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VIC distributed hydrological model to predict climate change impact in the Hanjiang Basin

GUO ShengLian†, GUO Jing, ZHANG Jun & CHEN Hua

State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, Wuhan 430072, China

The climate impact studies in hydrology often rely on climate change information at fine spatial resolution. However, the general circulation model (GCM), which is widely used to simulate future climate scenario, operates on a coarse scale and does not provide reliable data on local or regional scale for hydrological modeling. Therefore the outputs from GCM have to be downscaled to obtain the information fit for hydrologic studies. The variable infiltration capacity (VIC) distributed hydrological model with 9×9 km^2 grid resolution was applied and calibrated in the Hanjiang Basin. Validation results show that SSVM can approximate observed precipitation and temperature data reasonably well, and that the VIC model can simulate runoff hydrograph with high model efficiency and low relative error. By applying the SSVM model, the trends of precipitation and temperature (including daily mean temperature, daily maximum temperature and daily minimum temperature) projected from CGCM2 under A2 and B2 scenarios will decrease in the 2020s (2011—2040), and increase in the 2080s (2071—2100). However, in the 2050s (2041—2070), the precipitation will be decreased under A2 scenario and no significant changes under B2 scenario, but the temperature will be not obviously changed under both climate change scenarios. Under both climate change scenarios, the impact analysis of runoff, made with the downscaled precipitation and temperature time series as input of the VIC distributed model, has resulted in a decreasing trend for the 2020s and 2050s, and an overall increasing trend for the 2080s.

climate change, statistical downscaling, SSVM, VIC model, impact study

1 Introduction

Recently, there has been growing scientific evidences that global climate has changed. In December of 2007, the United Nations Climate Change Conference suggested that the climate change should be placed on the sustainable development agenda forever. According to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change[1], the global average surface temperature has increased by about (0.74±0.18)℃ and precipitation has decreased over much of the northern hemisphere sub-tropical regions by about 3% during the past 100 years. Such changes in climate will also have significant impact on local and regional hydrological regimes, which may in turn affect ecological, social and economical systems. There is an urgent need to improve our understanding of the global climate system to assess the possible impact of the climate change on hydrological process.

The general circulation model (GCM) which describes the atmospheric process by mathematical equations is one of the most important tools for studying the impact of climate change. Because of the limited representation of regional atmospheric processes, topography and land-sea distribution in GCM, the use of direct GCM-derived hydrological output and coupling GCM

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†Corresponding author (email: slguo@whu.edu.cn)
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with the macroscale hydrological model can only provide output at nodes of grid boxes, which are tens of thousands of square kilometers in size, whereas the scale of interest to hydrologists is of the order of a few hundred square kilometers. Therefore, the downscaling methods used to convert GCM outputs into local meteorological variables have been developed by many authors[2].

The statistical downscaling methods concern to derive empirical relationships that transform large-scale features of the GCM (predictors) into regional-scale variables (predictands), such as precipitation and temperature. The statistical downscaling of GCM outputs as input of hydrological model to study hydrological consequences of climate change is now a common practice[2,3].

In this study, the smooth support vector machine (SSVM) was applied to statistical downscaling of daily precipitation and temperature. The variable infiltration capacity (VIC) distributed hydrological model was used and calibrated in the Hanjiang Basin of China. Then the downscaled data were used as input of VIC model to assess the impact of climate change on runoff in the Hanjiang Basin using outputs from CGCM2 for A2 and B2 scenarios.

2 Statistical downscaling

2.1 Study area

The Hanjiang River is the largest tributary of Yangtze River. The river's length is 1570 km and its area is 159000 km^2. The basin has a sub-tropical monsoon climate and has, as a result, dramatic diversity in its water resources. Annual precipitation varies from 700 mm to 1100 mm, and 70%—80% of the total amount occurs in the wet seasons from May to October. The Hanjiang Basin plays critical roles in the flood control and water supply in China. The Danjiangkou Reservoir located in the middle reach of the Hanjiang River is the source of water for the middle route of the South-North Water Division Project (SNWDP), and the Jianghan Plain in the down basin is one of the most important bases for commodity grain production. Location of meteorological stations in the Hanjiang Basin and the middle route of the SNWDP are drawn in Figure 1.

2.2 SSVM model

The support vector machine (SVM) is a new machine learning method based on statistical learning theory and stresses for studying statistical learning rules under small sample conditions. The SVM solves many practical problems, such as small-sample, non-linear, high dimension number and global minimum points, by using a structural risk minimization principle. However, it has some drawbacks in dealing with the large-sample data, such as slow training speed, low implementation efficiency and inadaptability to noise. To overcome the drawbacks of the SVM for large-sample data, Lee et al.[4] proposed a new smoothing strategy for solving regression of the large-scale training data, called smooth support vector machine (SSVM), which has been verified as more efficient than the SVM algorithm. The detailed introduction of SVM and SSVM algorithms have been described by Lee et al.[4] and Chen et al.[5]. A tuning procedure which can automatically optimize parameters was applied to this study to estimate the parameters of SSVM[4,5].

2.3 Predictands and predictors

The predictands are daily precipitation, daily mean temperature (T_{mean}), daily maximum temperature (T_{mzx}) and daily minimum temperature (T_{min}) from 1961 to 2000, which were provided by the Chinese National Climatic Centre. The locations of the 15 meteorological stations in the Hangjiang Basin are shown in Figure 1.

It is one of the most important steps in a downscaling exercise to select appropriate predictors, or characteristics from GCM. Precipitation is a consequence of mean sea level pressure (MSLP), geopotential height (GH) and specific humidity (SH) suggested by Wilby et al.[3], while a pair of predictors, one atmosphere temperature variable and one circulation variable, may achieve the best result for downscaling temperature[6]. Therefore, MSLP, surface air temperature (2 m), 500-hPa GH and SH, 850-hPa GH and SH were used as the predictors for predicting precipitation; 850-hPa temperature (TEM) and MSLP were considered as the predictors for predicting temperature. The observed daily data of large-scale predictor variables representing the current climate condition (1960—2000) derived from the reanalysis data set of the National Centers for Environmental Prediction / National Center for Atmospheric Research (NCEP/NCAR). The simulated daily data of the predictor variables by GCM were available from the second generation coupled global climate model of the Canadian centre (CGCM2). The NCEP/NCAR reanaly-

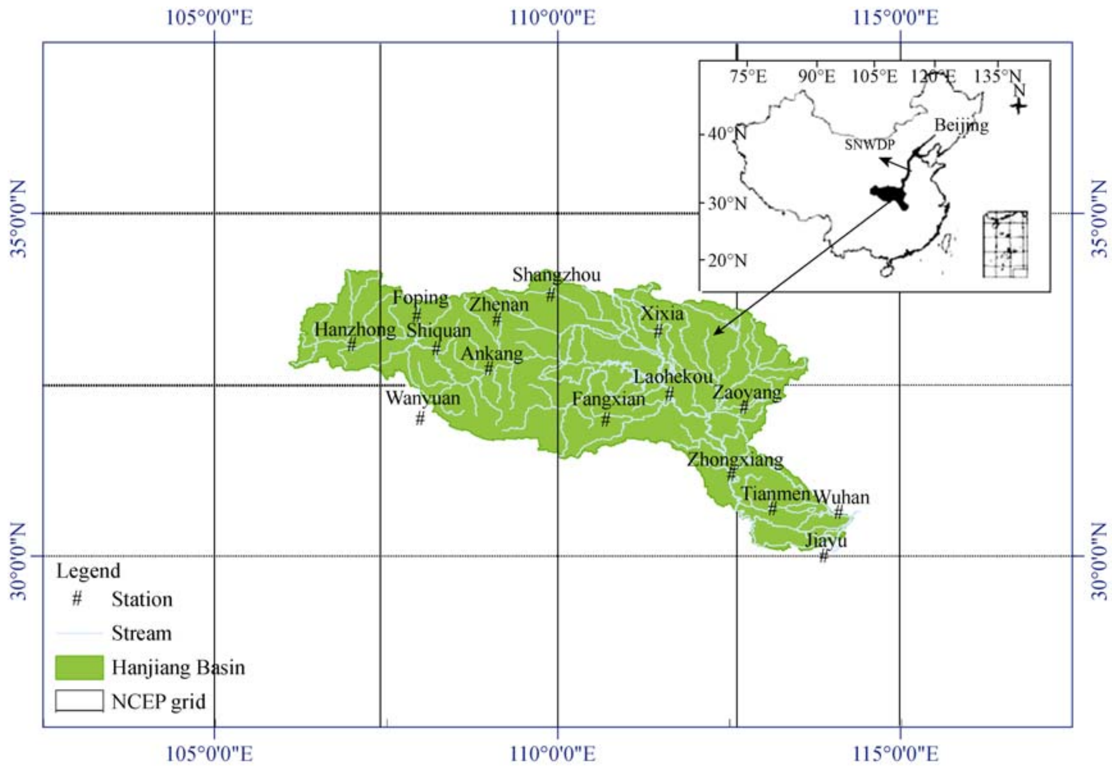

Figure 1 Locations of meteorological stations in Hanjiang Basin and the middle route of the SNWDP in China.

sis daily data and CGCM2 daily data were downloaded freely from the internet sites. The geographical domain, 102.5ºE－115ºE, 27.5ºN－37.5ºN, was chosen to include all areas with noticeable influence on the circulation patterns that govern weather in the Hanjiang Basin. Figure 1 shows the NCEP/NCAR grid points (2.5° (latitude) × 2.5° (longitude)) superimposed on the map of Hanjiang Basin. The inverse distance weighting (IDW) method was used to spatially interpolate CGCM2 grids (3.75° (latitude) × 3.75° (longitude) grids into the NCEP/ NCAR grids.

2.4 Results of SSVM

Prior to downscaling the predictors, NCEP/NCAR reanalysis data and GCM data were standardized to reduce systematic biases in the mean and variances of GCM outputs. The principal component analysis (PCA) has been widely used to reduce dimension and compress data while keeping most of the information content of the original dataset. It was observed that the first 8 PCs (principal components) for precipitation and the first 2 PCs for temperature have represented 90.0% of the information content of the original predictors. Therefore, the use of these PCs as input of SSVM to reduce the dimension of data set without decreasing the performance of statistical downscaling models.

3 VIC distributed model

The variable infiltration capacity (VIC) distributed hydrological model is a macro-scale hydrological model based on soil-vegetation-atmosphere transfer scheme (SVATS), which was designed to describe the land surface in numerical weather prediction and climate, describe the variation and transfer of water and energy[7]. It has widely been used for climate change impact study by many authors.

3.1 VIC model in the Hanjiang Basin

The hydrological data, DEM, forcing, soil and vegetation data, etc. are required for VIC model calibration. DEM data of 0.009° (around 1×1 km^2 cell size) spatial resolution for the Hanjiang Basin were derived and used to delineate the sub-basin boundary and stream network. Vegetation types data were taken from the global land cover classification collection generated by University of Maryland with a one kilometer per pixel resolution. Vegetation parameters were based on the vegetation from Land Data Assimilation System. The soil parameters were derived from the soil classification information of global 5 min data provided by the National Atmospheric and Oceanic Administration.

3.2 Calibration and validation results

The VIC model has six parameters that need to be calibrated for each sub-basin. Daily hydrological and meteorological data from 1980—1986 and 1987—1990 were used for calibration and verification, respectively. The Nash-Sutcliffe efficiency (R^2) and the relative error (RE) of the volumetric fit criteria were used to justify the performance of the model. The main parameterization procedures were described as follows: the model parameters were firstly calibrated for gauged sub-basins, and then the calibrated parameters were used as the initial values for the corresponding grids; finally, hydrological control stations were selected in the main streams of the Hanjiang River to test and optimize the grid parameters through a trial and error method. The mean value of the Nash-Sutcliffe efficiency coefficient (R^2) was 90.4% in calibration period and 81.98% in validation period. As for the RE of the volumetric fit, the mean values were 2.88% and 4.32% during calibration and validation periods, respectively. These results demonstrated that the VIC distributed hydrological model is able to simulate runoff hydrograph in the Hanjiang Basin.

4 Hydrologic impact on climate change

4.1 Downscaling climate variables

The validated SSVM downscaling model was used to downscale the future climate change scenario simulated by GCM. This means that the large-scale predictor variables derived from A2 and B2 scenarios of CGCM2 were used as input of the SSVM downscaling model. Daily precipitation, daily mean, maximum and minimum temperatures were downscaled by SSVM for the following four periods, namely the current (1961—2000), the 2020s (2011—2040), 2050s (2041—2070) and 2080s (2071—2100).

The results of annual precipitations were presented in Figure 2 by using box-plots which represent the inter-quartile range of the simulated (or observed) precipitation. It can be seen that the trend of annual precipitation in the Hanjiang Basin will be upward in the future. The monthly mean statistics of downscaling results for precipitation and mean temperature for different periods were summarized and plotted in Figure 3. It is shown that there is a decreasing trend in the monthly precipitation for the 2020s under both the climate change scenarios and the 2050s under A2 scenario, an increasing trend for the 2080s under both the climate change scenarios, with no obvious changes for the 2050s under B2 scenario. For the cases of daily mean temperature, Figure 3 also shows a consistent decreasing trend and increasing trend in the monthly mean temperature for the 2020s and 2080s, respectively under both the climate change scenarios.

From the current simulated annual mean values, the deviations of simulated precipitation and temperature in different periods of future were listed in Table 1. Between the current and the 2080s, there are average increases in precipitation by about 18.04% under A2 scenario and about 10.17% under B2 scenario. In the same

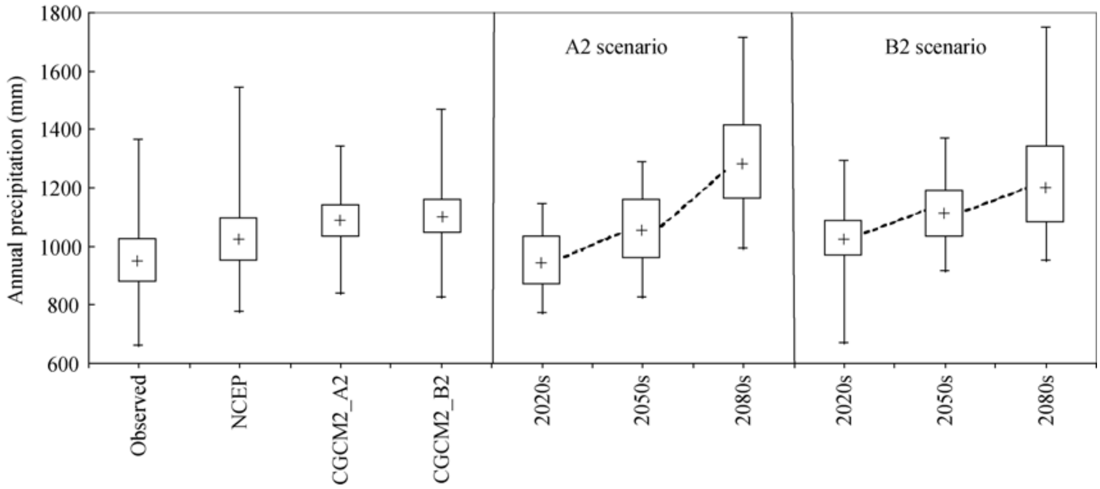

Figure 2 Typical results from SSVM downscaling model based on CGCM2 for A2 and B2 scenarios in the Hanjiang Basin using box plots. The cross denotes the mean values of observed and simulated annual precipitation. The dotted line connecting the solid squares in the middle and right parts of the figure depict the mean trends simulated by SSVM downscaling model.

period, there are average increases in T_{max} and T_{min} by about 1.86℃ and 1.28℃ under A2 scenario and about 1.41℃ and 0.93℃ under B2 scenario. This implies a corresponding increase in T_{mean} by about 1.63℃ and 0.80℃ under A2 and B2 scenarios.

4.2 Hydrological impact on climate change

The inverse distance weighting method was used to interpolate the downscaled hydrological and meteorological data. The downscaled precipitation and temperature data were input to the VIC distributed hydrological model to simulate the runoff corresponding to future climate change scenario in the Hanjiang Basin. The simulated results were summarized in Table 1.

Table 1 lists the relative changes of mean annual runoff in the Hanjiang Basin. Under A2 scenario, the mean annual changes of runoff will be about −30.21%, −14.38% and 31.04% for the 2020s, 2050s and 2080s,

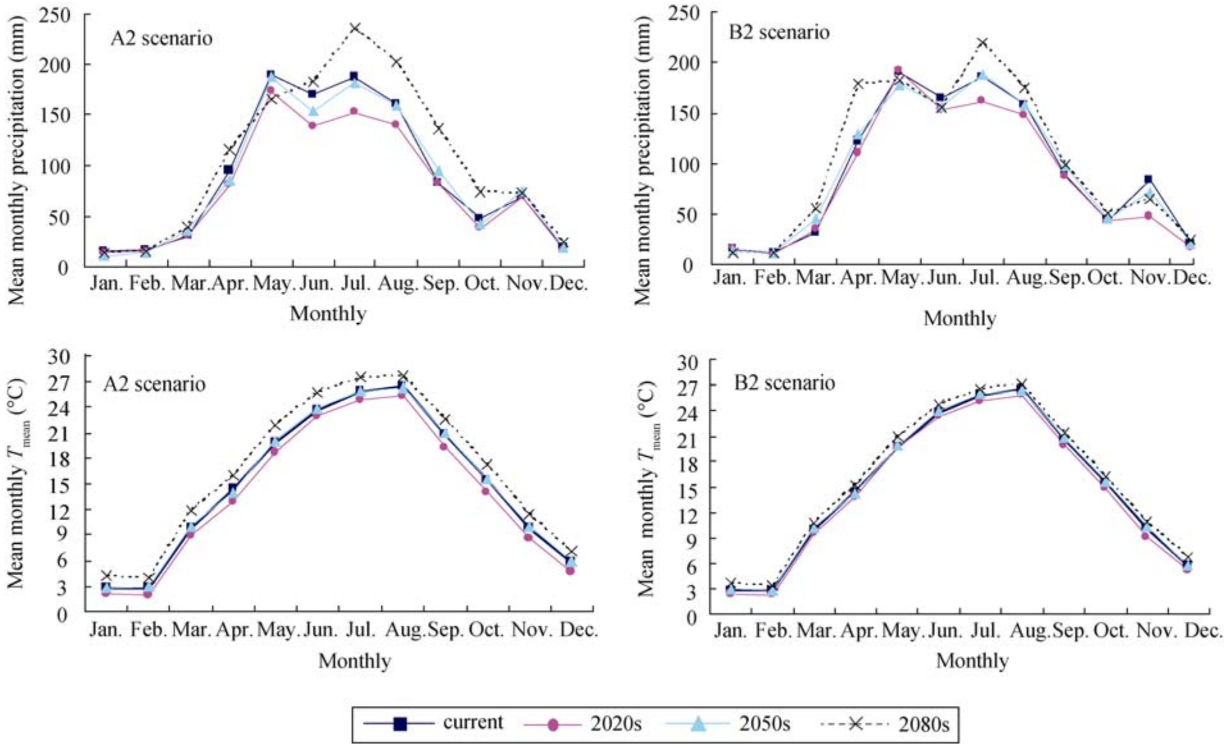

Figure 3 General trends in precipitation and mean temperature downscaled by SSVM in the Hanjiang Basin.

Table 1 Simulated changes in precipitation, temperature and runoff under the A2 and B2 scenarios of CGCM2

Values	A2 scenario				B2 scenario			
	Current	2020s	2050s	2080s	Current	2020s	2050s	2080s
Mean annual precipitation (mm)	1082	953	1060	1278	1118	1022	1117	1232
ΔP (%)	–	−11.96	−2.10	18.04	–	−8.61	−0.07	10.17
Mean annual T_{mean} (℃)	14.80	13.68	14.89	16.43	14.79	14.24	14.91	15.59
T_{mean} (℃)	–	−1.20	0.09	1.63	–	−0.55	0.12	0.80
Mean annual T_{max} (℃)	20.15	18.83	20.25	22.01	20.14	19.17	20.25	21.55
ΔT_{max} (℃)	–	−1.32	0.10	1.86	–	−0.97	0.11	1.41
Mean annual T_{min} (℃)	11.06	10.16	11.13	12.34	11.06	10.37	11.14	11.99
ΔT_{min} (℃)	–	−0.90	0.07	1.28	–	−0.69	0.08	0.93
Mean annual runoff ($10^8 m^3$)	571.62	398.96	489.45	749.05	621.20	515.32	597.92	717.63
ΔR (%)	–	−30.21	−14.38	31.04	–	−17.04	−3.75	15.52

Note: ΔP and ΔR are percentage changes of mean annual precipitation and mean annual runoff, T_{mean}, ΔT_{max} and ΔT_{min} are changes of mean annual T_{mean}, mean annual T_{max} and mean annual T_{min} between current (1961—2000) and future scenario periods (the 2020s, 2050s and 2080s) in the Hanjiang Basin.

respectively; while under B2 scenario, the changes will be about −17.04%, −3.75% and 15.52%, respectively.

5 Conclusions

The objective of this study was downscaling of large scale atmospheric variables from GCM outputs to climate variables at regional and local scale in order to investigate the hydrological impact on future climate change. The SSVM mode was applied to statistical downscaling of daily precipitation and temperature. The SSVM model approximates the observed climate data reasonably well, except that it has underestimated the variance of precipitation and temperature. The VIC distributed model was used with 9×9 km^2 grids and the results showed that it could simulate runoff hydrograph well in the Hanjiang Basin.

For downscaling precipitation, the results corresponding to both business-as-usual climate change scenarios by the SSVM model showed a decreasing trend in the 2020s, an increasing trend in the 2080s, and a mixed trend in the 2050s. The similar conclusions were drawn for the downscaling temperature. The downscaled precipitation and temperature data corresponding to both business-as-usual climate change scenarios were used as input to the VIC distributed hydrological model. Finally, the impact analysis of runoff in the Hanjiang Basin showed a similar trend in future under the both climate change scenarios to precipitation and temperature downscaled by SSVM model. Moreover, the VIC distributed model also gave the spatial distributed changes of runoff and it was seen that the runoff for almost the entire basin in the 2020s and most regions of the basin in the 2050s will be decreasing under the both climate change scenarios, while the runoff in the whole basin in the 2080s will be increasing significantly.

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