Runoff Response of Zamu River Basin to IPCC Climate Change Scenarios in Northwest China

Sufen Wang and Xin Liu

Center for Agricultural Water Research in China, China Agricultural University, Beijing, 100083, China
wangsuf@cau.edu.cn, wwwsf71@163.com

Abstract. Predicting runoff response to climate change is useful in making the decision of water resources management in arid region. This study investigated the impact of climate change on the runoff of Zamu River, one of the inland rivers in the arid region of northwest China using Soil and Water Assessment Tool (SWAT) model. Climate-change was predicted by the UK Hadley Centre's Climate Model (HadCM3) under IPCC A2 and B2 scenarios, and downscaled by statistical downscaling model (SDSM) for two periods: 1961–1990 (control) and 2010–2099 (scenario) to drive the SWAT model. SDSM predicted an increase trend of maximum and minimum temperature and precipitation in the study area during the period of 2010–2099. Simulated runoff under IPCC SRES A2 and B2 scenarios changed by -10.6% - +1.17% and - 4% - +13%, respectively. The runoff tended to decline more significantly under SRES A2 (high GGa emissions) than under SRES B2 (low GGa emissions) in the future. The linear trend values were -0.048 and -0.018, respectively.

Keywords: Climate change; Runoff; Downscaling; SWAT; SDSM.

1 Introduction

There are scientific evidences about hydrologic system affected by the global climate change. The global temperature is increasing and the 100-year trend (1906-2005) of 0.74 [0.56 to 0.92] °C is larger than the corresponding trend of 0.6 [0.4 to 0.8] °C (1901-2000) given in the TAR (IPCC, 2007) [1]. The global climate change has impacts on regional precipitation, precipitation distribution and runoff [2],[3],[4],[5],[6]. Global warming results in evaporation increase. Many studies have proved that runoff is very sensitive to climate change [7],[8],[9],[10]. Runoff conditions are strongly controlled by climate [11]. Climate change could therefore have positive or negative impacts on runoff [12].Hydrological model sensitivity to climate change can be defined as the response of a particular hydrological model to a known quantum of climate change [13],[23],[24],[25].

One way to assess possible impact of climate change on hydrological cycle is to apply different climate change scenarios to hydrological models to estimate hydrologic cycle factors [14],[15]. General climate models (GCMs) and regional climate models (RCMs) are frequently used to model future climate scenarios. The building of hydrological model and the generation of future climate change scenarios are essential

F. Bian et al. (Eds.): GRMSE 2013, Part II, CCIS 399, pp. 223–231, 2013.

to water cycle assessment. The output of climatic factors by GCMs was used to drive hydrological models to study hydrological response to global climate change [16],[17],[18]. Many studies have investigated the impact of climate change on annual mean water flow under IPCC A2 and B2 GHG scenarios [19],[22]. The simulating scale of climate models has great difference to that of hydrological models. However, the general circulation models and regional climate models are among the most advanced tools in estimating future climate change scenarios. Therefore the output from GCMs and RCMs has to be downscaled to obtain the information relevant to hydrologic studies. Downscaling approach was widely used for constructing climate scenarios to drive the hydrologic models. The approaches to downscale the outputs of GCMs are as the follows: Dynamic downscaling method, statistical downscaling method and interpolation method. Dynamic downscaling method, as a Regional Climate Model, is embedded into GCM, but the method had complicated design and application condition, so it is not widely selected for downscaling. Compared to the dynamic downscaling method, the statistical downscaling method is most widely used to downscale the climate scenarios because of less demanding application condition. Statistical downscaling method is to derive empirical relationships that transform large scale features of the GCM (Predictors) to small scale variables (Predictants) based on the basic data. Precipitation and temperature can be predicted. There are three implicit assumptions involved in statistical downscaling method [21]. Interpolation methods include bilinear interpolation and non-equidistant Lagrange three-point interpolation method, through which the output of GCMs can be interpolated to appropriate site.

Arid regions frequently suffer from years of acute shortages of water resources. Climate is a key factor affecting the runoff formation of inland river basin of the arid area in the northwest China. The objective of this study was to evaluate the runoff changes under different climate change scenarios in the Zamu river basin of northwest China. The Statistical downscaling approach (Wilby et al., 2001)[21] and Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998)[20] distributed hydrological model were chosen for this study.

2 Materials and Methods

2.1 Study Watershed

The Zamu River originates in the Qilian Mountains and has a catchment area of 851 km^2. It is the only unregulated river in the Shiyang river basin in the arid region of northwest China and has a glacier area of 3.74 km^2 in the mountain area in the upper reach. The location of the study area was shown in Fig. 1. The only gauging station in the catchment is Zamusi hydrologic station. The elevation of the catchment varies from 2000 m to 4802 m above sea level and its catchment shape is plumose. Mean flow of the river (1955-2005) measured by the Zamusi hydrologic station is 7.75 m^3/s. The upper Zamu river catchment has good vegetation cover, with alp meadow, alp grassland, shrub and arbor. Forestland is patchy, with mixed distribution of grassland and forestland. Major land use type can be divided into grassland, forestland, farmland, rural resident land and uncultivated land [26].

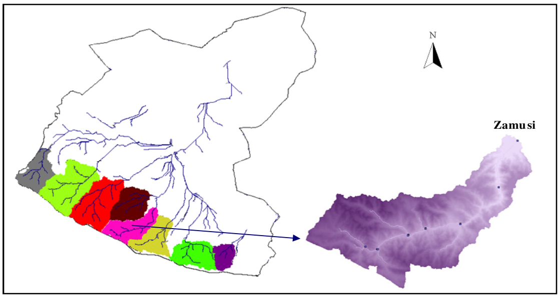

Fig. 1. The map of location o f the study area

2.2 SWAT Hydrological Model

SWAT (Soil and Water Assessment Tool) (Arnold et al., 1998)[20] is physically based hydrological model. Hydrologic Response Units (HRUs) is the basic calculating units, which is consisting of unique combinations of land cover and soils in each sub-basin. SWAT allows a number of different physical processes to be simulated in a basin. It can be used to simulate the hydrological response to changed environment in different time steps (http://www.brc.tamus.edu/swat/swatmanual, swat2000theory). The hydrologic cycle as simulated by SWAT is based on the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_{\alpha} - w_{seep} - Q_{gw}) \tag{1}$$

where SW_t is the final soil water content (mm H_2O), SW_0 is the initial soil water content on day i (mm H_2O), t is the time (days), R_{day} is the amount of precipitation on day i (mm H_2O), Q_{surf} is the amount of surface runoff on day *i* (mm H_2O), E_a is the amount of evapotranspiration on day i (mm H_2O), w_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm H_2O), and Q_{gw} is the amount of return flow on day i (mm H_2O).

2.3 Statistical Downscaling Model

Statistical downscaling model (SDSM) was used to calculate statistical relationships between large-scale (the predictors) and local climate variables (Predictants) based on multiple linear regression technique. These relationships are developed using the observed weather data, assuming that these relationships remain valid in the future. They can be used to obtain downscaled local information for some future time period by driving the relationships with predictors simulated by GCMs [21]. There are following key steps: 1) verifying of observing materials; 2confirming predictors; 3) model calibration and verification and 4) driving future climate change scenarios. The established model for predicting daily maximum and minimum temperatures is an unconditional model, but the model for predicting precipitation is a conditional model.

2.4 Climate Change Scenario

Scenarios of climate change used in this study were IPCC SRES A2 and B2, which were projected by the UK Hadley Centre's HadCM3 model under corresponding emissions scenarios. The predictor variables can be obtained online (http://www.grida.no/climate/ipcc/emission). A2 describes a very heterogeneous world with high population growth, slow economic development and technological change. B2 describes a world with intermediate population and economic growth, emphasizing local solutions to economic, social, and environmental sustainability (IPCC, 2007). Climate scenarios A2 and B2 are close to the development of study area. The output of HadCM3 was downscaled to the daily series data of corresponding weather station.

2.5 SDSM Calibration and Validation

Weather factors under different emission scenarios will be obtained based on the NCEP (National Centre for Environmental Prediction) data from 1961 to 1990. Daily rainfall and maximum and minimum temperatures were analyzed in this study.

Correlation coefficient (R), relative error (RE), Nash–Sutcliffe efficiency (NSE) are the criterion to evaluate the model performance . The Nash–Sutcliffe efficiency was calculated as follows:

$$NSE = 1 - \sum_{i=1}^{i=n} (V_{obs_m} - V_{dow_m})^2 / \sum_{i=1}^{i=n} (V_{obs_m} - \overline{V_{obs}})^2 \quad (2)$$

where $Vobs_m$ is observed value, $Vdow_m$ is downscaled value, $\overline{V_{obs}}$ is mean observed value, and n is the number of measurement. NSE value can range from -∞ to 1. 1 corresponds to perfect match of downscaled value to the observed data.

The representation meteorological stations selected are Tianzhu and Wuwei in Zamu river basin. The positions and averages of the temperature and precipitation were shown in Table 1. Tianzhu is the mountain observing station whereas Wuwei station is the plain observing station. Selected predictors for established downscaling model are shown in Table 2. The positive correlation coefficients of the variables are the selected predictors for establishing the downscaling model. Data from 1961-1975 was used for calibration and data from 1976-1990 was used for validation. Table 2 shows that predictor variables of P500 (500 hPa geopotential height) and tem (the average temperature of the ground 2 meters) are important in predicting the climate variables.

Table 1. Statistics of two representative meteorological stations

Station	Longitude (°N)	Latitude (°E)	Elevation (m)	Mean precipitation (mm)	Mean temperature (°C)	data
Tianzhu	102°52′	37°12′	3045	411.1	0.05	1951-2005
Wuwei	102°40′	37°55′	1531	167.2	8	1951-2005

Table 2. Predictor variables selected for downscaling

Predictor	Predictant					
	T_{max}(°C)		T_{min}(°C)		Prec(mm)	
	Tianzhu	Wuwei	Tianzhu	Wuwei	Tianzhu	Wuwei
p-u(Surface zonal velocity)	0.13	0.26	0.09	0.02	-0.01	-0.06
p-v(Surface meridional velocity)	-0.18	-0.18	-0.26	-0.18	-0.09	-0.13
p-z (Surface vorticity)	0.18	-0.28	-0.07	-0.26	-0.12	-0.03
p500(500 hPa geopotential height)	0.27	0.20	0.43	0.23	0.03	0.05
r500(Relative humidity at 500 hPa)	-0.30	-0.19	-0.07	-0.01	0.08	0.07
Shum(Surface specific humidity)	-0.08	-0.03	-0.07	-0.01	0.06	0.11
tem (Mean temperature at 2m)	0.59	0.69	0.56	0.53	0.04	0.03
rhum (Near surface relative humidity)	0.01	0.02	0.06	0.07	0.03	0.13

Table 3. Statistics of SDSM validation (1976-1990)

Item	T_{max}(°C)		T_{min}(°C)		maximum wet-spell length(days)		Mean wet-day precipitaion(mm)	
	Tianzhu	Wuwei	Tianzhu	Wuwei	Tianzhu	Wuwei	Tianzhu	Wuwei
Observed	5.59	15.17	-4.72	1.28	15.40	8.00	3.21	2.65
Downscaled	5.40	14.69	-4.70	1.31	15.20	7.65	2.89	3.38
R^2	0.98	0.99	0.99	0.99	0.96	0.76	0.96	0.96
RE(%)	-3.40	-3.16	-0.42	2.34	-1.30	-4.38	-9.97	27.55
NSE	0.99	0.997	0.99	0.996	0.96	0.965	0.99	0.837

Table 3 shows the results of observed and downscaled daily maximum temperature, minimum temperature and precipitation for the validation period in Tianzhu station and Wuwei station. Both correlation coefficient and Nash-Suttclife efficiency coefficient (NSE) are more than 0.75, especially the result of downscaled temperature was better than that of daily precipitation. So daily maximum and minimum temperatures under climate change scenarios A2 and B2 from 2010 to 2099 were generated by SDSM based on the data from 1961 to 1990. The results show that maximum temperature (T_{max}) and minimum temperature (T_{min}) have an increasing tendency in the future under different IPCC scenarios in the Zamu river basin (Fig.2). The precipitation have an increasing tendency begin 2010s under SRESA2 and SRESB2 (Fig.3).

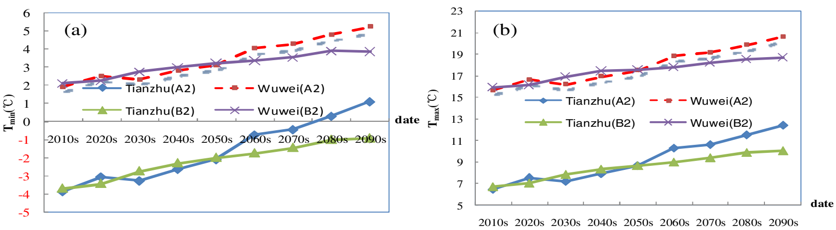

Fig. 2. Average Tmin (a),Tmax (b),under SRES A2 and B2

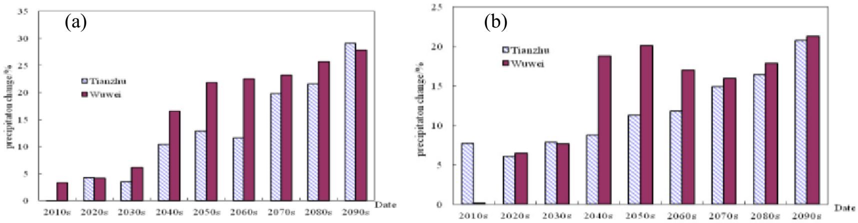

Fig. 3. Precipitation under SRES A2(a) and B2(b) relative 1980s

2.6 SWAT Model Validation

SWAT model can be used to simulate the runoff under the observed climate data in Zamu river basin [26] .Downscaled climate data based the NCEP from 1985 to 1990 was used to driven the SWAT hydrological model for validation in this study. Fig. 4 shows monthly simulated runoff with downscaled climate data well matched the observed value. Correlation coefficient (R) of validation of SWAT model with downscaled climate data is 0.79. SWAT model can be used to simulate runoff driven by downscaled data. Peak observed and simulated runoff under downscaled climate data is greater than those under observed weather data (Fig.4). The difference is caused by different spatial scale between observed data and downscaled data.

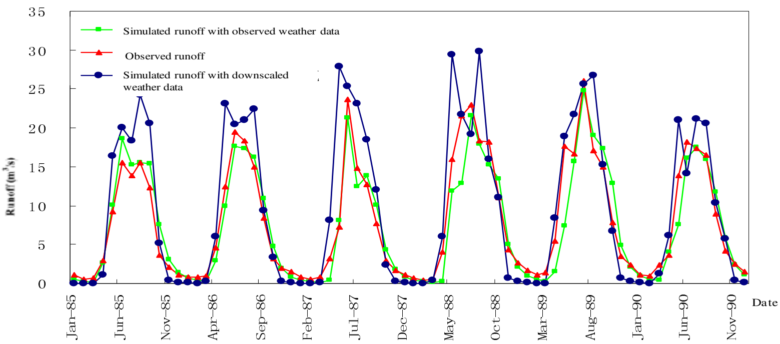

Fig. 4. Validation of SWAT model using downscaled data (1985-1990)

3 Results and Discussion

Tables 4 and 5 show the comparison of the baseline runoff and projected values for different scenarios corresponding to the downscaled precipitation and temperature under SERS A2 and B2, respectively. The projected runoff shows the decreasing tendency under SERS A2 climate scenario in future except that in the early 21st century. The runoff decreased with the increasing of precipitation in 2070s, 2080s and 2090s. Runoff was influenced by precipitation and temperature. The temperature has negative effects on runoff. The runoff was reduced by less than 10% in 2080s, 5% in

2050s and 10.6% in 2060s under SRES A2 respectively. From Table 5, the runoff was reduced by less than 5% in 2020s, 2040s and 2080s under SERS B2 scenario. The runoff generally was changed by less than 10% in the future decades along with the change of temperature and precipitation in Heihe river basin [22], which is similar to the results of this study.

Table 4. Change of Simulated Runoff, Precipitation, T_{max} and T_{min} under SRES A2 relative to baseline(1980~1989)

Years		2010s	2020s	2030s	2040s	2050s	2060s	2070s	2080s	2090s
Runoff change(%)		1.2	0.8	-5.4	-8.9	-2.2	-10.6	-2.4	-8.9	-3.4
Precipitation Change(%)	Tianzhu	0.2	4.3	3.5	10.4	12.9	11.6	19.8	21.6	29.1
	Wuwei	3.3	4.1	6.1	16.5	21.8	22.5	23.2	25.6	27.8
T_{max} Change (℃)	Tianzhu	1.2	2.2	1.9	2.6	3.4	5	5.3	6.2	7.1
	Wuwei	1.1	2.1	1.7	2.4	2.9	4.3	4.6	5.3	6.1
T_{min} Change (℃)	Tianzhu	0.9	1.7	1.5	2.1	2.7	4	4.3	5	5.8
	Wuwei	0.6	1.2	1	1.5	1.8	2.7	2.9	3.5	3.9

Table 5. Change of Simulated Runoff, Precipitation, T_{max} and T_{min} under SRES B2 relative to baseline(1980~1989)

Years		2010s	2020s	2030s	2040s	2050s	2060s	2070s	2080s	2090s
Runoff change(%)		12.9	-1.8	1.2	-3.9	8.3	1.3	2.4	-2	6.8
Precipitation Change(%)	Tianzhu	7.7	6.1	7.8	8.8	11.2	11.8	14.8	16.4	20.7
	Wuwei	0.1	6.5	7.6	18.8	20.1	17	15.9	17.8	21.2
T_{max} Change (℃)	Tianzhu	1.4	1.7	2.5	3	3.4	3.7	4.1	4.6	4.7
	Wuwei	1.4	1.6	2.3	2.9	3	3.2	3.6	4	4.1
T_{min} Change (℃)	Tianzhu	1.1	1.3	2	2.5	2.8	3	3.3	3.7	3.8
	Wuwei	0.8	0.9	1.4	1.7	1.9	2	2.2	2.5	2.5

The runoff in the mountain reaches varied from -10.6% to +1.17% under SRES A2 and -4% to +13% under SRES B2 in the future. The runoff had a decline tendency in the future (Fig. 5), The linear trend values under SRES A2 and B2 are -0.048 and -0.018 separately.The runoff declined more obviously under SRES A2 than under SRES B2.

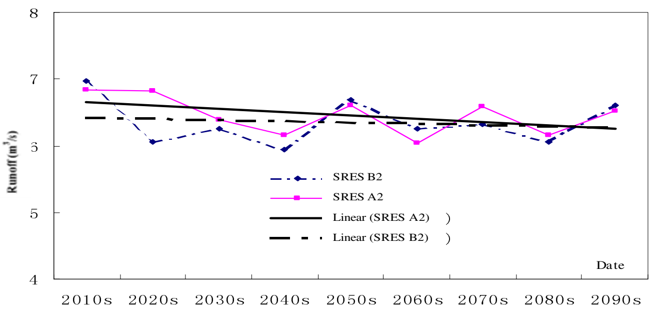

Fig. 5. Simulated runoff under SRES A2 and B2 in future

4 Conclusions

The response of the runoff in the mountain reaches to the climate change under IPCC SRES were simulated by combining the climate model and distributed hydrological model. According to the predictions made by the HADCM3 model, which is downscaled by SDSM, future climates predict increased warming under two different climate change scenarios.

With climate change, runoff change in Zamu river basin appeared. The simulated runoff of the mountain reaches under different climate change scenarios shows that runoff under high GGa emissions has a more obvious decline tendency than that under low GGa emissions in the future. Predictions regarding runoff response to climate change in this paper can give some advices for water resources management and ecological environment decisions in arid regions.

Acknowledgements. This research was supported by Chinese National Nature Science Fund (51109211).

References

1. Intergovernmental Panel on Climate Change (IPCC), Climate Change 2007: the Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA (2007)
2. Sefton, C.E.M., Boorman, D.B.: A regional investigation of climate change impacts on UK steamflows. Journal of Hydrology 195, 26–44 (1997)
3. Guo, S.L., Wang, J.X., Xiong, L.H., Ying, A.W., Li, D.F.: A macro-scale and semi-distributed monthly water balance model to predict climate change impacts in China. Journal of Hydrology 268, 1–15 (2002)
4. Chen, M., Pollard, D., Barron, E.J.: Hydrologic processes in China and their association with summer precipitation anomalies. Journal of Hydrology 301, 14–28 (2005)
5. Hans, T.: The influence of climate change on stream flow in Danish rivers. Journal of Hydrology 333, 226–238 (2007)
6. Gardner, L.R.: Assessing the effect of climate change on mean annual runoff. Journal of Hydrology 379, 351–359 (2009)
7. Gleick: Methods for evaluating the regional hydrologic impacts of global climatic changes. Journal of Hydrology 88(1), 97–116 (1986)
8. Jones, R.N., Chie, F.H.S., Boughton, W.C., Zhang, L.: Estimating the sensitivity of mean annual runoff to climate change using selected hydrological models. Advances in Water Resources 29, 1419–1429 (2006)
9. Vaze, J., Post, D.A., Chiew, F.H.S., Perraud, J.M., Viney, N.R., Teng, J.: Climate non-stationarity – Validity of calibrated rainfall–runoff models for use in climate change studies. Journal of Hydrology 394, 447–457 (2010)
10. Zarghami, M., Abdi, A., Babaeian, I., Hassan, Y., Kana, R.: Impacts of climate change on runoffs in East Azerbaijan, Iran. Global and Planetary Change 78, 137–146 (2011)
11. Kling, H., Fuchs, M., Paulin, M.: Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios. Journal of Hydrology (424-425), 264–277 (2012)

12. Nunes, J.P., Seixas, J., Keizer, J.J.: Modeling the response of within-storm runoff and erosion dynamics to climate change in two Mediterranean watersheds: A multi-model, multi-scale approach to scenario design and analysis. Catena 102, 27–39 (2013)
13. Viner, D., Hulme, M., Raper, S.C.B.: Climate change scenarios for the assessments of the climate change on regional ecosystems. J. Therm. Biol. 20(1/2), 175–190 (1995)
14. Booij, M.J.: Impact of climate change on river flooding assessed with different spatial model resolutions. Journal of Hydrology 303, 176–198 (2005)
15. Nigel, W.A.: Climate change and global water resources. Global Environmental Change (9), 31–49 (1999)
16. Nigel, W.A.: Relative effects of multi-decadal climatic variability and changes in the mean and variability of climate due to global warming: future streamflows in Britain. Journal of Hydrology 270, 195–213 (2003)
17. Sperna, W.F.C., Van, L.P.H., Weerts, A.H., Bierken, M.F.P.: Extracting information from an ensemble of GCMs to reliably assess future global runoff chang. Journal of Hydrology 412-413, 66–75 (2012)
18. Wilby, R.L., Dawson, C.W., Barrow, E.M.: SDSM – a decision support tool for the assessment of regional climate change impacts. Environmental and Modelling Software 17, 145–157 (2001)
19. Shivam, T., Sriniva, V.V., Nanjundiah, R.S.: Downscaling of precipitation for climate change scenarios: A support vector machine approach. Journal of Hydrology 330, 621–640 (2006)
20. Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R.: Large area hydrologic modeling and assessment part I: model development. American Water Resources Association 34(1), 73–89 (1998)
21. Arnell, N.W.: Factors controlling the effects of climate change on river flow regimes in a humid temperate environment. Journal of Hydrology 132, 321–342 (1992)
22. Lan, Y.C., Ding, Y.J., Liu, J.Q., Kang, E.S., Wei, Z.: Change of Water Resources in Mountainous Area of Heihe River under Global Warming Scene. Journal of Desert Research 25, 863–868 (2005)
23. Andersson, L.W.J., Martin, C.T.: Impact of climate change and development scenarios on flow patterns in the Okavango River. Journal of Hydrology 331, 43–57 (2006)
24. Chiew, F.S., Teng, J., Vaze, J., Post, D.A.: Influence of global climate model selection on runoff impact assessment. Journal of Hydrology 379, 172–180 (2009)
25. Julie, W., Martin, C.T., Denis, A.H., Anton, E., Dominic, K., Russel, L., Hubert, H.G.: Impact of climate change and development scenarios on flow patterns in the Okavango River. Journal of Hydrology 331, 43–57 (2006)
26. Wang, S.F., Kang, S.Z., Zhang, L., Li, F.S.: Modeling the hydrological response to different land-use and climate change scenarios in the Zamu River Basin of Northwest China. Hydrological Processes 22, 2502–2510 (2008)