Impact of climate change on the streamflow in the headwater catchment of the Yellow River basin

FANGFANG ZHAO, ZONGXUE XU & JUNXIONG HUANG

Key Laboratory of Water and Sediment Sciences, Ministry of Education, College of Water Sciences, Beijing Normal University, Beijing 100875, China zongxuexu@vip.sina.com

Abstract A coupled system integrating GCMs output, a downscaling model and a distributed hydrological model are proposed in this study. First, the Statistical DownScaling (SDS) model for the simulation of historical climate (1961–1990) and three future scenarios (2020s, 2050s and 2080s) are calibrated and validated. Then the distributed hydrological model, Soil and Water Analysis Tool (SWAT), is applied to simulate the streamflow for headwater catchment of the Yellow River basin. Finally, the coupled system is applied to investigate the hydrological response to climate change in the study area. The results show: (a) the SDS model is successful in reproducing the main features of the observed hydrometeorology from the baseline climate simulation, when it is used to the HadCM3 GCM output; (b) the monthly streamflow simulated by SWAT corresponds well with the measured ones, and the model can satisfactorily capture the seasonal tendency; (c) the hydrological processes in the study area are very sensitive to climate changes in the future.

Key words climate change; downscaling; scenario; streamflow; SWAT model; Yellow River

INTRODUCTION

With the scientific understanding of global warming, the concerns are growing about the impact of climate change on the water cycle among the public, governmental and non-governmental authorities in the world. Streamflow, especially extreme floods and droughts, are several of the hydrological processes easily affected by global warming (Bürger & Chen, 2005). The issue of the impact of climate change on runoff in ungauged and poorly gauged basins is a great challenge. The current approach for this problem is the coupling of climate model with hydrological models. It is noted that these kinds of studies cannot be regarded as predictions, but should be regarded as a scenario analyses (Piling & Jones, 1999). Downscaling methods are also usually used because of the coarse spatial resolution of GCMs. Presently, the method of GCM-downscaling, especially statistical downscaling, is well developed as an appropriate tool for regional climate impact studies (Wilby & Wigley, 1997).

In this study, the statistical downscaling (SDS) technique to drive local climatic parameters on a daily time scale for input in the distributed hydrological model SWAT (Soil and Water Assessment Tool) is used. The investigation is focused on the impact of climate change on streamflow characteristics and related processes in the headwater catchment of the Yellow River basin. The objectives of this study include: (a) to generate three climate scenarios for future periods (2020s, 2050s and 2080s); (b) to calibrate and validate the hydrological component of SWAT over a 15-year period (1986–2000) by using historical climate data, and comparing the simulated output with observed streamflow measured at Tangnaihai station; and (c) to evaluate the impact of climate change on monthly and annual streamflow in response to future climate scenarios with the SWAT model.

METHODOLOGY

Statistical downscaling

Statistical downscaling (SDS) is based on the fact that the regional climate may be regarded as a physical process by two factors: the large scale climatic state and regional/local physiographic features (IPCC, 2001). From this viewpoint, regional or local climate information is derived by first determining a statistical model which relates large-scale climate variables (or "predictors") to

regional and local variables (or "predictands"). Then the predictors from a GCM simulation are fed into this statistical model to estimate the corresponding local and regional climate characteristics.

In this paper, a software package, Statistical DownScaling Model (SDSM), is used. It can directly employ GCM output in the scenario construction processes, so this model is widely used in the hydrological and agricultural research communities (Wilby *et al.*, 2002, 2004). The key procedure to use the SDSM are as follows: (a) selection of downscaling predictor variables; (b) model calibration; (c) synthesis of observed data; (d) generation of future climate scenarios; (e) result analysis including diagnostic testing, statistical analyses and graphing model output, etc.

Hydrological model

Most of the watershed models, such as HSPF, HEC-HMS, and CREAMS, have a lot of limitations, including scale problems, continuous-time problems, simulation problems, number of sub-watershed problems, etc. (Saleh *et al.*, 2000). The SWAT model was developed to overcome these limitations. It incorporates features of several ARS models and is a direct outgrowth of the SWRRB model. It was developed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time. In SWAT, a watershed is divided into multiple sub-watersheds, which are then further subdivided into a large number of homogeneous hydrological response units (HRUs) representing unique combinations of soil and land use. The hydrological model is based on the water balance equation in the soil profile where the processes simulated include precipitation, infiltration, surface runoff, evapotranspiration, lateral flow and percolation (Bouraoui *et al.*, 2005; Neitsch *et al.*, 2005). The SWAT is used worldwide and has been validated for a lot of watersheds for its strong merits (Arnold *et al.*, 1999; Saleh *et al.*, 2000; Santhi *et al.*, 2003).

STUDY CATCHMENT AND DATA DESCRIPTION

The headwater catchment of the Yellow River basin (HYRB), a poorly gauged basin, is upstream of Tangnaihai station, with a drainage area of 122 000 km² (see Fig. 1). It is the main part of the Qinghai-Tibetan plateau at the elevation ranging from approx. 3000-4500 m, formed by great rising of Himalayas movement. The climate belongs to the Qinghai-Tibetan plateau climate system. The annual mean runoff is 203.9×10^8 m³, but the runoff has obviously decreased during past decades.



Fig. 1 Location of HYRB and hydrological and weather stations in and around the study area.

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Three data sets were compiled for the purpose of climate scenario generation and hydrological model application: (a) observed station data; (b) NCEP reanalysis data; and (c) HadCM3 GCM simulations of current and future climatic conditions. Daily precipitation (PRCP) and maximum and minimum temperatures (TMAX and TMIN) in and around HYRB and obtained from the Meteorological Data Center, China Meteorological Administration. The atmospheric predictor variables used to calibrate the SDS model were extracted or calculated from the daily grid point data of the NCEP reanalysis (Table 1). All variables were regridded to conform to the HadCM3 GCM grid and were standardized by their respective 30-year averages and standard deviations (Wilby *et al.*, 2002). The first 15 years data (1961–1975) were used for model calibration, the remaining 15 (1976–1990) for independent model validation. Two time series of predictor variables, the baseline (1961–1990) and the future climate conditions (2020s, 2050s and 2080s), were extracted from the HadCM3 GCM grid box nearest to the study area.

Table 1 Candidate predictor variables.

	PRCP	TMAX	TMIN
Predictor variables	Specific humidity Lag-1 mean sea level pressure	Mean sea level pressure Zonal velocity component	Mean sea level pressure 500 hPa geopotential height
	500hpa relative humidity Vorticity	500 hPa geopotential height 850 hPa geopotential height 850 hPa zonal velocity component	850 hPa geopotential height850 hPa vorticity2 metre temperature
		2 metre temperature	850 hPa zonal velocity component

Table 2	Statistics	for the	simulated	daily PRCP	, TMAX and TMIN.
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Statistics	Month mean wet-day amounts (mm/d)	Monthly wet- day frequencies (%)	Monthly maximum dry-spell length (d)	Monthly maximum wet-spell length (d)	Monthly variation of wet-day amounts (mm ²)	Daily TMAX (°C)	Daily TMIN (°C)
Observed	3.22	41.22	76.83	32.26	11.52	5.92	-7.97
Downscaled	3.19	28.32	84.10	22.64	12.51	6.24	-8.44
Bias	-0.03	-12.90	7.27	-9.62	0.99	0.32	-0.47
\mathbf{R}^2	0.97	0.96	0.92	0.98	0.95	1.00	1.00
Ens	0.90	0.70	0.79	0.75	0.94	0.99	1.00

MODEL APPLICATION AND RESULT ANALYSIS

Future climate scenarios generation

The compiled data sets were used to develop three future climate scenarios to investigate the impact of climate change on streamflow in the PUB region, HYRB in the future. The downscaling model based on multiple linear regression equations is developed during the model calibration process. Combining the observed data with the predictor variables, the empirical relationships between meso-scale atmospheric variables and sub-grid scale surface climate variables (daily PRCP, TMAX and TMIN) are established. To evaluate the dependability of the downscaling model, a validation process should be made. In order to quantitatively describe the above results, model bias, correlation coefficient (R^2) and Nash-Suttcliffe coefficient (*Ens*) are applied to evaluate the model performance. Table 2 lists the statistics to evaluate the model for the downscaled daily PRCP, TMAX and TMIN. The results show that the SDS model can capture the main characteristics of the daily PRCP, TMAX and TMIN.

The future climate scenarios are generated by downscaling the HadCM3 GCM output with the relationships between predictand and predictors. Figure 2 shows the climate change for the PRCP

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in the future periods (2020s, 2050s and 2080s). It shows an obviously decreasing tendency in December and February for the future PRCP. At the same time, a distinct increasing trend is represented by June and September, other months show little change. For the annual mean change, the PRCP will increase by 3.47%, 6.42% and 8.67% in the future periods compared with the baseline. In conclusion, the PRCP will show an increasing trend with a distinct season cycle in the future, but the increasing trend is not significant. Figure 3 lists the monthly mean daily TMAX and TMIN and their changes, respectively. The downscaled data for the daily TMAX and TMIN in the future are shown in Fig. 3(a) and Fig. 3(b). The downscaled daily TMAX will increase quickly. Almost parallel increasing tendency resulted in the future climate scenarios as shown in Fig. 3(c), and the daily TMAX will increase 1.34°C, 2.60°C and 3.90°C in the future, respectively. Different seasons and months show different features, and it is most obvious for the TMAX in spring and autumn. Compared with scenarios of daily TMAX, the scenarios of daily TMIN in the future are not very obvious, it will increase by 0.87°C, 1.49°C and 2.27°C, respectively, and the distinct seasons are summer and autumn. In a word, it is inevitable that the temperature will increase for the study area in the future.



Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

Fig. 2 Changes (%) in monthly mean wet-day amounts in headwater of the Yellow River basin for three typical periods.



Fig. 3 Downscaled data and scenarios of TMAX and TMIN in headwater catchment of the Yellow River basin: (a) downscaled TMAX; (b) downscaled TMIN; (c) TMAX scenarios; (d) TMIN scenarios.

Streamflow simulation with measured climate variables

Based on the integrity of obtained data, considering wet, average and dry years, the data from 1986–2000 at Tangnaihai hydrological station is selected, and 1986–1995 for calibration, 1996–2000 for validation. In this study, combined with the auto-sensitivity of SWAT model, nine parameters were chosen (CN2, SURLAG, TIMP, CH_K2, ESCO, ALPHA_BF, SMTMP, SMFMN and SOL_AWC). Then the model was calibrated and validated for streamflow using the measured data at Tangnaihai station in the HYRB.

A time-series plot of the measured and simulated monthly streamflow (Fig. 4) shows that the magnitude and trend in the simulated monthly flows closely followed the measured data well, although some peak-flow months were over predicted (e.g. 1986 and 1995) and some were under predicted (e.g. 1989 and 1993). Because the snowmelt parameters (TIMP, SMTMP and SMFMN) were calibrated, the model simulated the streamflow in dry periods well. The statistical evaluation yielded an R^2 value of 0.80, an *Ens* value of 0.73, and an annual mean error (*Re*) of 9.54%, as shown in Table 3, indicating a strong correlation between the measured and simulated flows.

The validation was conducted using the streamflow data for the period from 1996 to 2000. In the validation process, the model was run with parameters obtained during the calibration process without any change. Figure 5 shows the time series plot of monthly measured and simulated streamflows, and indicates an acceptable correspondence of simulated streamflows with the measured values. The R^2 , *Ens* and *Re* values between the measured and simulated streamflows are 0.77, 0.59 and 20.12%, respectively, as shown in Table 3.



Fig. 4 Comparison between the measured and simulated monthly mean streamflow during the calibration period.

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Periods	Monthly mean flow (m ³ /s)		Re	R^2	E_{ns}
	Observed	Simulated			
Calibration	605.36	666.32	9.54%	0.80	0.73
Validation	543.40	655.48	20.12%	0.77	0.59

Long-term streamflow simulation under different climate scenarios

The impact of climate change on the hydrological cycle was quantified by driving the calibrated SWAT model with climate scenarios generated by SDSM corresponding to the contemporary and future conditions. A coupled atmospheric-hydrological model was developed, with the regionalized scenarios for future periods (2020s, 2050s and 2080s) served as input to the SWAT model. The future streamflow conditions in HYRB clearly depend on both temperature and



Fig. 5 Comparison between the measured and simulated monthly mean streamflow during the validation period.

precipitation. Figure 6 shows the simulated monthly mean streamflow for the baseline and future periods. The results can explain the seasonal characteristics for the hydrological response to future climate change and indicate a general decrease of flow over several months. Annual average streamflow will decrease by 88.61 m³/s (24.15%), 116.64 m³/s (31.79%) and 151.62 m³/s (41.33%) due to future climate change, with the largest decrease occurring in summer and autumn. This disproportionate change, i.e. 24.15%, 31.79% and 41.33% decrease in average annual streamflow vs 3.47%, 6.42% and 8.67% increase in average annual precipitation, can be attributed to more increased temperature rates. Apparently, in summer, increased temperature leads to an increase in evapotranspiration and thus results in a general tendency towards reduced streamflow (Menzel et al., 2002). The monthly simulation shows that future streamflow are different in each month, and the streamflow decreases for three benchmark periods during May to December, especially for the 2080s. According to the estimation of streamflow, it is concluded that the streamflow will decrease greatly in flood seasons, which is very disadvantageous for the development of industry and agriculture in the Yellow River basin. In conclusion, the streamflow in HYRB is very sensitive to future climate change. The streamflow in the study area will greatly decrease in the future. Similar results were also obtained by Hao et al. (2006). Therefore, it is inevitable that the streamflow in HYRB will obviously decrease, and water scarcity will be more serious in the future.



Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec Fig. 6 Comparison among simulated streamflow for SDS scenarios in different periods.

As the important runoff generation region of the Yellow River basin, the HYRB plays a pivotal function. Therefore, it is very important to analyse the spatial distribution of the runoff yield under future climate scenarios. In this study, the spatial distribution of HYRB runoff yield is predicted by using the SWAT for the scenarios in the baseline and three future benchmark periods, as shown in Fig. 7. From the baseline distribution, it is known that the large runoff yield region is mainly located in the southeastern part of the study area, especially the southern part from Maqu station. The runoff yield is small in the northeastern and northwestern part of the study area, and it is smallest in the downstream of HYRB. The comparison between the baseline and future runoff scenarios clearly reveals that the predicted runoff yields will decrease significantly across most of the area of the HYRB in response to the precipitation and temperature changes simulated in the statistical downscaling model. These results underline that the impact of climate changes within HYRB may be widespread and would not be limited to only local areas.



Fig. 7 Spatial distribution of predicted runoff yields in HYRB for future scenarios (mm).

DISCUSSION AND CONCLUSIONS

The study in this paper shows that the statistical downscaling model was successful in reproducing the main features of the observed hydrometeorology from the baseline climate simulation, when it was used with HadCM3 GCM output. It shows that the local scaling of the simulated large-scale precipitation and temperature is quite successful. There is a small increasing trend for the precipitation and an obvious increasing trend for the maximum/minimum temperature in the future.

The combination of different methods, the coupling of the HadCM3 GCM output to SDS, the application of downscaled climate data to the SWAT model and the subsequent simulation of streamflow has been demonstrated to be a useful tool for climate change studies. The investigation

of the climate change scenarios and its impact on climate and streamflow in the headwater catchment of the Yellow River basin shows a distinct sensitivity of hydrological response to future climate changes. The results show that the streamflow in the study area will decrease greatly in the future.

A single-direction coupling model was developed in this study, but the feedback process from the atmosphere to the land surface needs further study. The spatial variability of the hydrological process is far greater than that of the atmospheric process. A lot of uncertainties exist in the downscaling process. The uncertainties in downscaling result from: (a) the basic equation on which the downscaling models are based, and (b) the data used (Mohammad *et al.*, 2006). Climate models have some uncertainties when they are used to predict future climate changes. The coupling model of hydrological processes and atmosphere should be developed. In addition, climate change might cause secondary effects such as the changes in vegetation composition; future investigation on the impact of climate change should be extended by considering land cover, the modification of hydrological processes and its feedback to climate. The coupling model and the impact of anthropogenic activity and climate change on hydrological processes should be fully considered.

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