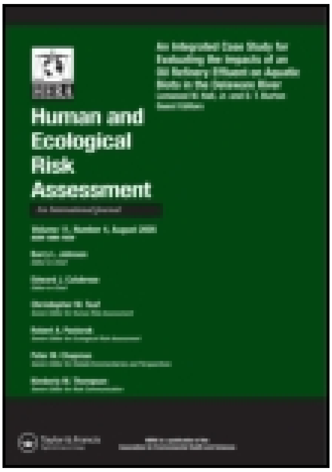

Human and Ecological Risk Assessment: An International Journal
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/bher20

Using a BP Neural Network for Rapid Assessment of Populations with Difficulties Accessing Drinking Water Because of Drought

Huicong Jia[a], Donghua Pan[b], Yi Yuan[b] & Wanchang Zhang[a]
[a] State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China
[b] National Disaster Reduction Center of China, Ministry of Civil Affairs of the People′s Republic of China, Beijing, China
Accepted author version posted online: 18 Feb 2014.Published online: 10 Jul 2014.

Human and Ecological Risk Assessment, 21: 100–116, 2015

ISSN: 1080-7039 print / 1549-7860 online
DOI: 10.1080/10807039.2013.879025

Using a BP Neural Network for Rapid Assessment of Populations with Difficulties Accessing Drinking Water Because of Drought

Huicong Jia,[1] Donghua Pan,[2] Yi Yuan,[2] and Wanchang Zhang[1]
[1]State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China; [2]National Disaster Reduction Center of China, Ministry of Civil Affairs of the People's Republic of China, Beijing, China

ABSTRACT

Accurately predicting the populations with difficulties accessing drinking water because of drought and taking appropriate mitigation measures can minimize economic loss and personal injury. Taking the 2013 Guizhou extreme summer drought as an example, on the basis of collecting meteorological, basic geographic information, socioeconomic data, and disaster effect data of the study area, a rapid assessment model based on a backpropagation (BP) neural network was constructed. Six factors were chosen for the input of the network: the average monthly precipitation, Digital Elevation Model (DEM), river density, population density, road density, and gross domestic product (GDP). The population affected by drought was the model's output. Using samples from 50 drought-affected counties in Guizhou Province for network training, the model's parameters were optimized. Using the trained model, the populations in need were predicted using the other 74 drought-affected counties. The accuracy of the prediction model, represented by the coefficient of determination (R^2) and the normalized root mean square error (N-RMSE), yielded 0.7736 for R^2 and 0.0070 for N-RMSE. The method may provide an effective reference for rapid assessment of the population in need and disaster effect verification.

Key Words: geographical factor, backpropagation (BP) neural network, populations with difficulties accessing drinking water because of drought, rapid assessment, 2013 Guizhou Extreme Drought of China.

Received 28 October 2013; revised manuscript accepted 17 December 2013.
Address correspondence to Donghua Pan, National Disaster Reduction Center of China, Ministry of Civil Affairs, No. 6 Guangbaidong Road, Chaoyang District, Beijing 100124, P.R. China. E-mail: pandonghua@ndrcc.gov.cn
Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/bher.

INTRODUCTION

Most parts of China's Guizhou Province have been gripped by hot ambient air temperatures and drought since early June 2013 as rainfall has been 70% less than the long-term average (1961–2013). Guizhou has received the least precipitation in the recent 50 years. The duration of more than 35° high temperatures in northeastern Guizhou Province was 11–20 days from late June 2013 to early August 2013. Water discharge from the Qingshui, Chishui, and Wuyang Rivers is 20%–50% less than normal. Water storage of the water conservancy project of Guizhou Province is 6% less than the average over the same period (*Economic Daily* 2013). According to the Guizhou Provincial Department of Civil Affairs, more than 12.19 million people in 76 of the province's cities and counties were suffering from drought. There were 14 extreme drought counties, 30 severe drought counties, 19 moderate drought counties, and 13 light drought counties. The drought has also affected 0.84 million hectares of crops and left 2.02 million persons short of drinking water, causing direct economic losses of more than 5 billion yuan (*Nanchang Daily* 2013). Severe drought has led to problems of difficulty in accessing drinking water (Figure 1).

At present, determination of populations with difficulties accessing drinking water because of drought in China is mainly based on disaster reporting by local governments. Until now, there is no efficient rapid assessment system for the quality of disaster data reported by local governments. Therefore, it is very important to accurately predict the occurrence and development of populations with difficulties accessing drinking water because of drought (hereafter referred to as "drought at-risk populations") and take appropriate mitigation measures, actions that will greatly minimize the economic loss and personal injuries. With the information, some possible mitigation measures may be taken by local governments, including use of

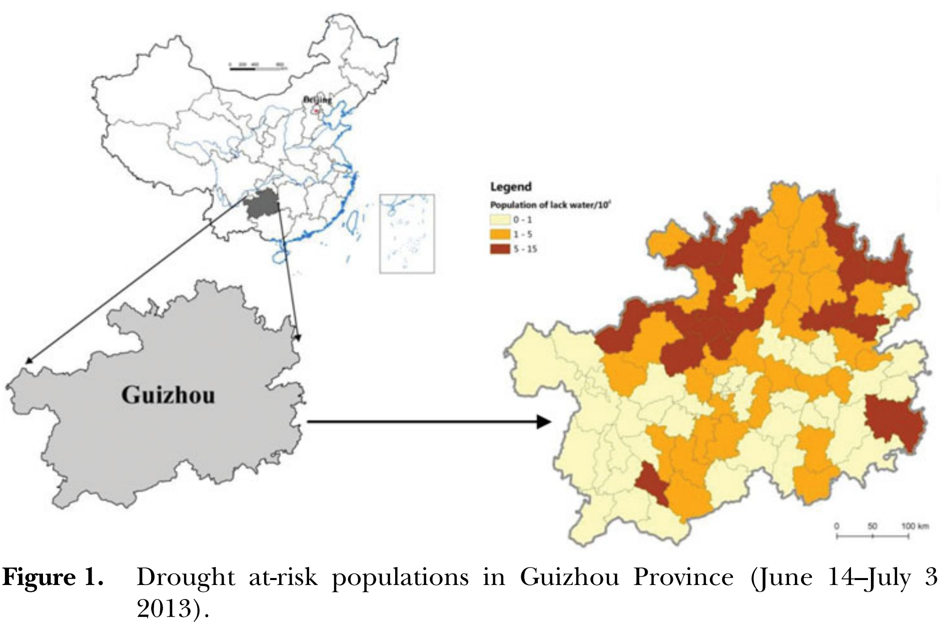

Figure 1. Drought at-risk populations in Guizhou Province (June 14–July 31, 2013).

water conservation technology, use of strategic groundwater, and water resources management.

A recent World Health Organization (WHO) review recommended a minimum of 7.5 liters water per capita per day to meet the requirements of most people under most conditions (Howard and Bartram 2003). The International Water Management Institute (IWMI) projects that 1.8 billion people will live in areas facing physical water scarcity by 2025 (Seckler *et al.* 1998). The amount of water use varies with distance from the water source and with climate conditions (Christine and Richard 2006). Many water-scarce areas in Africa and the Near East have some of the highest population growth rates in the world. In Africa, one-third of the people live in drought-prone areas (ECA 2000). Based on geographic information system (GIS) spatial analysis, an assessment with focus on water availability during drought conditions was conducted under pastoral livestock systems in the drought-prone Isiolo District, Kenya. Thematic information was gathered including rainfall distribution, land use-cover, drainage systems, and hydrogeology and so on (Mati *et al*. 2005). Studies carried out in Ghana, Malawi, South Africa, and Ethiopia highlight how rural livelihoods are affected by seasonal stress and long-term drought (Calow *et al.* 2010). Current and future social and environmental pressures on drinking water conditions, including climate change, were evaluated qualitatively in the Mediterranean area (Ana *et al.* 2007). Until now, few similar studies have been carried out. There is a lack of research on a rapid assessment model of population in drinking water access because of drought. In this respect, the present study contributes to drought prevention for use by local governments.

Artificial neural networks (ANNs), which emulate the parallel distributed processing of the human nervous system, have proven to be very successful in dealing with complicated problems, such as function approximation and pattern recognition (Bishop 1995; Jiang 2001). Due to their powerful capability and functionality, ANNs provide an alternative approach for many assessment problems that are difficult to solve by conventional approaches (Luk *et al.* 2000). The Backpropagation (BP) neural network is currently the most widely used ANN. It has been used increasingly in various aspects of geographical and ecological sciences because of its ability to model both linear and nonlinear systems without the need to make any assumptions as are implicit in most traditional statistical approaches (French *et al.* 1992; Chang *et al*. 2007; Luk *et al.* 2000; Wang and Wang 2011). A system of evaluation of urban land use intensity of Changsha City, China, which includes nine indexes (including population density, green cover percentage, and so on) was determined using a BP neural network. The level of intensified urban utilization from 1999–2006 in Changsha City was carried out by Zhu *et al*. (2009). A BP neural network has been applied to a water environmental quality evaluation in the Weihe River Baoji segment of China (Xie 2013). Generally speaking, the BP neural network used in the aforementioned studies was reported to yield significantly better results than conventional methods. Therefore, it was chosen for this article to provide a technical support for rapid assessment of drought at-risk populations.

The occurrence of drinking water problems is caused by many factors, and each factor presents a nonlinear and uncertain relationship. Taking the 2013 Guizhou extreme summer drought of China as an example, on the basis of collecting meteorological, basic geographic information, socioeconomic data, and disaster effect data for the study area, a rapid assessment model based on a BP neural network was constructed. The objective of this study is two-fold: (1) to build an index system that reflects the spatial distribution of drought at-risk populations and (2) to construct a rapid assessment model of drought at-risk populations based on geographical factors using a BP neural network. The results from this study are intended to help government agencies to judge and assist populations in need of drinking water during times of drought.

BASIC PRINCIPLES OF A BP NEURAL NETWORK

Theoretical Basis

A BP neural network is a feedforward network with a nonlinear transformation function and a multilayer perception algorithm. It consists of an input layer, a hidden layer, and an output layer. The learning process consists of two parts (*i.e.*, signal forward transmission and error back propagation). Forward propagation means that the input signals from the input layer pass through the hidden layer to the output layer. Error back propagation refers to when the output signal and the desired output signal do not match; the output error passes toward the error decrease direction through the hidden layer to the input layer, modifies the threshold value and the weight between the input layer and hidden layer, and the hidden layer and output layer, to reduce errors through repeated training (Rumelhart *et al.* 1986).

BP Neural Network

The BP algorithm model is shown in Figure 2. The algorithm is as follows.

(1) Initialize data. In order to make the input parameters equally important and avoid neurons in saturation, deal with the original data with Eq. (1), make the input data fall between 0 and 1.

$$\overline{x_i} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

(2) Training. Suppose the input initialized values are $x_1, x_2, x_3 \ldots \ldots x_n$, the weights between the input nodes and the hidden layer nodes are w_{ji}, the weights between the hidden layer nodes and the output nodes are v_{lj},the thresholds of the hidden layer and the output layer are θ_j and θ_l, respectively, then the input and output of nodes are calculated in Eqs. (2) and (3).

$$y_j = f\left(\sum w_{ji} x_i - \theta_j\right) \tag{2}$$

$$a = f\left(\sum v_{lj} y_j - \theta_l\right) \tag{3}$$

(3) Judge whether it meets the qualification. E stands for the error of output nodes. Expected value t is known, error is calculated according to Eq. (4). If it meets the qualification, the samples training are completed. If not, according to the principle of decreasing the errors, adjust v_{lj} firstly, and then adjust w_{ji} and θ_j, the

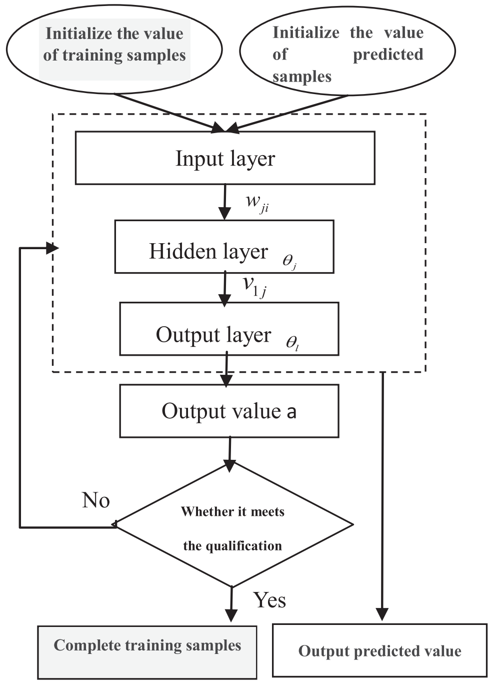

Figure 2. Flow chart for BP neural network.

network is trained using the revised values until it meets the requirements.

$$E = \frac{1}{2} \sum_{l} (t - a)^2 \tag{4}$$

(4) When the samples have completed training, input the initialized values of predicted samples into the network, the predicted values will be obtained.

ANALYSIS OF FACTORS THAT INFLUENCE AT-RISK POPULATIONS

Selection of Influencing Factors

According to the Ministry of Water Resources' standards of the People's Republic of China, the index for assessing drought at-risk populations is based on (a) distance to access the water (>1 km), (b) needing to climb greater than 100 m vertically, and (c) finding the water has F concentrations >1.1 mg/L (*People's Daily Online* 1984). Referring to the current assessment indexes of drought at-risk populations (Wang and Li 2001; Wang and Chen 2005; Yu 2008; Wang *et al.* 2006; Jia *et al.* 2009, 2011, 2012; Jia and Wang 2011), combined with environmental features of disaster-affected areas, the six factors were selected as precipitation, Digital Elevation Model (DEM), river density, population density, road density, and GDP. The data used come from: DEM data of Guizhou Province with 30 m resolution, Guizhou Province Administrative vector map, Guizhou Province 1:1,000,000 railways, national highways and provincial roads data, Guizhou Province 1:1,000,000 river maps, daily precipitation data download from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/) in Guizhou Province of 2000–2013 year, 2009–2012 *China Statistical Yearbook*, and county drought at-risk populations in Guizhou Province in 2013 provided by the National Disaster Reduction Center of China.

Factor Influence Analysis

Precipitation

Lack of water or using water of a poor quality are the basic reasons causing rural populations with drinking water access difficulties (Yu 2008). Since mid-June 2013, the South China Sea summer monsoon was continually weak, which made less rainfall in the regions of the Yangtze River and South China (Wu *et al.* 2003). The East Asian summer monsoon was continually strong from mid-May 2013, in addition to a slight weakening in early July 2013, the overall characteristic was strong. The strong East Asian summer monsoon made water vapor in the western Pacific Ocean to be transported northward. It resulted in more precipitation in North China, less precipitation in South China (Shi *et al.* 1996; Guo *et al.* 2003). Since late June 2013, controlled by the West Pacific subtropical high, the strong East Asian summer monsoon and the weak South China Sea summer monsoon made most parts of Guizhou Province hot and with less rainfall. The temperature of the northeast, east, and the Chishui River Valley regions of Guizhou Province exceeded 35°C. Rainfall was 70% less than the average for the same period. Extreme summer drought appeared in late July 2013 to early August 2013.

The precipitation patterns of Guizhou Province showed that southeast and southwest areas were higher than northwest and northeast areas. It is closely related to mountains, terrain, slope, and altitude. From June 2013 to July 2013, the average monthly precipitation of 13 weather stations in Guizhou Province was less than 20 mm (Figure 3). More severe drought disaster areas are concentrated in the northeast and northwest of Guizhou Province, which was consistent with lower average monthly precipitation. Drought weather of Guizhou Province caused water storage in reservoirs and ponds to be less than normal and declining underground water levels, making it difficult to guarantee basic drinking water supplies.

Terrain

Located in the center of eastern Asia is one of the world's three Karst concentrated regions, Guizhou Province is the central area in China's Karst regions, with a provincial Karst area of about 30×10^4 km^2, accounting for 73.0% of the province's total land area. Guizhou Province is the largest Karst landform distribution area, the strongest developments of Cone Karst in China, even the world (Sweeting 1993; Li 2004). Under this particular Karst topography and geological environmental conditions of Guizhou, rainfall mostly flows away in the form of surface runoff; storage of water is difficult. Poor water-retaining ability and deep underground water in Karst counties made water resources' development and utilization more difficult. Guizhou Province is located in China's western mountain plateau. The terrain's topography relief in the west is higher than that of eastern Guizhou Province, with

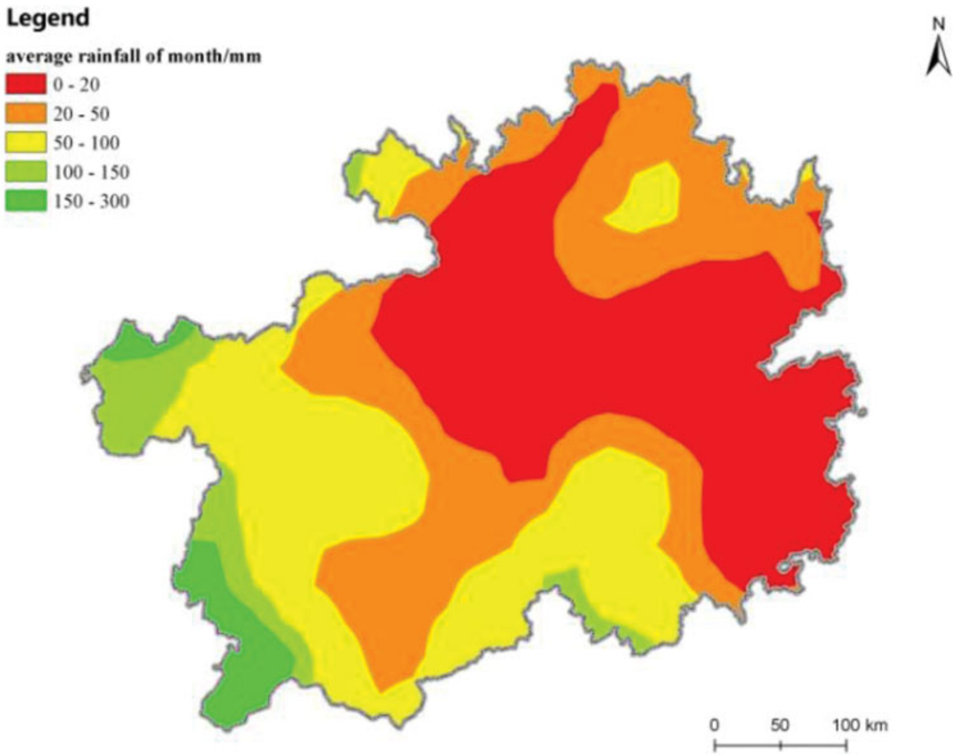

Figure 3. The average monthly precipitation in Guizhou Province (June to July 2013).

an average elevation of 1100 m (Figure 4). The province's landscape can be broadly divided into three basic types: plateaus, hills, and basins, of which 92.5% of the area is mountains and hills (Fu and Gu 2012).

Through analyzing the relationship between terrain elevation and drought at-risk populations, the severe drought area (population in drinking water access difficulties >50,000) was mainly distributed in mountainous and hilly regions in northern Guizhou Province. People have to get their drinking water from rivers or wells. The mean height above sea level of these regions is more than 2000 m. Mountain Fohn Wind further exacerbates the effects of drought. Through analysis, the number of the drought at-risk populations and terrain elevation were positively correlated. In addition, hilly areas are far from water sources, making obtaining water relatively difficult. It also will increase the cost of obtaining water in the hilly areas.

River system distribution

There is a total of 106.2 billion m^3 water in Guizhou Province (including groundwater resources of 26 billion m^3), which ranks sixth in China. Guizhou is a province that has relatively abundant water resources, but the distributions of population

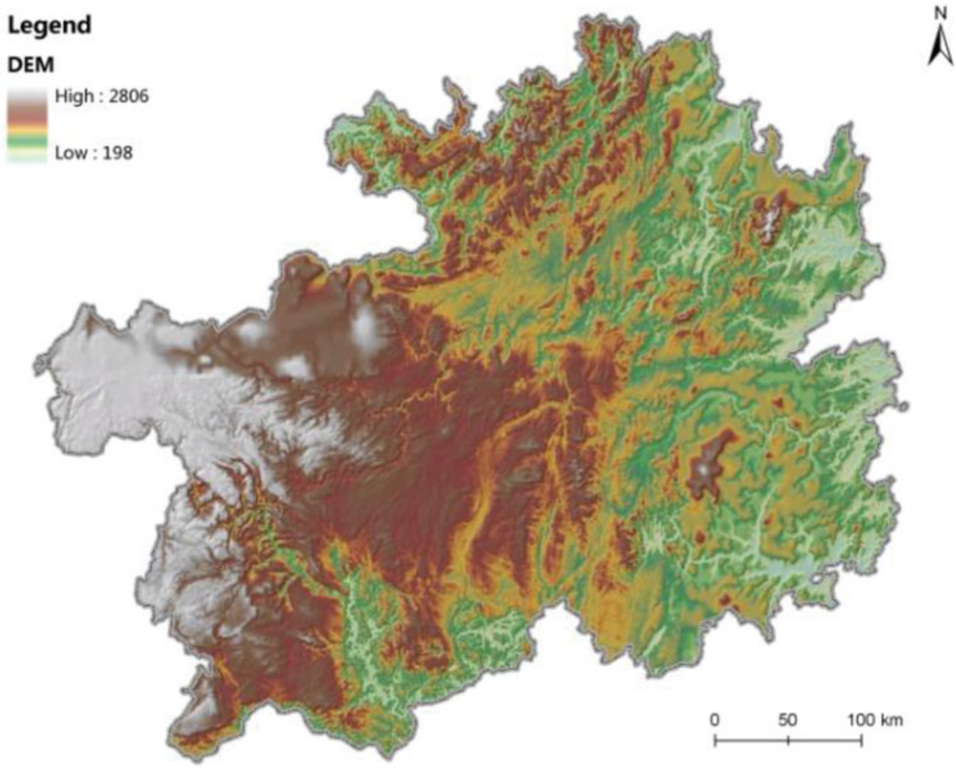

Figure 4. DEM of Guizhou Province (spatial resolution 1 KM).

and water resources are not balanced in Guizhou Province. The midwest and the northern regions (including Guiyang City, Liupanshui City, Zunyi City, Anshun City, Autonomous Prefecture of Buyi Nationalities in Southeastern Guizhou, Bijie Prefecture) accounted for 57.7% of the land area and 68.7% of the population, but the province's water resources only accounted for 54.7% (Yang 2006). Guizhou Pearl is located in the watershed area of the Changjiang River water system and the Pearl River water systems. The terrain topography relief of western Guizhou Province is higher than that of east, so water complies with the general trend of terrain from west and central north, to the east and south. With a dense river network, Guizhou has 984 rivers with length >10 km, basin area >20 km^2; 167 rivers with river basin area >300 km^2; and 7 rivers with river basin area >1000 km^2 (Wu *et al.* 2005). The river density of Guizhou Province is 0.71km/km^2 and river density of eastern Guizhou is higher than that of the west (Figure 5).

Through analyzing the relationship between river density and drought at-risk populations, we found that there were more affected populations with the decrease of river density. The severe drought area (population in drinking water access difficulties >50,000) were mainly distributed in northwest and northeast areas that have sparse river density in Guizhou Province.

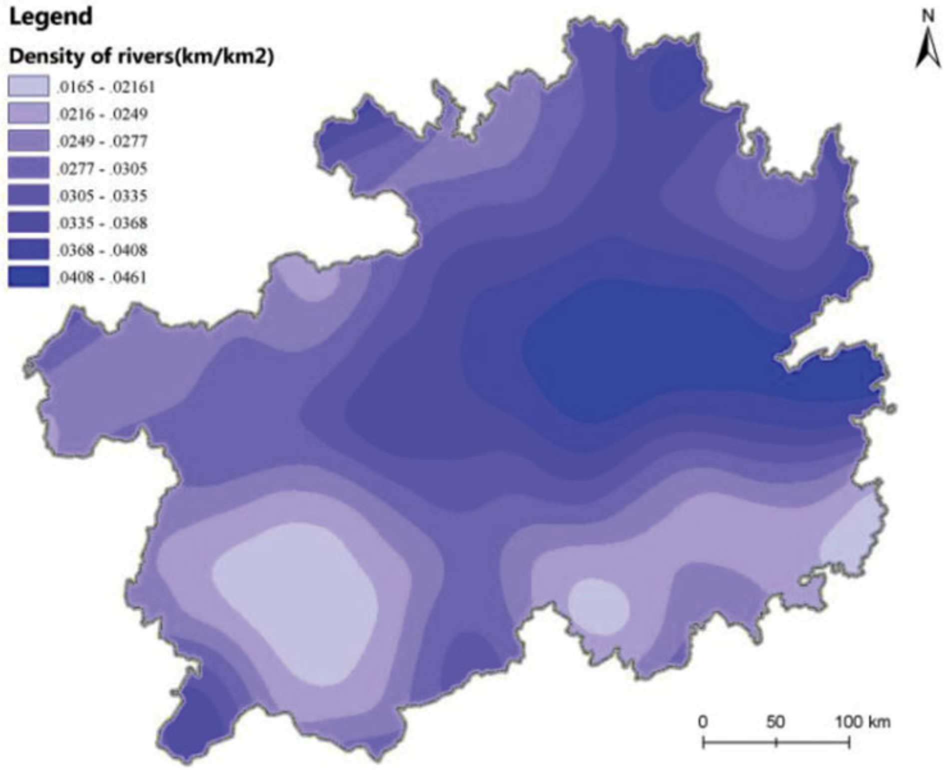

Figure 5. River density of Guizhou Province.

Population

The unique mountain plateau and Karst geological conditions lead to an uneven distribution of population in Guizhou Province. In the plateau regions, the distribution of the population is affected by altitude, landforms, terrain slope, and other environmental factors. Further, the population distribution of plateaus in Guizhou Province also has a special characteristic: Population distribution does not decrease with increasing altitude. A Karst geological condition is the main factor constraining spatial transfer of population distribution. In the non-Karst areas, population distribution is influenced by eroded areas, showing a lowland directivity characteristic (Figure 6).

In recent years with the increase in population density and urbanization development, people's living and production of water gradually increased, coupled with increased demand for food, and cultivated land returning to grass, led to more severe drought under the same precipitation.

Roads

Guiyang City, as Guizhou's provincial capital, is the main railroad junction in southwest China. Taking Guiyang as the center, Guizhou-Guangxi, Sichuan-Guizhou,

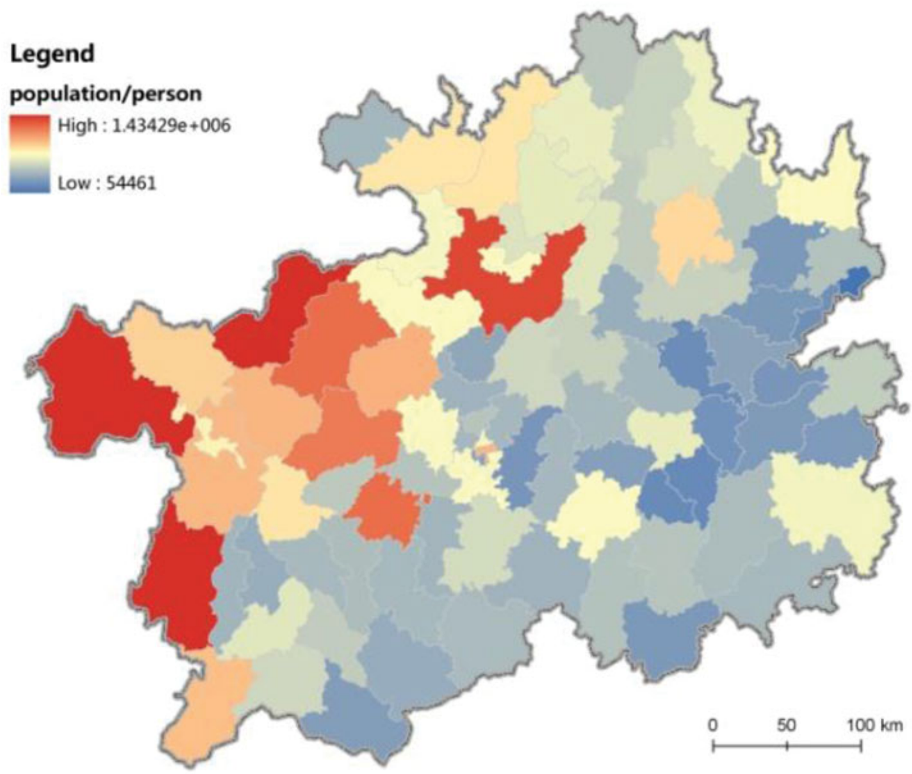

Figure 6. Population density of Guizhou Province (2010).

Guiyang-Kunming, and Zhuzhou railways are the four railway lines that run through Guizhou Province. The total operating mileage is 1468 km.

Highways are one of the most important transportation routes to carrying water for arid areas in Guizhou Province. With the increase of construction land for towns, railroads, highways, and reservoirs, some higher ground was used as the compensation for the original comparatively low-lying land. Accordingly, the soil's water-holding capacity is decreased, resulting in a reduced ability of local drought resistance (Figure 7).

Economic factor

The economic center zone of Guizhou includes Guiyang City, Zunyi City, Anshun City, Qiandongnan Miao, and Dong Autonomous Prefecture. The regional economic differences are obvious, counties (cities, districts) of more than 10 billion yuan of gross domestic product (GDP) in 2010 were distributed in Guiyang City, Zunyi City, Anshun City, and so on (Figure 8), showing that the undeveloped counties have less financial resources to solve their drinking water problems.

To promote coordinated regional economic development and utilization of water resources, water safety is a precondition. Rational development of rural economic development and comprehensive planning should be made to ensure rural

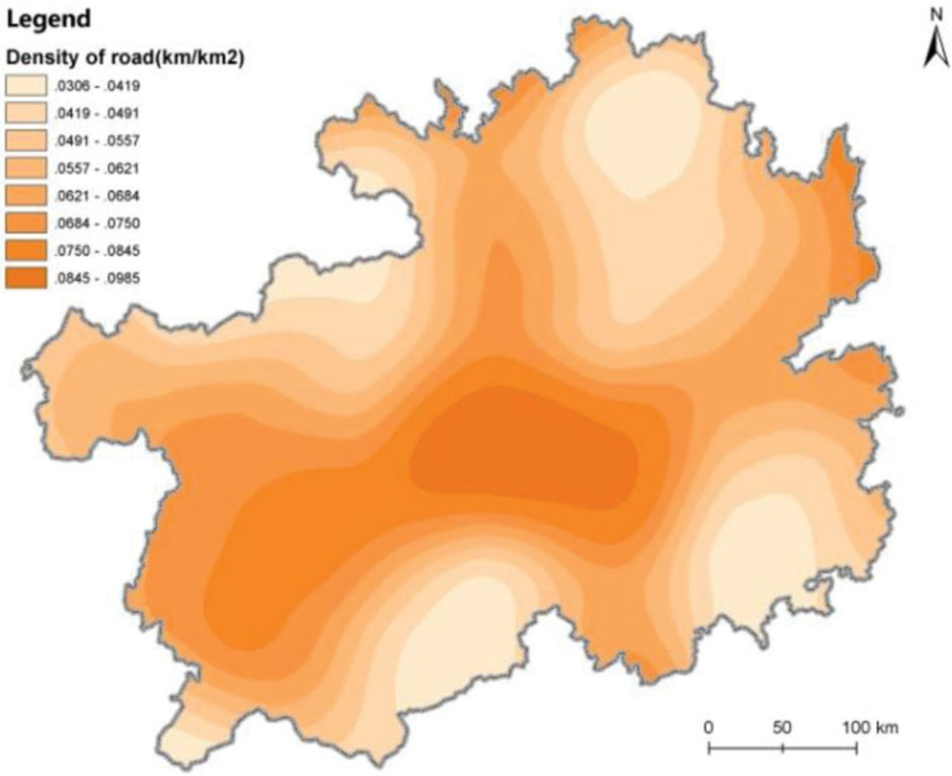

Figure 7. Road density of Guizhou Province.

drinking water supplies. These actions will promote the development between rural economies and the sustainable use of water resources.

CONSTRUCTION OF RAPID ASSESSMENT MODEL

Sample Selection and Data Preprocessing of Data

The structure of our BP neural network is shown in Figure 9. It can be seen from the model's structure that the model consists of three layers of neurons: an input layer, a hidden layer, and an output layer. The input layer's neurons are the six indicators counted by county in Guizhou Province: the average monthly precipitation, DEM, river density, population density, road density, and GDP. The output layer's neurons are the assessment results of drought at-risk populations. The number of neurons in the hidden layer is important for the entire network. So scientifically determining the number of nodes in the hidden layer is extremely important.

In principle, a three-tier network that has m neurons in the input layer, $2m + 1$ neurons in the hidden layer, and n neurons in the output layer can accurately achieve any given continuous mappings. Therefore, whenever a new neural network model is created, the hidden layer's nodes should be confirmed first. According to previous

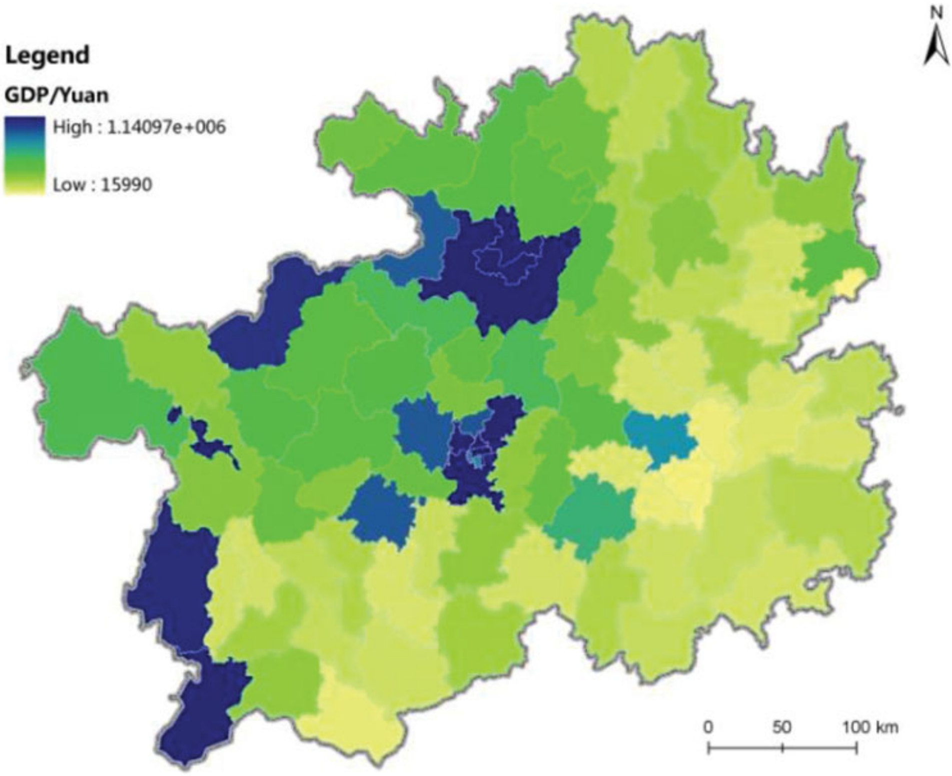

Figure 8. GDP of Guizhou Province (2010).

experience (Wen et al. 2003) m can be designed based on the following equation.

$$m = \sqrt{w + n} + R(10) \tag{5}$$

$$2^m \geq n \tag{6}$$

where m is the hidden layer's nodes; n is the input layer's nodes; w is the output layer's nodes; *R (10)* is a constant between 1 and 10.

Training and Verification of the Rapid Assessment Model

Using the standardized six indexes as the input values of samples in MATLAB software, choosing the 50 drought-affected counties for network learning and training, the model's parameters were optimized under trial, and the hidden layer's neurons were adjusted. The transfer function of a hidden layer was a logarithmic S-type function (Logsig). The transfer function of an output layer was a linear function (purelin). The number of nodes in the hidden layer was 13. Deviation from the goal was 0.01. Network topology was fixed as 6-13-1. In statistics, the mean squared error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. MSE measures the average of the squares of the "errors." When the number of training

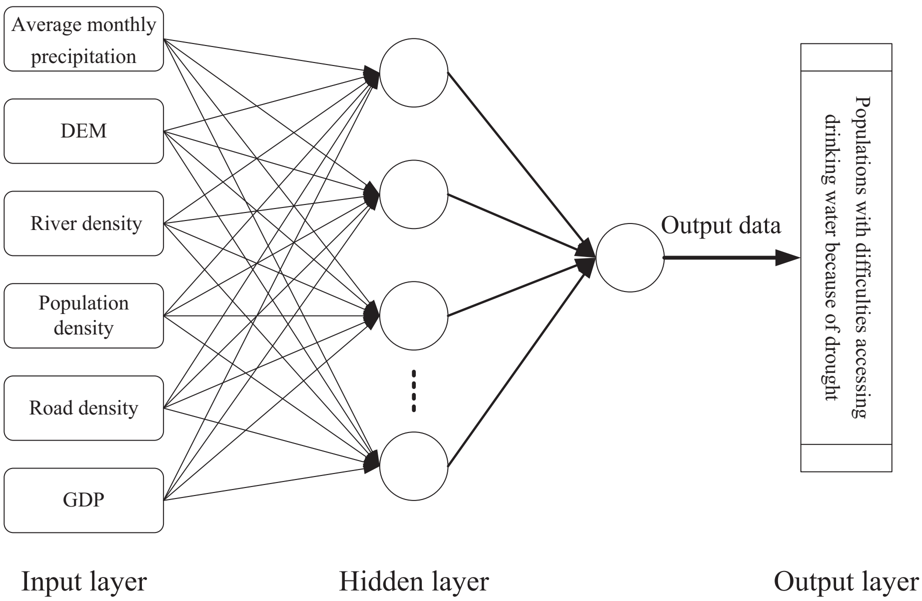

Figure 9. Three layers of the BP network for drought at-risk populations.

trials reached 12, the network converged, and the MSE was 0.1804 (Figure 10). It shows that the network's convergence speed of the model is very fast.

Using the trained neural network to predict the populations in water shortage for the remaining 74 counties, a linear regression result was obtained. The actual values and simulated values were both standardized in Figure 11. In general, the simulated values using the BP neural network method were a little lower than the actual data. The quality of the BP neural network predictions was assessed using the normalized root mean square error (N-RMSE) and the coefficient of determination (R^2) (Figure 11). It shows that the BP neural network method can effectively predict the drought at-risk populations.

DISCUSSION AND CONCLUSION

Presently, the judgment of populations with difficulties accessing drinking water because of drought in China is mainly based on disaster reporting by local government, not a rapid assessment system of the data quality. This article took the 2013 Guizhou extreme summer drought as an example and a rapid assessment model based on geographical factors was constructed. It provided a scientific base for rapid assessment of drought at-risk populations and verification of disaster effects. The model showed that:

1. The selected six input factors of the average monthly precipitation, DEM, river density, population density, road density, and GDP could be used to reflect the spatial distribution of drought at-risk populations.

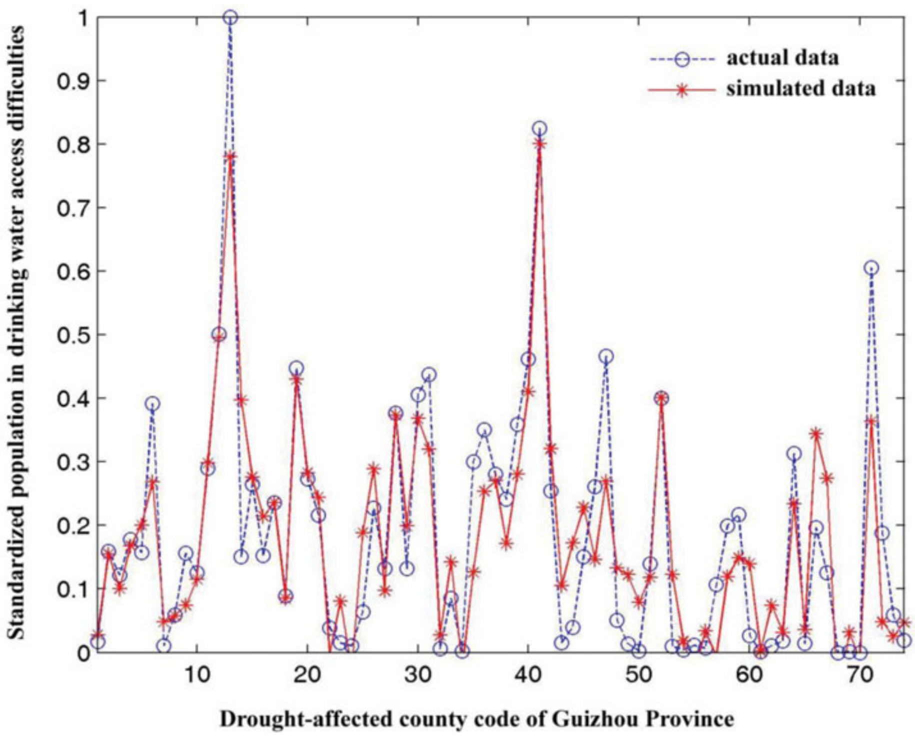

Figure 10. Serial contrast between actual and simulated drought at-risk populations.

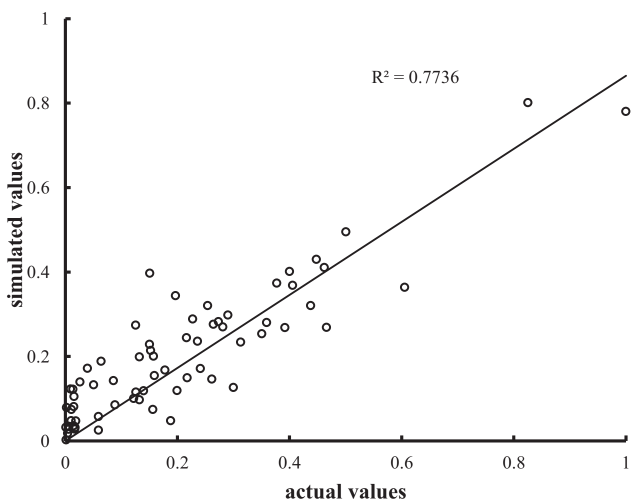

Figure 11. Linear fitting results between BP neural network simulated and actual values.

2. Under the circumstances of more parameters and unknown weights, using a BP neural network to construct an assessment model of drought at-risk populations is feasible. Linear regression results R^2 and N-RMSE between simulated and actual values are 0.7736 and 0.0070, respectively.
3. Taking data availability into consideration primarily, the six input factors were chosen in this study. There are some other input factors that should be considered. In a further study, Principal Component Analysis and cluster analysis should be used to classify variables to determine the representative indicators of drought at-risk populations.
4. In the next stage, we should increase the sample coverage. The model should contain main input factors as many as possible that may affect the output results. Appropriate convergence error should be determined. All can be further improved for prediction accuracy.
5. The modeled outputs will be used by the government officials to assist population in need. The assessment results can provide a scientific basis for determining the regions and how many people should be aided, and then the disaster preparedness and risk relief activities will be carried out. Risk management measures may be taken by local governments including technology (rainwater harvesting initiatives), use of strategic groundwater, and water resources development in daily life.

ACKNOWLEDGMENTS

The authors thank all the people who helped with the article.

FUNDING

This article has been supported by the National Natural Science Foundation of China (41301593), the National High Technology Research and Development Program of China (2013AA12A302), the National Basic Research Program of China (973 Program) (No. 2012CB955402).

REFERENCES

Ana I, Luis G, Francisco F, *et al.* 2007. Challenges to manage the risk of water scarcity and climate change in the Mediterranean. Water Resour Manage 21:775–88

Bishop CM. 1995. Neural Networks for Pattern Recognition. Oxford University Press, Oxford, UK

Calow RC, Macdonald AM, Nicol AL, *et al.* 2010. Ground water security and drought in Africa: Linking availability, access and demand. Ground Water 2:246–56

Chang Q, Wang YL, Wu JS, *et al.* 2007. Urban land use intensity assessment based on artificial neural networks: A case of Shenzhen. China Land Sci 21(4):26–31

Christine LM and Richard DR. 2006. Global challenges in water, sanitation and health. J Water Health 04(suppl):41–57

ECA (Economic Commission for Africa). 2000. Safeguarding life and development in Africa. A vision for water resources management in the 21st century. Proceedings of the Second World Water Forum, pp 4–7. The Hague, The Netherlands. Addis Ababa, March 18

Economic Daily. 2013. Extreme Summer Drought Hit Guizhou Province. Available at http://paper.ce.cn/jjrb/html/2013-07/30/content_166045.htm (accessed July 28, 2013)

French M, Krajewski W, and Cuykendall RR. 1992. Rainfall forecasting in space and time using a neural network. J Hydrol 137:1–31

Fu FJ and Gu XP. 2012. Analysis on the causes of frequent occurrence of drought in Guizhou Province. J Agricult Catastrophology 2(4):58–60

Guo QY, Cai JN, Shao XM *et al.* 2003. Interdecadal variability of east-Asian summer monsoon and its impact on the climate of China. Acta Geographica Sinica 58(4):569–76

Howard G and Bartram J. 2003. Domestic Water Quantity: Service Level and Health. World Health Organization, Geneva, Switzerland

Jia HC and Wang JA. 2011. Progress in research at home and abroad on risk assessment of drought in different regional scales. J Natural Disasters 20(2):138–45

Jia HC, Wang JA, Yue YJ, *et al.* 2009. Construction and application of index system of winter wheat drought risk assessment-A preliminary cognition based on fieldwork of spring drought in North China in 2009. J Catastrophology 24(4):20–5

Jia HC, Wang JA, Pan DH, *et al.* 2011. Maize drought disaster risk assessment based on EPIC model: A case study of maize region in Northern China. Acta Geographica Sinica 66(5):643–52

Jia HC, Wang JA, Cao CX, *et al.* 2012. Maize drought disaster risk assessment of China based on EPIC model. Internat J Digital Earth 5 (6):488–515

Jiang ZL. 2001. Introduction to Artificial Neural Network, pp 2–4. Higher Education Press, Beijing, China (in Chinese)

Li RL. 2004. The Nature Settings and Their Diversity in Different Regions in the Progressing of Rocky Desertification in Guizhou Karst Area. Doctoral Dissertation. Institute of Geochemistry, Chinese Academy of Sciences, Beijing, China

Luk KC, Ball JE, and Sharma A. 2000. A study of optimal model lag and spatial inputs to artificial neural network for rainfall forecasting. J Hydrol 227:56–65

Mati BM, Muchiri JM, Njenga K, *et al.* 2005. Assessing water availability under pastoral livestock systems in drought-prone Isiolo District, Kenya. Working Paper 106. International Water Management Institute (IWMI), Colombo, Sri Lanka

Nanchang Daily. 2013. Extreme Drought of Guizhou Province. Available at http://news.163.com/13/0801/15/957158QJ00014AED.html (accessed July 28, 2013)

People's Daily Online. 1984. Provisional regulations of ministry of water conservancy and electric power to work on rural drinking water. Available at http://www.people.com.cn/item/flfgk/gwyfg/1984/112403198404.html (accessed July 18, 2013)

Rumelhart DE, Hinton GE, and Williams RJ. 1986. Learning representations by back propagating errors. Nature 323:533–6

Seckler D, Amarasinghe D, Molden D, *et al.* 1998. World Water Demand and Supply, 1990–2025: Scenarios and Issues. International Water Management Institute Report 19. International Water Management Institute, Colombo, Sri Lanka

Shi N, Zhu QG, and Wu BG. 1996. The East Asian-climate anomaly summer monsoon in relation to summer large scale weather in China for last 40 Years. Scientia Atmospherica Sinica 20(5):575–83

Sweeting MM. 1993. Reflections on the development of Karst geomorphology in Europe and a comparison with its development in China. Z Geomoph 37:127–36

Wang SS, Liu KP, and Liu QC. 2006. Study on the standard system of rural water supply. J Beijing Univ Technol 32(9):836–40

Wang TT and Chen J. 2005. Classification and countermeasure of rural drinking water access difficulties in China. J Econ Water Resources 23(1):42–3
Wang YF and Wang XY. 2011. Flood prediction model of Daoshui River based on artificial neural network. Water Resources Res 32(2):43–8
Wang YS and Li PH. 2001. Cause analysis and countermeasure of rural drinking water access difficulties in China. Water Supply and Drainage 27(7):23–5
Wen X, Zhou L, Li X, *et al.* 2003. MATLAB Neural Network Simulation and Application. Science Press, Beijing, China (in Chinese)
Wu SS, Liang JY, and Li CH. 2003. Relationship between the intensity of South China Sea summer monsoon and the precipitation in raining seasons in China. J Tropical Meteorol 19(Suppl.):25–36
Wu SZ, Zhu WX, Su WC, *et al.* 2005. Water resources and water saving irrigation in Guizhou Province. J Guizhou Normal Univ (Natural Sciences) 23(3):24–7
Xie HX. 2013. Analysis of water environmental quality in Weihe River Baoji segment using BP Artificial Neural network. Henan Sci 31(4):509–12
Yang XH. 2006. The cause of drought formation & counter measures of reducing drought loss. Guizhou Water Power 20(1):15–18
Yu ZD. 2008. Analysis of causes and countermeasure of rural drinking water access difficulties in west and center of China. Modern Agricul 3:121
Zhu HM, Zhou ZY, Huang C, *et al.* 2009. Application of BP artificial neural network in urban use intensity assessment-A case of Changsha City. Econ Geography 29(5):836–9