szidarovszky, M. Poulton, and E. Charles. 2003b. Artificial neural network approach for predicting transient water levels in a multilayered ground water system under variable state, pumping, and climate conditions. *Journal of Hydrological Engineering* 8, no. 6: 348–359.
- Coulibaly, P., F. Ancil, R. Aravena, and B. Bobee. 2001. Artificial neural network modeling of water table depth fluctuation. *Water Resources Research* 37, no. 4: 885–896.
- Coulibaly, P., F. Ancil, and B. Bobee. 1999. Hydrological forecasting using artificial neural networks: the state of the art (in French). *Canada Journal Civil Engineering* 26, no. 3: 293–304.
- Cui, Y., and J. Shao. 2005. The role of ground water in arid/semiarid ecosystems, Northwest China. *Ground Water* 43, no. 4: 471–477.
- Daliakopoulos, I., P. Coulibaly, and I. Tsanis. 2005. Ground water level forecasting using artificial neural networks. *Journal of Hydrology* 309, no. 1–4: 229–240.
- Fan, Z.L., Y.J. Ma, and F. Ji. 2001. Change of oasis and ecology balance related to utilization of water resources in Talimu river basin. *Journal of Natural Resources* 16, no. 1: 22–26.
- French, M.N., W.F. Krajewski, and R.R. Cuykendall. 1992. Rainfall forecasting in space and time using a neural network. *Journal of Hydrology* 137, no. 1–4: 1–31.
- Govindaraju, R.S., and A. Ramachandra Rao. 2000. *Artificial Neural Network in Hydrology*. Amsterdam, The Netherlands: Kluwer Academic Publishing.
- Horton, J.L. 2001. Physiological response to ground water depth varies among species and with river and with river flow regulation. *Ecological Applying* 11, no. 4: 1046–1059.
- Hu, R.J., Z.L. Fan, and Y.J. Wang. 2002. Ground water resources and their characteristics in arid lands of northwestern China. *Journal of Natural Resources* 17, no. 3: 321–326.
- Huo, Z.L., S.Y. Feng, S.Z. Kang, X.Q. Dai, W.C. Li, and S.J. Chen. 2007. The response of water-land environment to human activities in arid Minqin oasis, northwest China. *Arid Land Research and Management* 21, no. 1: 21–36.
- IAHS. 2001. *Impact of Human Activity on Groundwater Dynamics*. IAHS Publication no. 269. Wallingford, U.K.: IAHS Press.
- Kang, S.Z., X.L. Su, and L. Tong. 2004. The impact of human activities on the water-land environment of the Shiyang River basin, an arid region in northwest China. *Hydrological Science Journal* 49, no. 3: 413–426.
- Lallahem, S., J. Maniaa, and A. Hani. 2005. On the use of neural networks to evaluate ground water levels in fractured media. *Journal of Hydrology* 307, no. 1–4: 92–111.
- Ma, J.Z., X.S. Wang, and W.M. Edmunds. 2005. The characteristics of ground-water 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 Environment* 61, no. 2: 227–295.
- Ma, X.W., B.G. Li, and C.R. Wu. 2003. Predicting of temporal-spatial change of ground water table resulted from current land use in Minqin oasis. *Advance in Water Science* 14, no. 1, 85–90.
- Ma, X.W., B.G. Li, and C.R. Wu. 2002. Modeling the influence of land use on ground water in oasis. *Resources Science* 24, no. 2: 49–55.
- Maier, H.R., and G.C. Dandy. 2000. Neural networks for the prediction and forecasting of water resources variables: A review of modeling issues and applications. *Environmental Modeling and Software* 15, no. 1: 101–124.
- Mao, X., S. Shang, and X. Liu. 2002. Ground water level predictions using artificial neural networks. *Tsinghua Science and Technology* 7, no. 6: 574–579.
- New York Times. 2006. *A Sea of Sand is Threatening China's Heart*. June 8, Late Edition-Final, Section A, Page 1, Column 2.
- Qiu, H.X., B.C. Wang, and B. Adams. 1998. Water resources exploitation and sustaining development in arid area. *Marine Geology and Quaternary Geology* 18, no. 4: 97–108.
- Rao, S.V.N., B.S. Thandaveswara, and S.M. Bhallamudi. 2003. Optimal ground water management in deltaic regions using simulated annealing and neural networks. *Water Resources Management* 17, no. 6: 409–428.
- Swingler, K. 1996. *Applying Neural Network*. San Diego, California: Academic Press Inc.
- Tang, Q.C., and J.B. Zhang. 2001. Water resources and environment protection in the arid regions in northwest of China. *Progress in Geography* 20, no. 3: 327–333.
- Wang, Q., J.A. Shi, G.J. Chen, and L.H. Xue. 2002. Environmental effects induced by human activities in arid Shiyang River basin, Gansu province, northwest China. *Environmental Geology* 43, no. 1–2: 219–227.