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Applicability Analysis of SDSM Technology to Climate Simulation in Xingtai City, China

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Abstract. With global warming, it is having a significant impact on the variation of precipitation and temperature. Both of them bring extreme discomfort to human's life and social development. The city of Xingtai in China, have suffered from many high temperatures and floods, which are resulted from climate change. Therefore, the purpose of this paper is to study the influence of climate change (precipitation and temperature) on water resources in Xingtai city by using the Statistical Downscaling Model (SDSM). SDSM is a coupled downscaling method based on multivariate regression and weather generator, which can effectively solve the spatial scale mismatch problem of small-scale hydrological response and large-scale climate information. Compared with other statistical methods, SDSM can be operated more simply and easily, and its results would be much better. The results show that: (1) the performances of calibration SDSM model are basically acceptable; (2) SDSM can better simulate the trend of precipitation and temperature; (3) The determination coefficients (R^2) of measured and simulated values about minimum temperature, maximum temperature, average temperature and precipitation in the verification period can be above 95%, 94%, 93% and 64% respectively.

1. Introduction

The issue of climate change is related to environmental change, economic sustainable development, the relationship between countries and so on, which is attracting more and more attention of the international community. The city of Xingtai, located in Hebei Province, China, has an important political, economic and social status. Due to the barrier effect of Taihang mountain on the cold air in the west, the high temperature disaster weather in Xingtai city has been intensified. The famous heavy rain of “63.8”, “96.8” and “7.19” brought serious disaster to the lives and property of people in Xingtai city. The direct cause of such heavy rainfall is a variable meso-scale weather system in both time and space, which is sometimes difficult to reveal. Therefore, the occurrence of the rainstorm process is often sudden and has great difficulty in forecasting. So it needs a suitable climate prediction model to predict future climate change and reduce the occurrence of disasters in Xingtai city.

General Circulation Model (GCM) is the current research on climate change and is one of the important means of climate predictions. GCM can well simulate large-scale annual or seasonal mean climate characteristics and provide accurate information on future climate change. However, it can



only reflect the average characteristics of climate change in large scale grid of 100 km² or more [1]. And the error of it in simulating precipitation and surface temperature is more significant on regional scale than large scale [2]. In order to describe the local climate better, it is necessary to downscale the results of GCM. Therefore, the downscaling method is widely used to compensate for the deficiency of GCM in predicting regional climate change scenarios [3]. SDSM is a statistical downscaling method coupled with multiple regression and weather generator [4]. According to the technology, its working principle is based on large scale climate [5]. SDSM not only can make the physical significance distinct by selecting prediction factors with clear physical meaning, but also has the advantages of simple and fast calculation. So it is widely used in climate impact assessment and hydrology research in the simulation of regional climate change [6-8]. Domestic scholars had been using SDSM to simulate and predict the regional climate. Chen et al. [9] used SDSM method to simulate extreme temperature in Jianghuai basin in 2012. The results showed that the simulated values are in good agreement with the observed values and can effectively correct the "cold deviation" of the coupled model. In 2015, Hao et al. [10] simulated the future temperature and precipitation in Hexi Corridor based on SDSM. The results revealed that the simulation effect of temperature is obviously better than precipitation. In 2016, Wang et al. [11] applied SDSM in Baiyangdian to simulate the maximum temperature and minimum temperature in the future, which proved that the simulation effect of this model is better.

It is noted that Xingtai city belongs to small scale hydrological space. And SDSM is an effective statistical downscaling method to solve the spatial scale mismatch problem of large scale climate information and small scale hydrological response. Therefore, the objective of this paper is to adopt SDSM to study the impact of climate change (precipitation and temperature) on water resources in Xingtai city. The regression relationship between 12 atmospheric predictors and four predictands based on measured and simulated data is studied to illustrate the applicability of SDSM. The results will help the managers to identify the trend of climate change in Xingtai city and thus offer ways to predict the occurrence of disasters. Therefore, it can provide the basis for the security and stabilization of social development.

2. Methodology

2.1. SDSM

SDSM is one of the effective methods to solve the spatial scale mismatch problem of large scale climate information and small scale hydrological response [12]. SDSM is a statistical downscaling method coupled with multiple regression and weather generator [4]. The statistical method is mainly to establish the statistical relationship between the forecast object and the forecast factor, through establishing the empirical statistical relationship between the scale grid, to achieve scale conversion. Since the good simulation effect and easy operation, SDSM has been widely used in climate impact assessment.

2.2. Process of SDSM

According to Zhao and Xu [13], SDSM includes five important parts: (1) select the atmospheric predictors of large scale, that is to filtrate the predictor variables; (2) select and calibrate the statistical downscaling pattern; (3) test the pattern using independent observational data; (4) apply the statistical pattern to GCM, and produces future climate scenarios; (5) diagnosis and analyse the future climate scenarios, including statistical analysis of output data, model output, mapping and so on.

The process of SDSM in this paper is as follows: (1) use reanalysis data from the U.S. Environmental Center (NCEP) and observation data of China Meteorological Data Network to establish a correlation model of weather predictand and predictors by SDSM technology; (2) use measured data from 1981 to 2000, 2001 to 2010 and NCEP atmospheric variables to calibrate and validate SDSM respectively; (3) compare the measured and simulated data to calculate R^2 and the

standard error (SE) between them; (4) analyse the applicability of SDSM technology in simulating climate change in Xingtai city.

3. Case study

3.1. The profile of research area

Xingtai city is located in the south of Hebei Province, with an area of $12.5 \times 10^3 \text{ km}^2$, between north latitude $36^\circ 50' \sim 37^\circ 47'$, east longitude $113^\circ 52' \sim 115^\circ 49'$, as shown in figure 1. Xingtai city belongs to warm temperate subhumid monsoon climate. The four seasons are distinct, the temperature varies greatly and the precipitation is concentrated during the year. The annual average temperature is 12 to 14 °C. In which, January is the coldest, whose average temperature is about -2°C, and the extreme minimum temperature can reach -20 °C. July is the hottest, with an average temperature of 27 °C and an extreme maximum temperature of 41 °C [14].



Figure 1. Administrative region of Xingtai city

3.2. Datum

3.2.1. Method of data download. The atmospheric predictors of large scale are from the reanalysis daily data [15] (abbreviated as NCEP), jointly launched by the National Centers for Environmental Prediction (NCEP) in U.S. and the National Center for Atmospheric Research (NCAR). The method is to download all the predictors on the official website of global reanalysis data, and then extract the related regions and related predictors. And the Final (FNL) data coding uses the binary lattice format recommended by the World Meteorological Organization to process the GRIdded Binary (GRIB) version of the data. Current FNL data in this paper collected the measured data of the past 6 hours at least, for global data analysis four times a day (universal time 0, 6, 12, 18), such as: fnl_20000101_00_00.grib1, directly using the Grid Analysis and Display System (GrADS) software for decoding.

3.2.2. Data. In the study, the maximum temperature, minimum temperature, daily average temperature and daily average precipitation are selected as predictand, whose daily data sequence from 1981 to

2010 in each site are derived from China Meteorological science data sharing service network. Before computation, the consistency, completeness, and extreme value of the data need to be tested to show that the quality is good. To be consistent with the format of the GCM output data, the resolution is converted from 1.875×1.875 to 2.50×3.75 [16]. The data contains a total of 12 atmospheric predictors (including surface wind speed, 850hPa, and 500hPa height field of the absolute humidity, geopotential height, specific humidity and mean sea level pressure and 2m at atmospheric temperature and so on, as shown in table 1).

Table 1. Partial data of predictors

mslp	rhun	p850	p_u	r500	p5_u	r850	temp	shum	p500
0.15	-1.78	-0.93	-0.55	-1.20	3.15	-1.07	-1.57	-1.11	-1.73
0.85	-0.93	-0.04	-2.37	-0.62	3.07	-0.41	-1.43	-1.06	-1.76
1.39	-0.84	0.29	-1.67	0.50	2.63	-0.30	-1.74	-1.14	-1.64
1.26	-0.91	0.52	-0.46	0.23	1.75	0.10	-1.72	-1.08	-1.16
1.35	0.13	1.07	-0.95	0.19	-0.04	0.46	-1.07	-0.86	-0.70
0.76	1.36	0.13	-2.20	2.43	-0.50	2.07	-0.92	-0.68	-1.13
0.72	1.23	-0.17	-0.47	0.73	-0.10	1.27	-0.99	-0.75	-1.04
1.06	0.94	0.42	-1.40	1.12	0.95	1.05	-1.21	-0.84	-1.23
0.77	1.10	-0.38	0.58	-0.58	1.71	-0.17	-1.44	-0.93	-1.87
0.09	0.56	-1.41	-1.07	-0.04	2.41	-0.52	-1.80	-1.01	-2.22
0.69	1.00	-0.77	-1.76	-0.10	1.97	-0.24	-1.89	-1.05	-1.99

3.3. Predictor of large scale

3.3.1. Selection method of predictor. The selection of predictors generally follows four criteria.

- (1) The selected predictors must be strongly correlated with the predictand.
- (2) It must be able to represent important physical processes and large scale climate variability of large scale climate.
- (3) The selected prediction factors must be able to be accurately simulated by numerical models, in order to correct the systematic errors of numerical models.
- (4) The predictive factors applied to statistical models should be weakly correlated or unrelated.

Using the "screening variable" function of SDSM to select the predictors and their conversion variables from the candidate variables, which are suitable for downscaling of daily average temperature, daily maximum temperature, daily minimum temperature and daily average precipitation.

3.3.2. Determination of Predictor. The partial correlation coefficient can be used to determine the predictors, and the higher the partial correlation coefficient is, the stronger the correlation is. The partial correlation coefficients of predictors and predictands are shown in table 2. It can be seen that the partial correlation coefficients between the maximum temperature, average temperature and the predictors of temp, mslp, P500 are relatively high. The partial correlation coefficients between the minimum temperature and the predictors of temp, P500, p5_u are higher as shown in table 3. However, the partial correlation coefficients of precipitation are relatively low, and the correlation between the predictors and the predictand is a little bit worse as shown in table 4. In a word, in order to establish a better forecast model for the whole year, it is necessary to ensure that the selected predictors have certain correlation with the predictands.

Table 2. Partial correlation analysis between temperature and predictor

	mslp	p_u	p5_u	p500	p850	shum	temp
Maximum Temperature	-0.49	-0.28	0.19	-0.81	0.47	0.27	0.77
Average Temperature	-0.38	-0.19	0.60	-0.76	0.38	0.41	0.69

Table 3. Partial correlation analysis between minimum temperature and predictor

Predictors	mslp	p_u	p5_u	p500	shum	temp
Partialr ^a	-0.6	-0.31	0.91	0.98	0.32	0.62

^a The partial correlation coefficient.

Table 4. Partial correlation analysis between precipitation and predictor

Predictors	p_u	r500	r850	rhum	shum
Partialr ^a	0.48	-0.48	-0.14	-0.56	-0.35

^a The partial correlation coefficient.

The types of models used by each station are shown in table 5. Since there is a direct relationship between temperature and large scale predictors, the model for temperature downscaling is an unconditional process, but for precipitation downscaling is a conditional process.

Table 5. Predictors of downscaling model

Model	Daily Precipitation	Daily Average Temperature	Daily Maximum Temperature	Daily Minimum Temperature
Predictors	(shum)	(mslp)	(mslp)	(mslp)
	(r850)	(p500)	(p500)	(p500)
	(r500)	(p850)	(p850)	(shum)
	(p_u)	(shum)	(shum)	(temp)
	(rhum)	(temp)	(temp)	(p_u)
		(p_u)	(p_u)	(p5_u)
Model Type		(p5_u)	(p5_u)	
	Daily model; Fourth root transformation; conditional process	Daily model; linear model; unconditional process	Daily model; linear model; unconditional process	Daily model; linear model; unconditional process

3.4. Calibration of SDSM

SDSM model is calibrated by the measured data from 1981 to 2000 and the atmospheric variables of NCEP, respectively. It also gives the interpretation variance and standard error when calibrating the annual regression model. These statistical eigenvalues can reflect the importance of SDSM in evaluating future climate change. The accuracy of the model is tested by the interpretation variance and standard error. Among them, the standard error of the model reflects the sensitivity of the predictand to the circulation factor, and the percentage of interpretation variance indicates the correlation between the local predictand and the circulation factor [17].

Table 6 shows the average interpretation variance (%) and standard error of the calibration model for Xingtai city. It can be seen that the interpretation variance of SDSM model is more than 74% when simulating the daily average temperature, maximum temperature, minimum temperature and daily average precipitation, meaning that the selected predictors can explain the variance of the predictand

over 74%. In comparison, the simulation effect of daily average temperature is the best, with the interpretation variance being above 77%, and the standard error being about 2.36°C. The next are maximum temperature and minimum temperature, whose standard errors are about 3.09°C and 2.52°C, respectively. Compared with the air temperature, the simulation effect of daily rainfall is poor, whose interpretation variance is about 42%, and the standard error is about 0.37mm.

Table 6. The average interpretation variance and standard error of the calibration model (1981~2000)

Predictands	Daily Maximum Temperature	Daily Minimum Temperature	Daily Average Temperature	Daily Average Precipitation
(SE)	3.09°C	2.52°C	2.36°C	0.37mm
(E)%	76	74	77	42

4. Results Analysis

4.1. Method of SDSM independence test

Firstly, according to the calibrated model, the weather generator can manually generate the daily sequence of the predictand by using the observation data of the predictors (or NCEP reanalysis data). At the same time, the degree of coincidence between the generated and measured sequence can be compared and analysed, that is to verify SDSM by independent observation data. Secondly, select the measured data from 2001 to 2010 to verify the model, compare and analyse the simulated and measured values of the daily maximum temperature, daily minimum temperature, and daily average precipitation in Xingtai city during the verification period. Finally, select the determination coefficient (R^2) to evaluate its simulation results.

4.2. Results of SDSM independence test

From figure 2 to figure 5, it can be seen that the simulated and measured values of the daily average temperature, the daily maximum temperature and the daily minimum temperature during the validation period are well fitted in Xingtai city. The simulated values of the maximum temperature are higher than the measured values, and the simulation effect is better in April and July, with the average deviation of -0.4°C. The simulation effect of average temperature in September and October is the best, with the average deviation of -0.48°C. The simulation results of the minimum temperature in April, May, June and July are better, with the average deviation of -0.43°C. The simulation effect of daily average precipitation is worse. At the same time, the results in table 7 furtherly show that SDSM has good simulation effect on air temperature, with the R^2 being above 0.92, and general simulation effect on precipitation, with the R^2 being 0.64. it is noted that the higher the R^2 , the better the regression equation fitting data, and the stronger the linear relationship. Under this condition, it can be obtained that SDSM can well simulate the changes of future temperature and precipitation in Xingtai city.

Table 7. The determination coefficient (R^2) in validation period (2001~2010)

Predictands	Average Temperature	Minimum Temperature	Maximum Temperature	Average Precipitation
(R^2)	0.95	0.94	0.92	0.64

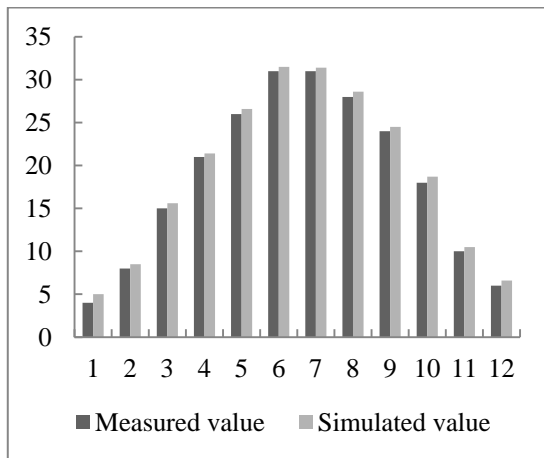


Figure 2. Measured and simulated values of maximum temperature (2001~2010)

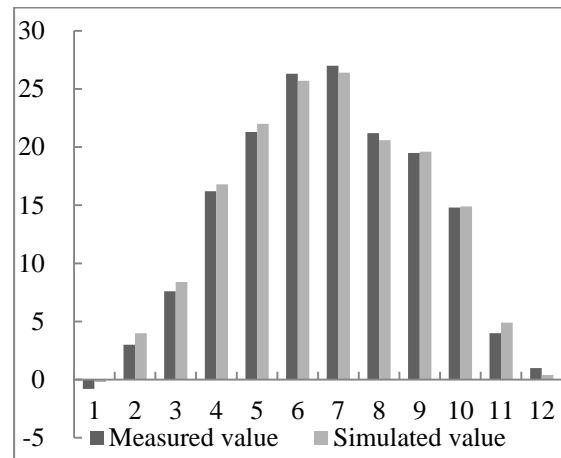


Figure 3. Measured and simulated values of average temperature (2001~2010)

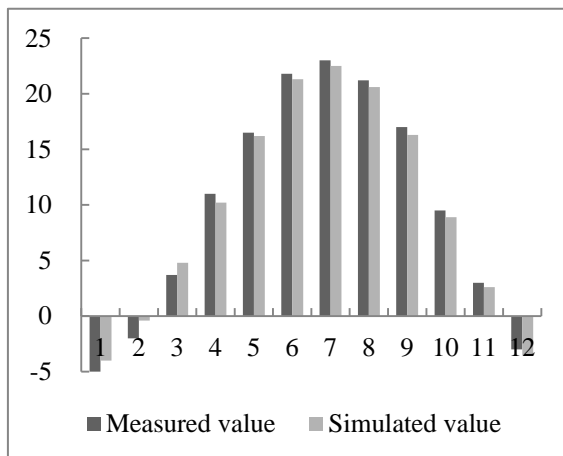


Figure 4. Measured and simulated values of minimum temperature (2001~2010)

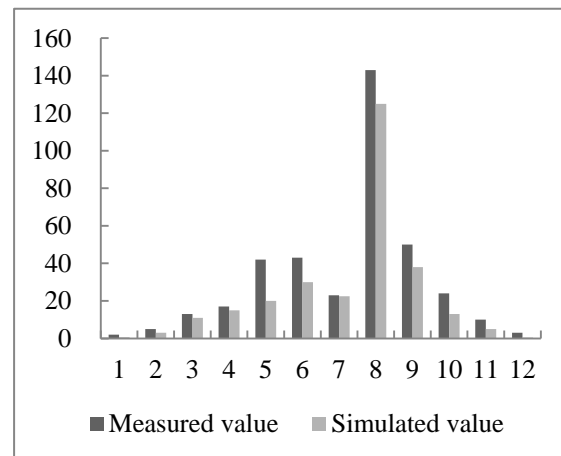


Figure 5. Measured and simulated values of daily average precipitation (2001~2010)

5. Conclusions

SDSM is an effective coupled downscaling method based on multivariate regression and weather generator to solve the spatial scale mismatch problem. Its main processes in this study include: (1) select the average temperature, maximum temperature, minimum temperature and daily average precipitation as predictand; (2) select the suitable NCEP atmospheric circulation factor as the predictor; (3) establish the regression relationship between predictand and predictors; (4) calibrate and validate SDSM using the measured data and the atmospheric variables of NCEP and analyse its applicability.

In this paper, SDSM has been applied to Xingtai city for climate simulation. The results show that the simulated and measured values of daily average temperature, daily maximum temperature, daily minimum temperature and daily average precipitation of SDSM in Xingtai city are well fitted. The simulated frequency analysis of precipitation and temperature shows that the selected SDSM method can basically simulate the distribution characteristics. In a word, SDSM a suitable climate prediction model to predict future climate change in Xingtai city. Therefore, it can provide the basis and support to climate simulation and prediction, in order to reduce the occurrence of disasters and guarantee the security and stabilization of social development.

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