Surface runoff response to climate change based on artificial neural network (ANN) models: a case study with Zagunao catchment in Upper Minjiang River, Southwest China

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ABSTRACT

Climate change and its hydrological consequences are of great concern for water resources managers in the context of global change. This is especially true for Upper Minjiang River (UMR) basin, where surface runoff was reported to decrease following forest harvesting, as this unusual forest–water relationship is perhaps attributed to climate change. To quantify the hydrological impacts of climate change and to better understand the forest–water relationship, an artificial neural network (ANN)-based precipitation–runoff model was applied to Zagunao catchment, one of the typical catchments in UMR basin, by a climate scenario-based simulation approach. Two variables, seasonality and CTsm (cumulative temperature for snow melting), were devised to reflect the different flow generation mechanisms of Zagunao catchment in different seasons (rainfall-induced versus snow melting-oriented). It was found that the ANN model simulated precipitation–runoff transformation very well ($R^2 = 0.962$). Results showed runoff of Zagunao catchment would increase with the increase in precipitation as well as temperature and such a response was season dependent. Zagunao catchment was more sensitive to temperature rise in the non-growing season but more sensitive to precipitation change in the growing season. Snow melting-oriented runoff reduction due to climate change is perhaps responsible for the unusual forest–water relationship in UMR basin.

Key words | artificial neural networks (ANN), climate change, land-use and land-cover change, Upper Minjiang River

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INTRODUCTION

Global climate change caused by growing atmospheric concentration of CO_2 and other trace gases has become evident. The acceptance that increasing CO_2 concentration in the atmosphere will cause global climate change, especially the change in precipitation and temperature, has led to an increased interest in the impact of climate change on region hydrology among scientists (Guo *et al.* 2002; Jiang *et al.* 2007a; Teutschbein & Seibert 2012; Naz *et al.* 2016). Global climate change is very likely to affect the hydrological cycle and consequently water resources by increasing evaporation due to rising air temperature and changing precipitation (Guo *et al.* 2002; Huntington 2006). In addition, global warming or its increased variability is expected to alter the timing and magnitude of runoff, the frequency and intensity of floods and droughts, rainfall patterns, extreme weather events, and the quality and quantity of water availability (Guo *et al.* 2002; Jiang *et al.* 2007a). These changes, in turn, influence the water supply system, power generation, sediment transport

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and deposition, and ecosystem conservation (Jiang *et al.* 2007a). Therefore, there is a need to investigate the hydrological consequences of climate change at basin scale for sustainable water resources management.

Hydrological precipitation (or rainfall)–runoff models and general circulation models (GCMs) or regional climate models (RCMs) are widely used to assess the impacts of climate change on water resources (Mernild *et al.* 2011; Teng *et al.* 2015). The choice of a model for a particular study depends on many factors, among which, the purpose of study and of data availability have been the dominant ones (Xu 1999; Jiang *et al.* 2007a). Hydrological models, regardless of structural diversity, generally fall into three broad categories, i.e., black box or system theoretical models, conceptual models, and physically based models. Although physically based and conceptual distributed hydrological models can explore the hydrological mechanism underlying the runoff dynamic process at catchment scale (Lin & Wei 2008; Kar *et al.* 2015; Yang *et al.* 2015), they are not applicable to catchments where detailed data and parameters for hydrological modeling are not available. In contrast, artificial neural network (ANN)-based hydrological models under the category of black box can achieve optimal results in the situation where the target system is poorly defined and understood and input data are incomplete and ambiguous by nature (Poff 1996). In addition, the ability of ANN models to simulate any complex relationship between input and output with any predictability (Chen & Adams 2006) makes ANN-based hydrological models an ideal tool for research on the hydrological consequence of climate change. Many studies have shown that ANN-based hydrological models behave better than traditional hydrological models (conceptual, physically based model or statistical model) in runoff prediction (Dawson & Wilby 1998; Imrie *et al.* 2000; Rajurkar *et al.* 2004; Solomatine & Dulal 2010; Mishra *et al.* 2014).

Like many places in China and the world, water shortage is a big problem in the Upper Minjiang River (UMR) basin in southwest China. Due to its special geographic location (the transition zone from Sichuan basin to Qinghai-Tibet plateau), the UMR basin is prone to climate change and so the study of the hydrological response of the UMR basin to climate change has many implications for the sustainable utilization and management of water resources. The UMR basin has experienced large-scale land-use and land-cover change (LUCC) resulting mainly from over-logging. Several forest–water studies in the UMR basin showed that the water yield decreased with the reduction of forest cover (Ma 1987; Zhang *et al.* 2011; Sun *et al.* 2016), which is inconsistent with many other similar studies (Brown *et al.* 2013). Climate variability may account for this particular hydrological phenomenon. In fact, LUCC (forest cover change in the UMR) and climate change in a basin are usually mixed, making it difficult to determine the pure hydrological effect of vegetation, especially forest landscape change on runoff. Due to the characteristics of high elevation and the corresponding low temperature in the UMR, snow-melting runoff is greatly affected by global warming, which may be a reason for the unusual forest–water relationship found in the UMR basin. The knowledge of surface runoff response of UMR to climate change, therefore, is expected to be helpful for understanding the eco-hydrological function of forest vegetation.

In this paper, an ANN-based precipitation–runoff model was used to study the hydrological response of Zagunao catchment, a typical catchment in the UMR basin, to climate change. The objectives of this study are as follows: (1) to study the runoff response of the UMR basin to climate change and provide baseline information for water resources management; and (2) to help understand the unusual forest–water relationship in the UMR basin by analyzing the hydrological consequences of climate change.

DATA AND METHODS

Study area

As an important branch of the Yangtze River, the UMR has a total drainage area of 22,900 km^2 basin (102–104′ E, 31–33′ N) and a total length of 340 km with an annual mean discharge of 469 m^3/s. Zagunao River, one of the main branches of the UMR, has a drainage area of 2,528 km^2 (102.58–103.22′ E, 31.18–31.93′ N). The elevation of Zagunao catchment ranges from 1,823 to 5,769 m above sea level and the area above the elevation of 3,800 m accounts for 56.80% of the whole catchment with permanent snow and ice cover scattered in the catchment. There is great spatial variation in precipitation and temperature as a result of large topographic variation. Mean annual precipitation ranges from 627.5 mm to 1,478.0 mm whereas mean annual air temperature varies between $-1.7\,^{\circ}$C and 12.2 °C. Due to large spatial variation in temperature means, snow-melting occurs in both winter–spring (non-growing) season (in low elevation areas) and summer–autumn (growing) season (in high elevation areas). The precipitation is usually manifested in low to middle intensity of rainfall in summer and autumn, and snowfall occurs in winter and spring (Sun *et al.* 2016).

Thanks to cold and humid climate conditions, subalpine conifer forest, which is mainly composed of *Picea asperata* and *Abies faxoniana*, is widely distributed on the north facing slope at elevations between 2,400 m and 3,900 m as the major vegetation type. *Quercus aquifolioides* normally occurs in the form of shrubs on the south facing slopes where soil is dry and shallow. Forest logging in the Zagunao catchment took place in the period 1958–1998, especially in the period 1958–1965 (accounting for about 70% of the total harvested timber volume) (Sun *et al.* 2016).

Hydrological and meteorological data

Three rain gauge stations located in Miyaluo, Zagunao, and Shangping are available for hydrological research in Zagunao catchment. The former two stations (Miyaluo and Zagunao) are within the study catchment whereas the last one (Shanping) is outside of Zagunao catchment. To better reflect the spatial variation of precipitation in Zagunao catchment, the precipitation record from Shangping rain gauge station was also used in this study. Many methods are available for estimating mean areal precipitation over an area (e.g., catchment) based on the observation records of stations, which include spline, inverse distance weight (IDW), trend surface, kriging and Thiessen polygons. However, as only three rain gauge stations were available for this study it means that many of the above-mentioned methods are not suitable for use. Here, the monthly precipitation data (Pcp) from the three stations were just simply averaged with equal weight to get monthly precipitation data.

There is only one climate station (Li county climate station) within the study area, and it is virtually in the same position as Zagunao rain gauge station, meaning that its precipitation data are of no use in this study. Monthly average relative humidity and monthly evaporation were calculated as input for the ANN model (below). Instead of the traditional monthly average air temperature, monthly cumulative temperature for snow melting (CTsm), a new temperature variable devised by us, was used as the input for the ANN model. CTsm is calculated by the following formula:

$$\mathrm{CTsm} = \sum_{i=1}^{n} T_i \ (T_i \geq 0^{\circ}\mathrm{C}) \tag{1}$$

where T_i is daily average temperature, n is the number of days in a month of interest. CTsm is a monthly counterpart to the variable of degree-day widely used in a snow-melting runoff model on a daily basis (Singh & Kumar 1996). In a degree-day based snow-melting runoff model, daily snow-melting runoff yield is calculated on active temperature above 0 °C (degree-day) rather than daily average air temperature to reflect the snow-melting physical mechanism, and a similar idea was applied to monthly snow-melting runoff calculation in this study. CTsm is expected to behave much better than monthly average temperature in predicting the impacts of climate change on surface runoff in Zagunao catchment given that the temperature change below zero, for instance, from $-30.0\,^{\circ}$C to $-10.2\,^{\circ}$C, contributes nothing to snow-melting.

A hydrological station (Zagunao hydrological station) was installed at the outlet of Zagunao catchment and daily runoff data are available since 1958. Given that large-scale timber harvesting occurred in the period 1958–1965 and that our main objective in this study is to investigate surface runoff response of UMR to climate change, we limited our hydrological records to the 34-year period of 1971–2004, when LUCC was relatively stable. The monthly average runoff was derived from daily runoff values and used as the output variable for the ANN model.

Precipitation–runoff transformation process is strongly influenced by the physical characteristics of the catchment in question, such as catchment geology, topography, soil and vegetation. Given that forest vegetation cover during the period 1971–2004 was relatively stable and soil characteristics and topographic features remained unchanged as well, the runoff dynamic in Zagunao catchment was assumed to be the result of climate change in this study.

Artificial neural network (ANN) model

ANN design is inspired by current understanding of the mammalian brain structure and nervous system. An ANN structure is composed of two main units: a processing element that is analogous to a neuron and interconnections (or weights) between these elements that imitate the synaptic strength in a biological nervous system, and an artificial neuron that receives signals from other neurons or outside through synaptic connections (Poff 1996). In an ANN architecture, the neurons are arranged in groups called layers. For instance, a multi-layer perception network (Figure 1) usually consists of three layers: an input layer where the incoming information is presented to the network; a hidden layer where the learning take place; and an output layer which generates network output (Poff 1996). What is worth pointing out here is that two or three hidden layers are not popular in ANN models even though some ANN models in previous references do have two or three hidden layers. More hidden layers means higher requirement for data points to estimate parameters.

The major advantage of an ANN is its ability to represent non-linearity by means of smaller number of parameters and to 'learn' from examples (i.e., from its environment). Moreover, the application of an ANN model, for instance (e.g., ANN based precipitation–runoff modeling), does not require any a priori assumption regarding the processes involved (Sajikumar & Thandaveswara 1999). In the development of the precipitation–runoff model used in this study, we selected a multi-layer perception network with one hidden layer, that is advocated by Dawson & Wilby (1998). Six variables, namely monthly precipitation (Pcp), antecedent precipitation ($Pcp_{-1,}$ precipitation in the previous month), CTsm, evaporation (Ep), relative humidity (RH), and seasonality (S, a Boolean variable), were used to estimate monthly runoff and formed the input layer of the neurons, while monthly runoff formed the output layer of the neuron. The precipitation–runoff transformation process in Zaguano catchment is season specific. In the non-growing season, runoff is mainly from snow-melting in lower elevation areas and precipitation cannot form runoff immediately, whereas in the growing season, precipitation directly contributes to runoff formation within a short time lag. To reflect such a difference, the Boolean variable of seasonality, which takes the value of 1 for the months from May to October and 0 for the months from November to April, was used in the ANN model, making it possible to study the hydrological response of Zagunao catchment to climate change on both an annual and seasonal base. Generally, there is a time lag between precipitation and runoff. The runoff in the month of interest likely comes from the previous month. Therefore, the incorporation of the precipitation in the previous month is essential and is expected to improve model performance.

It has long been recognized that catchment soil water storage is the most important factor influencing catchment-level precipitation–runoff transformation process. Water level and runoff (Campolo *et al.* 1999) in the previous day or month or precipitation-based variable (Anctil *et al.* 2004) are often used as a substitute for catchment soil water storage. In this study, RH and Pcp_{-1} were used as a substitute for catchment soil water storage in the ANN model on the assumption that the soil water capacity of Zagunao catchment is closely related to these two variables at month scale.

Two separate data sets were formed from historic data to train and validate the prediction ability of the ANN model. Given the high requirement for data points of ANN model training (the more, the better) and the limited data points for this study (only 34 years' data), a three-layer ANN model was used in this study and trained with data from 1971 to 2001 by means of the Levenberg–Marquardt back-propagation (LMBP) algorithm, whereas the data from 2002 to 2004 were used for model validation. The reason

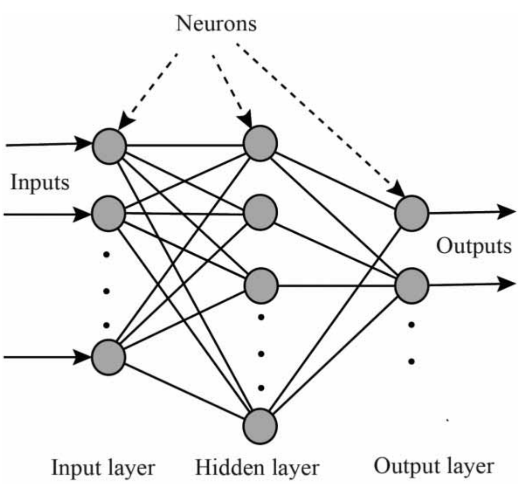

Figure 1 | A feed-forward artificial neural network structure.

that only 36 data points (three years) were used for model validation is related to limited data points. More data points were needed to train the ANN model. All input data were normalized by their values of means and variances to ensure they received equal attention during the training process. The activation functions for the hidden layer and the output layer were hyperbolic tangent sigmoid (Tan-sig) and linear transfer function, respectively. With the candidate number ranging from 9 to 14, the number of neurons in the hidden layer was determined by trial and error method such that the model has good performance in terms of the coefficient of determination (R^2) at both training and validation stages according to Shamseldin (1997). This is expected to be helpful in avoiding over-fitting in the training stage and guaranteeing the generality of the ANN model. All work was accomplished by MATLAB 6.5.

It is important to employ some criteria for judging the performance of a model before its usage. The first requirement of a model is that it should have the ability to reproduce the mean of observed values (here the monthly runoff) as indicated by mean absolute error (MAE). However, the mean value alone cannot fully indicate how well individual simulated values match observed values. To overcome this limitation, the percentage root mean squared error (PRMSE) and the coefficient of determination (R^2) were also employed to assess model performance. The formula for the indicators of PRMSE and MAE is given as follows:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |o_i - p_i|}{n} \tag{2}$$

$$\mathrm{PRMSE} = \sqrt{\frac{\sum_{i=1}^{n} (p_i - o_i)^2}{n}} \times \frac{1}{\bar{o}} \times 100\% \tag{3}$$

where o_i and p_i are the measured value and predicted runoff value in month I; $\bar{o}$ and $\bar{p}$ are the average of measured values and predicted values, whereas n is the number of points of time series data.

Surface runoff response to climate change

To investigate how surface runoff of Zagunao catchment responds to climate change, we designed six precipitation change scenarios and three temperature change scenarios in this study. Precipitation scenarios were defined by changes (including increase and decrease) in monthly precipitation of 5%, 10%, and 15% relative to the baseline precipitation data (1971–2001). Temperature change scenarios were derived by increasing daily temperatures 0.5, 1.0, and 1.5 °C relative to the baseline temperature data during the same period.

The established ANN model was used to study the runoff response of Zagunao catchment under the nine climate change scenarios. With a view to obtaining the difference of runoff generation mechanism and runoff pattern between the non-growing season and the growing season, the runoff response of Zagunao catchment to the defined climate scenarios was analyzed on an annual and seasonal basis, respectively.

RESULTS

ANN-based precipitation–runoff model

The climate and hydrological data from 1971 to 2001 were used to train the ANN-based precipitation–runoff model while those from 2002 to 2004 were used for model validation. The model behaviors in training and validation stages on an annual and seasonal basis are shown in Tables 1 and 2, respectively. As far as the model behavior in the training stage is concerned, the ANN model tracked the monthly runoff dynamics reasonably well, producing good agreement between observed values and predicted ones whether on an annual basis or seasonal basis (Figure 2 and Table 1). In addition, it is clear that model behavior in the growing season was much better than in the non-growing season and had the best goodness of fit on annual basis ($R^2 = 0.962$) in terms of R^2. However, when judged by

Table 1 | Performance of the ANN-based precipitation–runoff model at the training stage

	Annual	Growing season	Non-growing season
MAE	5.901 (64.51)	8.518 (102.235)	3.285 (26.782)
R^2	0.962	0.876	0.817
PRMSE (%)	15.97	11.37	15.19

Note: The values in parentheses are the monthly mean flow calculated on annual and seasonal basis with unit being m^3/s.

Table 2 | Performance of the ANN-based precipitation–runoff model at the validation stage

	Annual	Growing season	Non-growing season
MAE	9.152 (63.50)	13.42 (100.17)	4.883 (26.84)
R^2	0.915	0.741	0.719
PRMSE (%)	20.35	17.32	21.43

Note: The values in parentheses are the monthly mean flow calculated on annual and seasonal basis with unit being m^3/s.

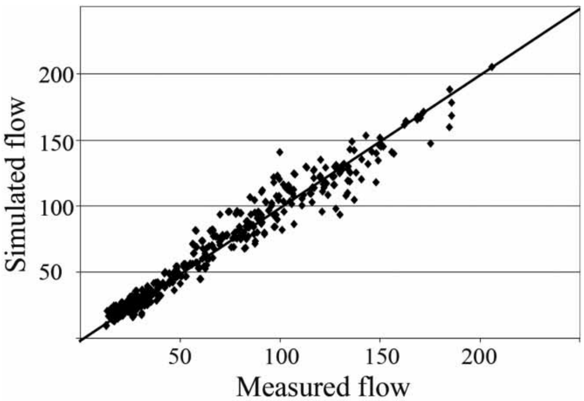

Figure 2 | Scatter plots of the simulated flow values versus the measured flow values in Zagunao catchment from 1971 to 2001 by the ANN model.

PRMSE and weighted MAE by mean monthly flow, the model behavior in the growing season was better than that on an annual basis, showing that the model behavior varied with season and the criterion used. Whether on annual basis or on seasonal basis, the R^2 value (larger than 0.817) and PRMSE values (less than 15.97%) suggested that the established ANN precipitation model was appropriate to simulate precipitation–runoff transformation.

The trained model was verified with climate and hydrological data from 2002 to 2004 (see Table 2 and Figure 3). It was also found that the performance of the established ANN model varied with season and criterion. In terms of R^2, the ANN model had the best performance on an annual basis ($R^2 = 0.915$) and the worst performance ($R^2 = 0.719$) in the non-growing season. However, when it comes to PRMSE, the ANN model resulted in the best goodness of fit in the growing season which is also supported by MAE when weighted by the mean values shown in parentheses in Table 2.

The model behavior was not as satisfactory in the validation period, especially on the seasonal basis ($R^2 = 0.719$ and PRMSE = 21.43% for the non-growing season), as in the training period. However, the performance of the ANN model on the annual basis ($R^2 = 0.915$, MAE = 9.15) suggested that the established model was eligible for the study of surface response to climate change, especially considering the fact that surface runoff of Zagunao catchment (26.84 m^3/s) in the non-growing season was much smaller than its counterparts in the growing season (100.17 m^3/s) and on annual basis (63.50 m^3/s).

Runoff response to climate change

Runoff response of Zagunao catchment to temperature change and precipitation change scenarios is shown in Figure 4. The scenario analysis of temperature change based on the precipitation–runoff model showed that runoff would increase by 1.41%, 3.76%, and 4.03% under the scenarios of T + 0.5, T + 1.0, and T + 1.5 on the annual

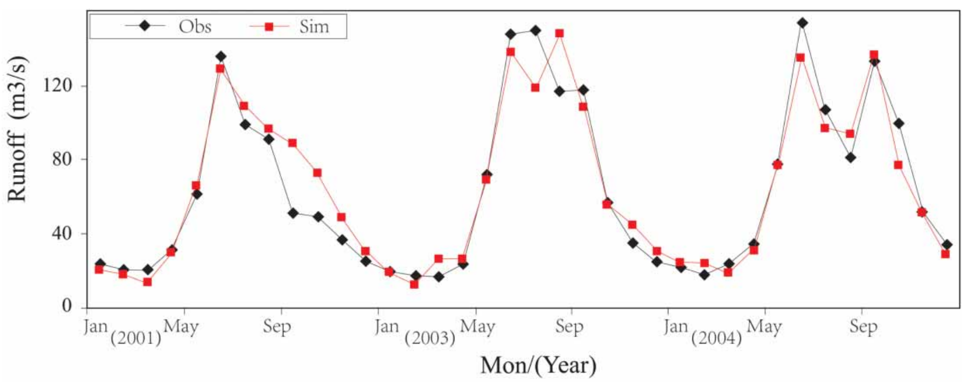

Figure 3 | Measured (Obs) and simulated (Sim) surface runoff in the validation period.

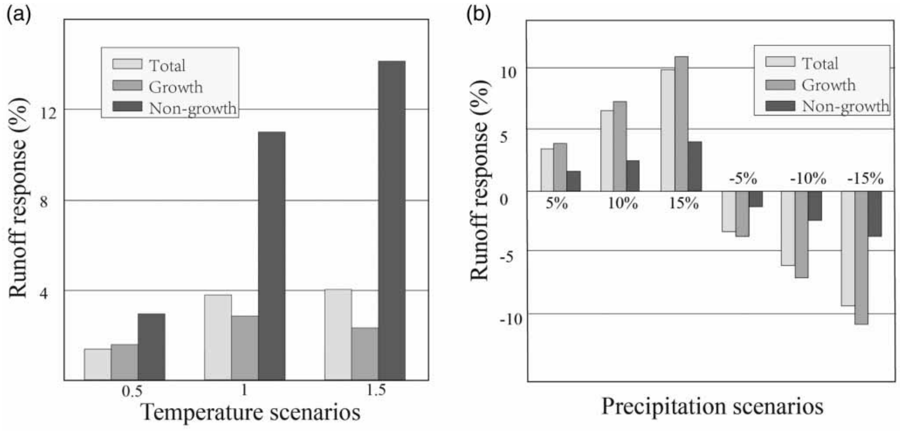

Figure 4 | The response of runoff in Zagunao catchment to rising temperature (a) and precipitation change (b).

basis. The runoff responses to rising temperature change varied with season. Runoff would increase by 2.84% in the growing season in parallel with high flow period in contrast to 10.95% in the non-growing season in coincidence with low flow period under the scenario of $T + 1.0$. This suggested that runoff response of Zagunao catchment was more sensitive in the non-growing season than in the growing season. For instance, the scenario analysis of precipitation change indicated that runoff would increase by 3.47–10.03% when the precipitation increased by 5–15% and would decrease by 3.28–9.48% when the precipitation decreased by 5–15%. Similarly, runoff response to precipitation change was also season-dependent. The response of runoff to precipitation change was much more sensitive in the growing season than in the non-growing season. Runoff would increase by 7.44% for the 10% increase in precipitation scenario in contrast with 2.65% increase in the non-growing season for the same scenario.

DISCUSSION AND CONCLUSIONS

In this study, an ANN-based precipitation–runoff model was used to study the runoff response of Zagunao catchment to climate change (temperature and precipitation) by a climate scenario-based simulation approach. A Boolean variable of seasonality was incorporated in the ANN model to reflect the different runoff generation mechanisms in different seasons (the growing season and the non-growing season). To better reflect the impact of temperature increase on snow-melting runoff generation, CTsm rather than traditional monthly mean air temperature was used as an input variable for the ANN model since temperature changes below 0 °C contribute little to runoff generation. The selection of input variables is very important for ANN models and the unrelated variables only spoil the predictability of ANN models. With the two variables used in the ANN model, the precipitation–runoff process in Zagunao catchment is expected to be better simulated.

Our temperature scenario simulation results showed that global warming would lead to runoff increase, especially in the non-growing season. It is inconsistent with many studies, which generally showed that runoff decreased with temperature increase in rainfall-dominated basins (Guo *et al.* 2002; Legesse *et al.* 2003; Jiang *et al.* 2007a). The snow-melting runoff increase with temperature rise is the main reason for this result. In the non-growing season (November to April), snow-melting occurs in low elevation areas, whereas in the growing season (May to October) the snow-melting occurs in high elevation areas. It is the large spatial variation of temperature in Zagunao catchment that explains this runoff response to temperature increase in both the growing season and non-growing season. In fact, our results are consistent with some studies in snow-dominant catchments (Singh & Kumar 1996; Jiang *et al.* 2007b; Fan *et al.* 2011). The study in Tarim headwater basin by Jiang *et al.* (2007b) found that runoff increased by

10–16% when surface temperature increased by 1.0 °C. In addition, Singh & Kumar (1996) reported that an increase of 2 °C in air temperature would increase total stream flow by 6–12% in a Himalayan river basin of snow and glacier coverage.

Some studies or observations in the UMR showed that stream flow or water yield decreased following forest harvesting (Ma 1987; Zhang *et al.* 2011; Sun *et al.* 2016), which is inconsistent with the general conclusion that forest harvesting results in an increase in stream flow or water yield (Lin & Wei 2008). Is the dynamics of snow-melting runoff, which is greatly affected by temperature changes, responsible for this particular hydrological phenomenon in the UMR basin? The results here are expected to provide some clues regarding this issue. According to Li *et al.* (2017), forest cover change and climate change play almost equal roles in annual water yield variation. The reduction of snow-melting-oriented surface runoff due to temperature change is perhaps one cause of post-logging surface runoff reduction reported in the Zagunao catchment. Whether this is the case or not is worth future research.

Some studies found that the impact of climate change on regional or catchment water resources are model dependent (Jiang *et al.* 2007a), which can be attributed to the assumptions regarding the various processes in the hydrological model. ANN models are distribution-free models and do not require any a priori assumption regarding the processes involved. Therefore, the ANN-based precipitation–runoff model used here is expected to do a better job in simulating the runoff response of the Zagunao catchment to climate change. In addition, in the era of large data and in the context of increased concern regarding climate change impacts on water resources, data-driven ANN models should be highly appreciated, especially when considering the fact that water resources managers are mainly concerned about how regional water resources respond to climate change rather than the mechanism behind such a response. After all, ANN-based hydrological models have a better performance than traditional hydrological models (Dawson & Wilby 1998; Imrie *et al.* 2000; Rajurkar *et al.* 2004; Solomatine & Dulal 2010; Mishra *et al.* 2014).

Zagunao catchment, a typical one in the UMR basin, was used as a case to study the impact of climate changes on water resources in the UMR region in this study. Given that water resources is becoming a limiting factor for sustainable development of the UMR region and that the impacts of climate change on water resources are increasingly self-evident, the result from this study is expected to provide scientific foundation for future water resources planning and management.

The main conclusions are summarized as follows:

1. With the variables of CTsm and seasonality incorporated into the input variable list, the proposed ANN precipitation–runoff model was capable of simulating precipitation–runoff transformation process reasonably well.
2. The runoff of Zagunao catchment increased with temperature increase and such response was season dependent. In comparison with the growing season, the non-growing season was more sensitive to global warming.
3. The runoff of Zagunao catchment to precipitation change was also season dependent with runoff in the growing season being more sensitive to precipitation change.

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