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climate MDPI

Type of the Paper (Article, Review, Communication, etc.)

Projection of future temperature over the Haihe River Bain, China based on CMIP5 models

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Received: date; Accepted: date; Published: date

Abstract: The future climate information is essential to develop adaptation and mitigation strategies for climate change. In this study, future daily maximum and minimum temperature projections over the Haihe River Basin of China during the period 2011-2100 was generated based the two CMIP5 models under two Representative Concentration Pathway (RCP2.6 and RCP8.5) via a statistical downscaling model (SDSM). Compared to the baseline period (1971-2010), future change in annual and seasonal maximum and minimum temperature was computed after bias correction. The spatial distribution and trend change of annual maximum and minimum temperature were also analyzed using ensemble projection method. The results show that: Under two future scenarios during the 2020s, 2050s and 2070s, the changes in annual mean maximum and minimum temperature would increase and magnitude of maximum temperature would be higher than minimum temperature. The increase in magnitude for the weather station in the mountains and along the coastline would be remarkably obvious. For annual maximum and minimum temperature, the significant upward trend will be obtained under RCP 8.5 scenario and the magnitude will be 0.37 and 0.39 ℃ per decade, respectively; the increase in magnitude under RCP 2.6 scenario will be upward in 2020s and then decrease in 2050s and 2070s, and the magnitude will be 0.01 and 0.01℃ per decade, respectively. The results obtained in this study could be used as references for decision-making of food production and environmental sustainability in the basin.

Keywords: Statistical downscaling; Temperature; CMIP5 models; Ensemble projection; Climate change projection

1. Introduction

The global average surface temperature increased 0.85 (0.65 to 1.06)℃ in the period 1880-2012, and each of the last three decades has been continuously warmer at the Earth's surface than any preceding decade since 1850 (IPCC 2013). Due to human activities including the burning of fossil fuel, deforestation and so on, the markedly increased concentration of greenhouse gas emissions cause the increasing air temperature, which further cause acceleration of the hydrological cycle, redistribution of water resources and crop growth on spatial and temporal scales (Acharya et al. 2012; Ju et al. 2013; Wang et al. 2014). This will inevitably affect the availability of water for the purpose of domestic, agriculture, hydropower generation, and ecological environment, which ultimately affect the social economy of the region.

General Circulation Models (GCMs) are the principal instrument for making projections of future climatic conditions, and have been applied extensively to the research on the response of natural system to future climate change(Araya et al. 2015; Pumo et al. 2016; Sun et al. 2013; Wang et al. 2015).However, their remain relative coarse in resolution so that are unable to resolve important sub-grid scale features such as topography and clouds (Wilby et al. 2002). Thus, the raw GCMs' outputs do not meet the needs of regional impact studies of climate change. Fortunately, downscaling technology have been developed in the past decades to bridge the gap between the outputs from the GCMs and the requests for the regional impact studies. There are many downscaling techniques, but they can be mainly divided into two categories: dynamic downscaling and statistical downscaling (Wilby et al. 2002). Dynamic downscaling needs a GCM to define the atmospheric boundary conditions, and statistical downscaling establishes the statistical relationship between large-scale atmospheric variables (predictors) deprived from the GCM and local ground observations (predictands). Comparing to dynamic downscaling, statistical downscaling is comparatively cheap and computationally efficient and have been widely used all over the world in regional impact studies (Ahmadi et al. 2014; Ye and Grimm 2013; Zhang et al. 2012).The most common statistical downscaling method are transfer functions, this further dividing into traditional linear and nonlinear regression technology. The first of these includes linear regression (Sachindra et al. 2014), canonical correlation analysis (Jha et al.) and principal component analysis (Dibike and Coulibaly 2005); the others includes artificial neural network (Chen et al. 2010; Duhan and Pandey 2015) and support vector machine(Raje and Mujumdar 2011; Srinivas et al. 2014). Among the above mentioned techniques, Statistical DownScaling Model (SDSM) developed by Wilby et al. (2002) incorporate both deterministic transfer function (regression models)and stochastic components (stochastic weather generator) and has its advantage of being simple and easy to implement, the excellent user interface. Therefore, SDSM has been extensively used applied in statistical downscaling studies for climate variables all over the world (Chu et al. 2010; Kazmi et al. 2015; Liu et al. 2011; Singh et al. 2015; Tatsumi et al. 2015; Tryhorn and DeGaetano 2011).Meanwhile, the comparison researches on simulation ability for the historical climate variables between SDSM and the other statistical techniques have presented that SDSM performed well(Hassan et al. 2014; Hu et al. 2013; Khan et al. 2006).

The latest generation of state-of-the-art GCMs is the five phase of the Coupled Model Intercomparison Project (CMIP5) models, which provides scientific support for the IPCC AR5. Compared with CIMP3 models, there are some improvements in CMIP5 models (Bauer et al. 2008; Moss et al. 2010; Taylor et al. 2012). Meanwhile, the studies on the comparison of the performance evaluation for temperature between CMIP3 and CMIP5 have shown that the CMIP5 models overall perform well CMIP3 models (Chen and Frauenfeld 2014). To our knowledge, CMIP3 models have been extensively applied in regional impact studies, there is few contribution of CMIP5 models to regional impact studies exist all over the world (Palomino-Lemus et al. 2015; Rashid et al. 2015), much less in China (Wu et al. 2015). Taking into consideration the adverse effect of the increased temperature to nature system, the future maximum and minimum temperature (Tmax and Tmin, hereafter) at the regional scale are the very important climatic variables to the decision-makers for watershed water resource, regional crop production and so on. The modeling techniques, including hydrological models, water quality models and crop models, are widely used to predict the effect of future climate change for the purpose of the formulation of the mitigation counter-measures. So the future prediction of Tmax and Tmin not only could provide the informative support for the local decision-makers, but also is also necessary input values for relevant models. Due to structural differences of the GCMs, future projections for climatic variables obtained by GCMs datasets vary from one GCM to another, thus causing different projections when outputs of GCMs are downscaled at the regional scale (Li et al. 2012; Souvignet and Heinrich 2011). Nowadays, most research on statistical downscaling of climate variables often adopt the outcome from only one model (Chu et al. 2010; Duhan and Pandey 2015; Hassan et al. 2014; Jeong et al. 2012; Kazmi et al. 2015). Avoid the uncertainty linked to choice of the GCMs (Huang et al. 2013), multiple GCMs is recommended to mitigate possible biases of the different GCMs and reduce the uncertainty related to GCMs while statistical downscaling techniques are applied for regional impact studies.

Hence, this paper aims at projection of future Tmax and Tmin by downscaling the atmospheric variables from the two CMIP5 models using SDSM model under RCP2.6 and RCP8.5 scenarios in the Haihe River Basin during the period 2011-2100. The future change of seasonal and annual Maximum and Minimum temperature of the basin under all GCMs and scenarios was analyzed. To reduce the uncertainty linked to GCMs, the ensemble projection is used to generate ensemble projections from multiple GCMs projection to a single projection. Thereafter, the spatial distribution and trend change of annual mean Tmax and Imin are also analyzed after bias correction and ensemble projections. The result will enhance the decision capacity of local water manager as well as provide supportive information for decision-maker with more rational estimates of potential impacts of climate change.

The paper is organized in four main sections. First, the study area and the data used in this paper will be described. The next section will introduce the methodology adopted in this work. After a description of the statistical downscaling method, the statistical test and analysis used in the uncertainty analysis will be presented. Thereafter, results for the performance evaluation and change of temperature under future climate change scenarios will be explored. Eventually, general concluding remarks will be summarized.

2. Materials and Methods

2.1 Study area

The Haihe River Basin (HRB), stretching between 112-120°E and 35-43° N, covers an area of approximately 31.8×104 km2, which accounts for 3.3% of the total area of China. The elevation of the basin varies between 100-3,059m above mean sea level, and the elevation gradient from high to low is from west to east. The basin comprises the mountains and plateaus in the north and west occupying nearly 60% of the total area, and the North China Plain in the east and south occupying the remaining 40% (Figure 1). To the north of the catchment is the Yanshan Mountains, to the west is the Taihang Mountains, to the east is the North China Plain, and to the south is the Yellow River. All rivers in the basin flow westward and drain into the Bohai Sea.

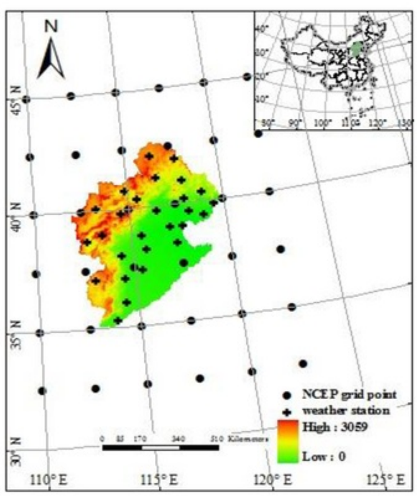

Figure 1. Location map of the Haihe River Basin

The basin is located in the transition zone from arid to humid climate in China. The predominant climate is the Asian Monsoon climate characterized by cold and dry winters and hot and rainy summers. The multi-year average rainfall in the basin, 75% of which mainly occurs during the period from July to September, ranges from 350 to 750 mm, and shows the trend that gradually decreases from southeast to northwest; the average annual Tmax and Tmin are -4.9 and 15℃, respectively. The spatial distribution of rainfall is also uneven; there is more rain along the coast due to strong sea-land wind and on the windward side of the Yan Mountains and Taihang Mountains due to the orographic uplift.

2.2 Data description

2.2.1 Temperature data

The daily observed maximum temperature (Tmax, hereafter)and minimum temperature (Tmin, hereafter) from 28 meteorological stations over the HRB were obtained from the China Meteorological Data Sharing Service System(http://cdc.cma.gov.cn/). All station records used in this study have complete series for the entire period (1971-2000) and have passed NMO data quality control. The details of the station are given in Table 1 and Figure 1.

Table 1. Location of weather station used during study periods

No	Station name	Lat.(N)	Long.(E)	Alt. m amsl	No	Station name	Lat.(N)	Long.(E)	Alt. m amsl
1	Anyang	36.05	114.4	62.9	15	Raoyang	38.23	115.73	19
2	Baoding	38.85	115.52	17.2	16	Shijiazhuang	38.03	114.42	81
3	Beijing	39.8	116.47	31.3	17	Tangshan	39.67	118.15	27.8
4	Chengde	40.98	117.95	385.9	18	Tanggu	39.05	117.72	4.8
5	Datong	40.1	113.33	1067.2	19	Tianjin	39.08	117.07	2.5
6	Duolun	42.18	116.47	1245.4	20	Weichang	41.93	117.75	842.8
7	Fengning	41.22	116.63	661.2	21	Weixian	39.83	114.57	909.5
8	Huailai	40.4	115.5	536.8	22	Wutaishan	38.95	113.52	2208.3
9	Huangye	38.37	117.35	6.6	23	Xinxiang	35.32	113.88	73.2
10	Huimin	37.48	117.53	11.7	24	Xietai	37.07	114.5	77.3
11	Leting	39.43	118.88	10.5	25	Yushe	37.07	112.98	1041.4
12	Nangong	37.37	115.38	27.4	26	Yuanping	38.73	112.72	828.2
13	Qinhuangdao	39.85	119.52	2.4	27	Zhangjiakou	40.78	114.88	724.2
14	Qinglong	40.4	118.95	227.5	28	Zunhua	40.2	117.95	54.9

Lat., long., Alt., and m amsl denote latitude, longitude, altitude and meter mean above sea level, respectively.

2.2.2 Predictors

The databases related to predictors include the following two categories: 1) daily predictors from the National Center for Environmental Prediction（NCEP）re-analysis dataset; 2) daily predictors from two GCMs dataset.

The daily predictors, derived from the National Center for Environmental Prediction（NCEP）re-analysis dataset (http://www.cdc.noaa.gov/cdc/reanalysis/)at a spatial resolution of 2.5°, was used as the observation data for developing statistical downscaling model. The NCEP reanalysis dataset is available from 1948 to the present. Relevant predictors were extracted for a six by six array of grid cells (2.5°×2.5°) covering the all meteorological weathers over the HRB. The data pertaining to the period for 1971-2000 were downloaded for each grid point in Figure 1. The 36 grid points surrounding the study region are selected as the spatial domain of the predictors to adequately cover the various circulation domains of the predictors considered in this study.

Two chosen GCMs datasets used in the present study were downloaded from the five phase of the Coupled Model Inter-comparison Project (CMIP5, hereafters). These are MPI-ESM-LP and CNRM-CM5(hereafters, MPI and CNRM, respectively). Table 1 itemizes the model name, originating group and atmosphere resolution of selected models. These two models' outputs under

RCP 2.6 and RCP 8.5 scenarios during the periods of 2011-2010 were used to provide the future large-scale atmospheric variables for projection future Tmax and Tmin changes.

Table 2. Details of the selected CMIP5 climate models

No	Model names	Originating groups	Atmospheric resolution (longitude by latitude)
1	CNRM-CM5	Centre National de Recherches Meteorologiques, Meteo-France, France	256×128
2	MPI-ESM-LR	Max Planck Institute for Meteorology	192×96

The overlaying large-scale atmospheric variables from the NCEP and GCM dataset are extracted as the candidate predictor. In this study, 24 daily predictors (1971-2000) such as temperature, geopotential height, zonal and meridional wind speeds at variable pressure level, sea level pressure and surface temperature were chosen for screening predictors (Table 3).

Table 3. The overlaying candidates predictor from NCEP and GCMs for downscaling models

No.	Abbreviation	Predictor
1	hur850	850 hPa relative humidity
2	hur700	700 hPa relative humidity
3	hur500	500 hPa relative humidity
4	zg850	850 hPa geopotential height
5	zg700	700 hPa geopotential height
6	zg500	500 hPa geopotential height
7	zg250	250 hPa geopotential height
8	ua850	850 hPa zonal wind speed
9	ua700	700 hPa zonal wind speed
10	ua500	500 hPa zonal wind speed
11	ua250	250 hPa zonal wind speed
12	va850	850 hPa meridional wind speed
13	va700	700 hPa meridional wind speed
14	va500	500 hPa meridional wind speed
15	va250	250 hPa meridional wind speed
16	ta850	850 hPa air temperature
17	ta700	700 hPa air temperature
18	ta500	500 hPa air temperature
19	ta250	250 hPa air temperature
20	tas	Surface temperature
21	mslp	Sea level pressure

Before the calibration and validation of SDSM model, the predictors should be processed to fit the need of the SDSM. The GCMs predictors were first interpolated by means of linear interpolation technique to NCEP grid resolution (2.5×2.5) to eliminate spatial differences. This utility of this interpolation method was checked in previous downscaling studies(Hu et al. 2013). Subsequently, the predictors from NCEP and GCMs were normalized by utilizing long-term mean and standard deviations of 1971-2000, respectively. These CMIP5 model were chosen based on our previous study related to the performance evaluation of CMIP5 models over the HRB.

RCP2.6 (a very-low forcing level) corresponds to the case of radiative forcing peak at approximately 3.0 W/m^2 before 2100 and then declines, which is equivalent to approximately 490 ppm CO_2. Similarly, RCP8.5 (a very high emission scenario) is defined as the case where the radiation is assumed to exceed 8.5 W/m^2, which means the equivalent CO_2 exceeds 1370 ppm(Moss et al. 2010; van Vuuren et al. 2011)

2.3 Statistical downscaling model descriptions

The SDSM, which was adopted in this study to establish the statistical relationship between large-scale atmospheric variables and local climatic variables, is a hybrid between a multivariate linear regression method and a stochastic weather generator(Wilby et al. 2002). The SDSM software implements statistical downscaling task through the following main processes: 1) quality control and data transformation;2) screening of potential downscaling predictor variables; 3) model calibration; 4) weather generation; 5) data analysis;6) graphing analysis; 7) scenario generation. The mathematical details were described by Wilby et al. (1999) and Chu et al. (2010).

For SDSM model, there are three kinds of sub-models: monthly, seasonal and annual sub-model. Monthly sub-model was used in this study considering the lag-1 day autoregression. The default parameter values including variance inflation and bias correction were used in this study.

2.4 Choice of predictor

In statistical downscaling, the relevance of relationship between large-scale predictors (variables from NCEP and GCMs datasets) and the regional predictands (Tmax and Tmin from weather station in this study) will determine the model ability to reproduce the historical climate change and to produce good climate projections over the study area. This is based on the assumption that the relationships between predictor and predictant under the current conditions still remain valid under future climate scenarios. This assumption allows the implement of statistical downscaling for future climate projects. Therefore, the choice of the suitable predictors is of particular importance in the development of statistical.

The basic principle for the choice of the predictor is that the selected predictors must be obviously correlated with the predictand, definite physically meaning, realistically represented by GCM, and multiyear variability captured(Liu et al. 2013; Wilby et al. 1999). Some statistical method such as partial correlation analysis, step-wise regression, correlation coefficient may be used to screen most promising predictor variables from the lots of candidate predictors(Jeong et al. 2012). In this study, the potential predictors were screened through a correlation analysis with climate variables at each of all 28 weather stations. Furthermore, experience and recommendations from similar studies over the HRB and neighbouring regions were also taken into account(Chu et al. 2010). The final set of predictors for downscaling of Tmax and Tmin were chosen as follows: air temperature at 850 hPa pressure level, Sea level pressure and meridional wind speed at 850 hPa pressure level and geopotential height at 250 hPa pressure levels.

There are 4 predictors at 36 NCEP grid point with a dimensionality of 144 for statistical downscaling models, multi-dimensionality of the predictors may lead to a computationally complicated. To reduce the dimensionality of the explanatory dataset, the principal component analysis (PCA) was then adopted to reduce the dimensionality of the predictors. Meanwhile, the use of principal components as input to the downscaling model is helpful to make the model more stable and at the same time reduces its computational burden. In this study, the first four principal components, which accounted for more than 90% of the total variance, were used as input to the SDSM.

2.5 Bias correction

Due to varying performance of historical climatic variables such as temperature and precipitation for different GCMs, the bias correction methods always are adopted to make the distribution of simulated values close to the historical observed pattern(Fowler et al. 2007). In this study, the change factor, which is ordinary bias correction method, is adopted to reduce the bias between downscaled values with GCMs predictors and observations(Hassan et al. 2014; Mahmood and Babel 2013). The bias between long-term monthly mean of historical observed variables and downscaled values in the baseline period (i.e., 1971-2000 in this study) are used to adjust the future downscaled daily time series according to their respective months. The specific equation is showed as follows:

$$X_i' = X_i - \left(\overline{X}_{GCM} - \overline{X}_{obs}\right)$$

Where X_i', X_i refer to raw and corrected downscaled variables for future period (i.e., 2011-2010), $\overline{X}_{GCM}$ and $\overline{X}_{obs}$ presents the long-term mean monthly variable from the historical observed variable and downscaling values.

2.6 *Model performance*

In this study, in addition to visual inspection of the figures of observed and simulated values, the performance of the model during calibration and validation periods is also evaluated by certain statistical measures/criteria for goodness-of-fit such as mean, standard error, normalized root mean square error (NRMSE) and coefficient of determination (R^2). The NRMSE and R^2 are explained as follows:

(1) NSMSE

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2}}{\sqrt{\frac{1}{n-1}\sum_{i=1}^{1}(O_i - \overline{O})^2}}$$

(2) R^2

$$R^2 = \left[\frac{\left(\sum_{i=1}^{n}(O_i - \overline{O})(P_i - \overline{P})\right)}{\left(\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2}\sqrt{\sum_{i=1}^{n}(P_i - \overline{P})^2}\right)}\right]^2$$

Where O and P are the modeled and observed values of time series *i* and n is the sample length. In general, higher R^2 indicate better accuracy of model simulation, whereas lower value of NRMSE show a better fit.

2.7 *Trend analysis and Sen slope estimator tests*

The Nonparametric Mann-Kendall trend test, a useful tool for non-parameter assessment of the significance of monotonic trends, has been widely used to trend detection analysis for the hydroclimatic time series (Duhan and Pandey 2015; Martinez et al. 2012; Xu et al. 2010). It has the following two advantages. Firstly, it can handle non-normalities involving seasonality, missing values, outliers, censoring. Secondly, it has a high asymptotic efficiency(Gan 1998). In addition to trend detection, it is also necessary to estimate the magnitude of the trend. Thus, Mann-Kendall trend test and Sen slope estimator test are adopted in this study.

3. Results and discussion

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation as well as the experimental conclusions that can be drawn.

3.1. *Calibration and validation*

3.1.1. Calibration

The daily downscaled Tmax and Tmin values from the SDSM model over the HRB for calibration period are compared with corresponding observed values (Figure 2). As shown in Figure 2, for Tmax and Tmin, the change of the simulated value matches consistently well with the observed values in all years. Especially, the good fit of peak values and valley value are also obtained. Reasonably high R^2 values during the calibration period for Tmax and Tmin are 0.975 and 0.971 respectively, and this shows satisfactory performance for the SDSM model during the calibration period. The NSMSE between observed and simulated values for Tmax and Tmin are 0.157 and 0.168, respectively.

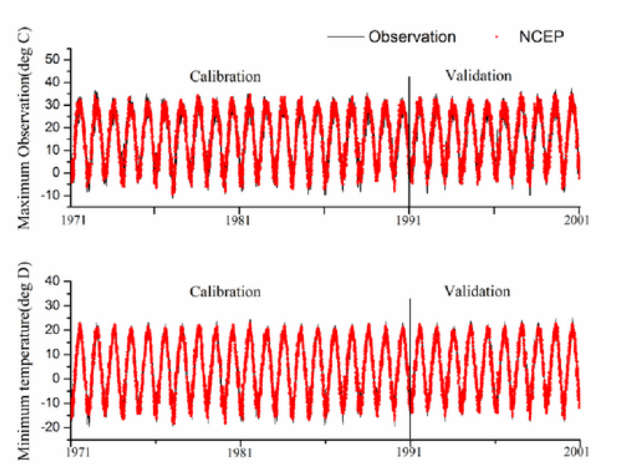

Figure 2. Comparison of observations and simulated Tmax (up)and Tmin(bottom) on daily time scale

As shown in Table 4, the mean and SD of observed mean monthly Tmax and Tmin during calibration is 15.94 and 10.78, 4.43 and 10.89 deg D, respectively. Overall, the mean and SD of simulated values of mean monthly Tmax and Tmin during calibration period is close to that of observed values. The error range for these two statistics measures is below 0.01 deg D. For Tmax, R^2 and NRMSE during calibration period are 0.996 and 0.061, respectively. For Tmin, R^2 and NRMSE during calibration period are 0.997 and 0.052, respectively. It is noted that, for Tmax and Tmin, the performance of model perform well in the monthly scale than in the daily scale during the calibration period, which is consistent with(Hassan et al. 2014; Huang et al. 2011).

Table 4. Statistical comparison of observed and downscaled mean monthly Tmax and Tmin during calibration period(1971-1990)

		Mean	SD	R^2	NRMSE
Tmax	Observed	15.94	10.78		
	NCEP-SDSM	15.95	10.78	0.996	0.061
Tmin	Observed	4.43	10.89		
	NCEP-SDSM	4.43	10.88	0.997	0.052

3.1.2 Validation

In the validation process, the model' ability to reproduce historical observations with the outputs from the NCEP and GCMs dataset are separately analyzed. Figure 2 shows, for Tmax and Tmin, the pattern of the daily simulated values matches consistently well with the observed values in all years as in the calibration period. Reasonably high R^2 values during the validation period for Tmax and Tmin are 0.976 and 0.977, respectively, and the NSMSE are 0.153 and 0.151, respectively. The statistical indices of the validation period are given in Table 5. It is seen in Table 5 that the mean and SD of observed mean monthly Tmax and Tmin using NCEP variables during validation period is 16.60 and 10.60, 5.19 and 10.59 deg D, respectively, and the R^2 value is 0.996 and 0.997, respectively. This shows that the simulated values from NCEP dataset are in good agreement with those of the observed values and that the SDSM model has the ability to reproduce historical observed data using the NCEP dataset, which is consistent with the excellent performance of SDSM model for temperature in other parts of the world(Khan et al. 2006; Souvignet et al. 2010).

In addition to NCEP dataset, the two sets of large-scale atmospheric predictors derived from MPI and CNRM are also validated during 1991-2000. The simulation error is caused when the model is driven by the MPI and CNRM. As for CNRM, the mean and SD value for simulated Tmax and Tmin values are 16.01 and 10.64, 4.55 and 10.8 deg D, respectively. As to MPI, the mean and SD value for Tmax and Tmin are 16.21 and 10.49, 4.69 and 10.69, respectively. As for MPI, the R^2 and NRMSE for simulated Tmax and Tmin values are 0.888 and 0.27, 0.898 and 0.29, respectively, which is better than that of CNRM. Compared with observed values for Tmax and Tmin over the HRB, the downscaled values from MPI and CNRM with R^2 of around 0.85 are not as well as that from NCEP, and the CNRM is a little worse than MPI. This is due to the simulation bias of predictor from the GCMs dataset compared to the NCEP reanalysis outputs. Meanwhile, it is generally acknowledged that both GCMs themselves and adopted downscaling techniques determine the downscaling result of climatic variables at the catchment scale(Rashid et al. 2015; Salathe et al. 2007). For example, the CNRM model has systematically cold bias over HRB presented by the Sun et al. (2014), and then the bias transfer to the downscaling climatic variables by downscaling techniques.

Table 5. Statistical comparison of observed and downscaled mean monthly Tmax and Tmin during calibration period over the HRB(1991-2000)

		Mean	SD	R^2	NRMSE	RE-mean	RE-SD
Tmax	Observed	16.61	10.61				
	NCEP	16.60	10.60	0.996	0.06	0.01	0.01
	MPI	16.21	10.49	0.888	0.27	0.4	0.12
	CNRM	16.01	10.64	0.855	0.37	0.6	-0.03
Tmin	Observed	5.45	10.67				
	NCEP	5.19	10.59	0.997	0.05	0.26	0.08
	MPI	4.69	10.69	0.898	0.29	0.76	-0.02
	CNRM	4.55	10.8	0.844	0.39	0.9	-0.13

The downscaled monthly, seasonal and annual mean Tmax and Tmin, with NCEP, MPI and CNRM predictors, are compared graphically with observed valued in Figure 3. As shown in Figure 3, the variation pattern of downscaled monthly mean Tmax and Tmin captured well by SDSM model with all three datasets (NCEP, MPI and CNRM) over the HRB for the validation period, and the downscaled result from NCEP variables performs best. Meanwhile, the similar result can be obtained in the patter of seasonal variation of Tmax and Tmin. Compared with the observed values, it is obvious that the downscaled monthly mean Tmax and Tmin with MPI and CNRM dataset underestimate in the month of February, December, July and August, this causing that the downscaled values for Tmax and Tmin are underestimated in winter and summer, especially distinct in winter. In addition, the simulated values for Tmax with MPI dataset are obviously overestimated in April and May.

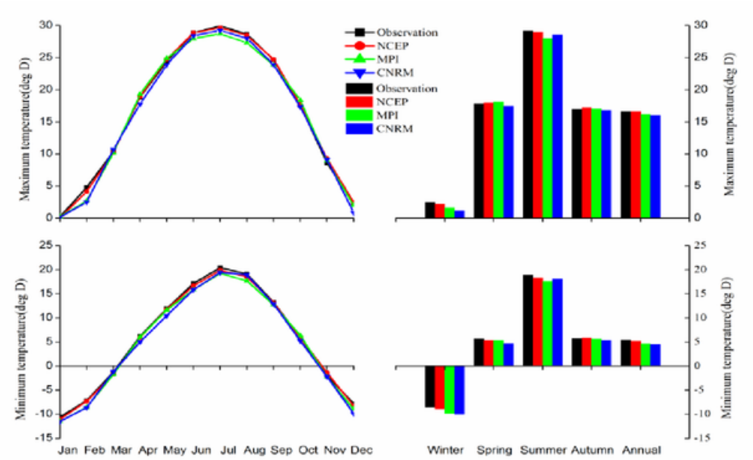

Figure 3. Observed and downscaled mean monthly, seasonal and annual maximum (up) and minimum (bottom) temperature for the period 1991-2000

Figure 4 and 6 show that the values of R^2 and NRMSE of daily and monthly mean Tmax and Tmin during the calibration and validation at all weather stations. The average R^2 between downscaled and observed daily Tmax and Tmin is are around 94% during the calibration and validation, and the average NRMSE is around 0.24. Similarly, all statistical measure in month scale at all weather stations is remarkably better in the daily scale than in the month scale for Tmax and Tmin. The average R^2 between downscaled and observed monthly Tmax and Tmin at all stations exceed 98% during the calibration and validation except the Wutaishan weather station with the altitude of 2208.3m.

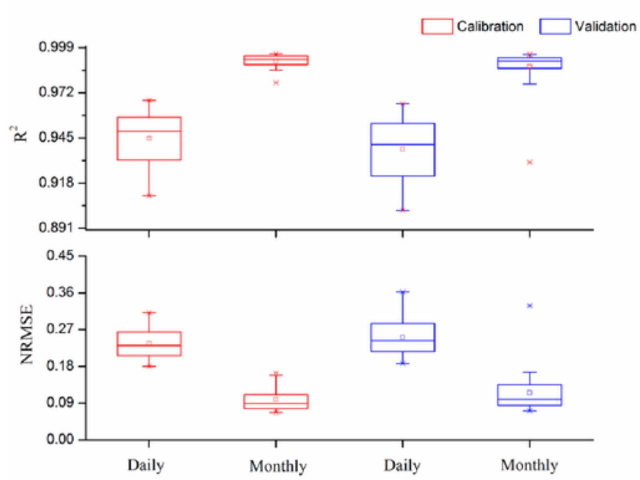

Figure 4. Box-plot of R^2 (up) and NRMSE (bottom)of maximum temperature for all weather stations

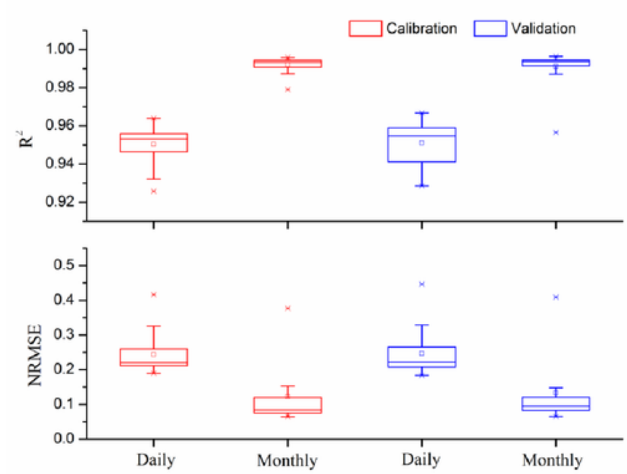

Figure 5. Box-plot of R² (up) and NRMSE (bottom)of minimum temperature for all weather stations

3.2 Downscaling of future maximum and minimum temperature

Like other impact studies, in this study, the period of 1971-2000 was taken as the baseline period which present the current climate, and the future period was divided into three thirty-year time slices, including 2020s(2011-2040), 2050s(2041-2070) and 2080s(2081-2100). The patterns of change about future Tmax and Tmin scenarios compared to the baseline period were analyzed with MPI and CNRM predictors under two scenarios(i.e.,RCP2.6 and RCP 8.5).The arithmeticmean was used to generate ensemble projections from multiple GCMs projection to a single projection for spatial distribution and trend of future Tmax and Tmin change.

3.2.1 The future change of seasonal and annual Minimum temperature and Maximum temperature

Compared to the observations during the baseline period (1971-2000), the projected changes in the seasonal and annual mean Tmin and Tmax of the basin in the 2020s, 2050s and 2080s with the MPI and CNRM datasets under the RCP2.6 and RCP8.5 scenarios are shown in Table 6 and 7.

There is a consistency among all GCMs and scenarios (RCP2.6 and RCP8.5) that annual mean Tmax and Tmin will increase during the period 2011-2100.The increase under RCP8.5 scenario will be more obvious than under scenario RCP2.6. In addition, the increases in magnitude of area annual mean Tmin will be higher than that of Tmax. As for Tmin, it is seen that under the RCP2.6 scenario, the changes of annual mean Tmax and Tmin in future periods (2020s, 2050s and 2080s) with two MPI and CRNM datasets over the whole basin will be 1.03 1.08 and 0.90 deg D, 0.79, 0.85 and 0.92 deg D, respectively. Under the RCP8.5 scenario, the changes for Tmax and Tmin will be 2.52, 3.21 and 3.98deg D, 1.74, 2.22 and 2.75deg D, respectively. As for Tmax, the changes in area annual mean Tmax and Tmin in future periods (2020s, 2050s and 2080s) under the RCP2.6 scenario will be 0.99 1.03 and 0.87 deg D, 0.75, 0.80 and 0.87 deg D, respectively. Under the RCP8.5 scenario, the changes will be 2.39, 3.03 and 3.79deg D, 1.62, 2.05 and 2.53deg D, respectively.

The projected changes in the area seasonal mean Tmax and Tmin with MPI and CRNM datasets under RCP2.6 and RCP8.5 scenarios will be markedly different. For MPI dataset, the higher increase in seasonal mean minimum temperature seasons under both RCP 2.6 and RCP 8.5 scenarios will be in spring; the highest increase in seasonal mean Tmax over the basin will be in spring under RCP 2.6 scenario and in autumn under RCP 8.5 scenario. For CNRM dataset, the highest increase for Tmin will be in winter under RCP 2.6 scenario and in autumn under RCP 8.5 scenario; the highest increase for Tmax will be in summer under RCP 2.6 and RCP 8.5 scenarios.

Under RCP 2.6 scenario, the seasonal and annual mean Tmax and Tmin with MPI datasets in different time slices will give the same trend, firstly increasing and then decreasing. However, the CRNM will show continuously increased trend. Under RCP 8.5 scenario, the change of seasonal and annual mean Tmax and Tmin with MPI and CNRM datasets in different time slices will have the same increased trend.

Table 6. Future changes in Tmin with respect to baseline (1971-2000) under RCP2.6 and RCP8.5 scenarios

Scenario	Period	MPI			CNRM		
		2020s	2050s	2080s	2020s	2050s	2080s
RCP2.6	Winter	0.99	1.10	0.86	1.07	1.24	1.36
	Spring	2.05	2.06	2.04	0.64	0.67	0.63
	Summer	-0.15	-0.10	-0.35	1.00	0.99	1.14
	Autumn	1.25	1.25	1.06	0.45	0.50	0.55
	Annual	1.03	1.08	0.90	0.79	0.85	0.92
RCP8.5	Winter	2.24	2.95	3.88	1.81	2.06	2.47
	Spring	3.44	4.16	4.65	1.68	2.28	2.87
	Summer	1.30	1.92	2.64	1.88	2.27	2.70
	Autumn	3.11	3.82	4.78	1.59	2.26	2.95
	Annual	2.52	3.21	3.98	1.74	2.22	2.75

Table 7. Future changes in Tmax with respect to the baseline period (1971-2000) under RCP2.6 and RCP8.5 scenarios

Scenario	Period	MPI			CNRM		
		2020s	2050s	2080s	2020s	2050s	2080s
RCP2.6	Winter	0.76	0.86	0.70	0.59	0.75	0.81
	Spring	1.51	1.51	1.44	0.63	0.66	0.66
	Summer	0.63	0.67	0.47	1.31	1.27	1.43
	Autumn	1.05	1.06	0.86	0.47	0.52	0.56
	Annual	0.99	1.03	0.87	0.75	0.80	0.87
RCP8.5	Winter	1.91	2.45	3.12	1.26	1.49	1.76
	Spring	2.50	3.05	3.44	1.40	1.84	2.26
	Summer	2.25	3.03	3.98	2.31	2.76	3.27
	Autumn	2.88	3.58	4.61	1.49	2.10	2.80
	Annual	2.39	3.03	3.79	1.62	2.05	2.53

3.3.2 Spatial distribution and trend analysis of future annual mean maximum and minimum temperature

The Figure 6 shows the spatial distribution of magnitude of annual mean Tmax and Tmin for all 28 weather stations (compared to baseline period) in 2020s, 2050s, and 2080s under RCP2.6 and RCP8.5 scenarios. For all weather stations, both increase in magnitude of annual mean Tmax and Tmin under RCP8.5 will be higher than that under RCP2.6. It is obvious that the increase in magnitude for all weather stations in the mountains and near the coastline will be obvious. For example, the maximum magnitude of Tmax and Tmin is Wutaishan station and Fengtai station, respectively. Compared to RCP2.6 scenario, the spatial distribution characteristics of the magnitude of Tmax and Tmin under RCP8.5 scenario will be more remarkable.

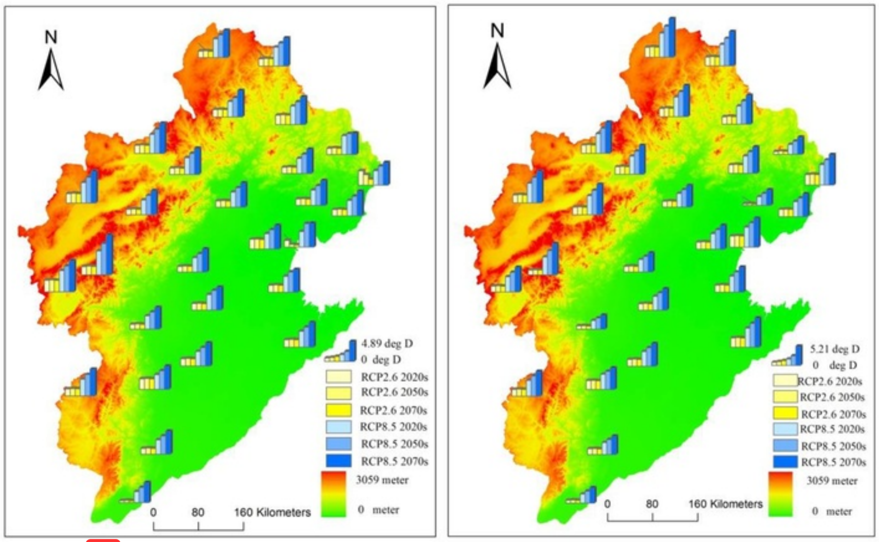

Figure 6. Spatial distribution of the change of annual mean Tmax (left) and Tmin(Bauer et al.)compared to baseline period in 2020s, 2050s and 2080s under RCP2.6 and RCP8.5 scenarios

The trend and magnitude of annual mean Tmax and Tmin of the basin using M-K trend test and Sen slope estimator test in the 2020s, 2050s and 2070s and during the periods 2011-2100 are shown in Table 8. The significantly increasing trends of Tmax and Tmin under RCP 8.5 scenario were obtained in all four time span (i.e., 2020s,2050s 2070s and 2011-2010). Overall, the magnitude of annual mean Tmax and Tmin will be 0.37 and 0.39 per decade, respectively. As to RCP2.6 scenario, the annual mean Tmax and Tmin of basin will increase in 2020s with magnitude of 0.26 and 0.27 deg D per decade, respectively, and then decrease in 2050s with a magnitude of -0.05 and -0.14deg D per decade and 2070swith magnitude of -0.01 and -0.02 deg D per decade, respectively. The magnitude of annual Tmax and Tmin will be the same,0.01 and 0.01 per decade, respectively.

Table 8. Annual trend and magnitude of Tmax and Tmin in the 2020s,2050s 2070s and 2011-2010 under RCP2.6 and RCP8.5 scenarios

Period	Scenario	Tmax		Tmin	
		Z	Slope (deg D/year)	Z	Slope (deg D/year)
2020s	RCP2.6	3.50	0.026	3.10	0.027
	RCP8.5	3.39	0.023	3.03	0.026
2050s	RCP2.6	-0.82	-0.005	-2.43	-0.014
	RCP8.5	5.74	0.038	5.60	0.042
2070s	RCP2.6	-0.32	-0.001	-0.46	-0.002
	RCP8.5	4.35	0.039	4.17	0.044
2011-2100	RCP2.6	1.05	0.001	0.75	0.001
	RCP8.5	11.83	0.037	11.65	0.039

4. Conclusions

A statistical downscaling model (SDSM) was constructed to generate future maximum and minimum temperature projection from the two CMIP5 models (MPI-ESM-LR and CNRM-CM5) to investigate possible future climate change under RCP2.6 and RCP8.5 scenarios during the period 2011-2100 over the Haihe River Basin, China. Firstly, the SDSM model was calibrated and validated using the both NCEP reanalysis data and ground observations (daily maximum and minimum temperature) during the period 1971-2010. The performance of SDSM model during the calibration and validation period was checked by visual inspection and statistical measures, including mean, standard error, determination of coefficient and normalized root mean square error. The GCMs predictors were downscaled to historical temperature to assess how the models perform. When bias between downscaled values with GCMs predictors and observations was observed, change factor bias correction method was employed in this study. The future change of seasonal and annual Maximum and Minimum temperature of the basin under all GCMs and scenarios was analyzed. To reduce the uncertainty linked to GCMs, the arithmeticmean is used to generate ensemble projections from multiple GCMs projection to a single projection. Thereafter, the spatial distribution and trend change of annual mean maximum and minimum temperature were also analyzed after bias correction and ensemble projections.

The major results in this study are as follows:

1.The variation pattern of observed daily and monthly mean Tmax and Tminof the basin are represented well by SDSM model with all three datasets (NCEP, MPI and CNRM) over the HRB, and the downscaled result from NCEP variables performs best. Compared with the observed values, the bias was observed using historical predictors from two CMIP5 models and the performance of CNRM is a little worse than MPI. The downscaled monthly mean Tmax and Tmin with MPI and CNRM dataset underestimate in February, December, July and August. In addition, the simulated values for Tmax with MPI dataset are obviously overestimated in April and May.

2.The downscaled projection of area annual mean Tmax and Tminin future period under both climate change scenarios (RCP2.6 and RCP8.5) over the HRB indicates an increase for all GCMs and scenarios. The increases in magnitude of area annual mean Tmin will be higher than that of Tmax. The projected changes in the area seasonal mean Tmax and Tmin with MPI and CRNM datasets under RCP2.6 and RCP8.5 scenarios will be markedly different.

3.Theincrease in magnitude of annual mean Tmax and Tmin for all weather stations under RCP8.5 are higher than under RCP2.6, and the weather stations in the mountains and near the coastline will have higher increase in magnitude of annual mean Tmax and Tmin. The significantly increasing trends of Tmax and Tmin under RCP 8.5 scenario are obtained in all four time span (i.e., 2020s,2050s 2070s and 2011-2010). Overall, the magnitude of annual mean Tmax and Tmin will be 0.37 and 0.39 per decade, respectively. Under RCP2.6 scenario, the annual mean Tmax and Tmin of the basin will increase in 2020s, and then decrease in 2050s and 2070s. The magnitude of annual Tmax and Tmin will be the same,0.01 and 0.01 per decade, respectively.

Future changes in maximum and minimum temperature will eventually affect the regional water resources and crop growth. The future water resources and crop production need be evaluated and to established adaptation and mitigation of strategy for future climate change. Meanwhile, the result is expected that the understanding of regional climate change from CMIP5 models will enhance the decision capacity of local water manager as well as provide supportive information for decision-maker with more rational estimates of potential impacts of climate change in the region.

Supplementary Materials: The following are available online at www.mdpi.com/xxx/s1, Figure S1: title, Table S1: title, Video S1: title.

Author Contributions: All authors contributed to the design and development of this manuscript. Xiaofeng Chen gathered the data information, performed the data analysis, prepared the first draft of the manuscript. WenJuan Chen operated the SDSM software. MingXiang Deng edited the manuscript prior to submission and conducted data processing. Hao Yang provided the original ideas and improved the discussion.

Funding: Please add: The study was supported by the Research Fund of Yunnan University of Finance and Economics for talents Introduction (No.80059900182), the National Social Science Fund of China (No.41562017) and Beijing Social Science Foundation Youth Project, China (No. 2019CN016).

Acknowledgments: We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups (listed in Table 1 of this paper) for producing and making available their model output.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The appendix is an optional section that can contain details and data supplemental to the main text. For example, explanations of experimental details that would disrupt the flow of the main text, but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data is shown in the main text can be added here if brief, or as Supplementary data. Mathematical proofs of results not central to the paper can be added as an appendix.

Appendix B

All appendix sections must be cited in the main text. In the appendixes, Figures, Tables, etc. should be labeled starting with 'A', e.g., Figure A1, Figure A2, etc.

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