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Papers

1. ANN-based statistical downscaling of climatic parameters using decision tree predictor screening method. 12 November 2018. Vahid Nourani, Zahra Razzaghzadef, Aida Hosseini Baghanam, Amir Molajou 伊朗

2. Projected temperature and precipitation changes on the Tibetan Plateau: results from dynamical downscaling and CCSM4. Xian Zhu, Zhigang Wei, Xiaohang Wen, Zhiyuan Zheng, Guangyu Chen, Yajing Liu. 27 April 2019 青藏高原

3. Probabilistic precipitation and temperature downscaling of the Twentieth Century Reanalysis over France. Laurie Caillouet, Jean-Philippe Vidal, Eric Sauquet and Benjamin Graff. 16 March 2016 法国

4. Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America. Jie Chen, François P. Brissette, Diane Chaumont and Marco Braun. 23 July 2013. 北美地区

伊朗（大不里士）

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ORIGINAL PAPER

ANN-based statistical downscaling of climatic parameters using decision tree predictor screening method

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Introduction

计算成本低、简便

降尺度

- 统计降尺度　建立GCM和所需尺度内水文气候变量间的经验统计关系 ✓
- 动力降尺度　基于物理方程以达到同样目的

Method

1. 15个GCMs(CMIP3(7个), CMIP5(8个))；

2. Tabriz station(Tabriz airport) for the period of 1951-2016；

时间： 1951-2000(calibration)、2020-2060(validation)

Fig. 1 Geographical location of the study area

Method

Table 1 The considered GCM models in order to select the suitable GCM for downscaling

	Model	Resolutions (lat° × lon°)	Country	Research center
(CMIP3) models	CSIRO-MK3.0	1.9° × 1.9°	Australia	Commonwealth Scientific and Industrial Research Organization
	CGCM3(T47)	3.8° × 3.8°	Canada	Canadian Center for Climate Modeling and Analysis
	CGCM3(T63)	2.8° × 2.8°	Canada	Canadian Center for Climate Modeling and Analysis
	FGOALS-g1.0	2.8° × 3°	China	Institute of Atmospheric Physics
	Had-CM3	3.8° × 2.5°	UK	UK Meteorological Office
	GFDL-CM2.1	2.5° × 2°	USA	Geophysical Fluid Dynamics Laboratory
	NCAR-CCSM3	1.4° × 1.4°	USA	National Centre for Atmospheric Research
(CMIP5) model	ACCESS1.0	1.2° × 1.9°	Australia	Commonwealth Scientific and Industrial Research Organization
	CSIRO-MK3.6.0	1.9° × 1.9°	Australia	Commonwealth Scientific and Industrial Research Organization
	Can-ESM2	2.8° × 2.8°	Canada	Canadian Centre for Climate Modeling and Analysis
	BNU-ESM	2.8° × 2.8°	China	Beijing Normal University
	FIO-ESM	2.8° × 2.8°	China	The First Institute of Oceanography, SOA
	IPSL-CM5B-LR	1.9° × 3.7°	France	Institute Pierre Simon Laplace
	HadGEM2-AO	1.2° × 1.9°	Korea	National Institute of Meteorological Research
	GISS--E2-R-CC	2° × 2.5°	USA	NASA/GISS (Goddard Institute for Space Studies)

Method

Table 2 List of the applied predictors in the current study

Predictors	Predictors description	Height
pr	Precipitation	Surface
prc	Convective precipitation	Surface
prw	Atmosphere water vapor content	Surface
hfls	Surface upward latent heat flux	Surface
evspsbl	Water evaporation	Surface
rsds	Downwelling shortwave flux	Surface
rtmt	Net downward radiative flux at top of atmosphere	Surface
rlus	Upwelling longwave radiation	Surface
rsdt	Toa_incoming shortwave flux	Surface
rlut	Toa outgoing longwave flux	Surface
sund	Sunshine hours	Surface
rsut	Toa outgoing shortwave flux	Surface
ts	Sea surface temperature	Surface
tauu	Downward eastward wind stress	Surface
tauv	Downward northward wind stress	Surface
tasmin	Minimum air temperature	Surface
tasmax	Maximum air temperature	Surface
ps	Surface air pressure	Surface
psl	Sea level pressure	Surface
wap	Lagrangian tendency of air pressure	Surface
clivi	Atmosphere mass content of cloud ice	Surface
clt	Cloud area fraction	Surface
clwvi	Cloud condensed water content	Surface
mslp	Monthly mean sea level pressure	Surface
snc	Snow area fraction	Surface
sci	Shallow convection time fraction	Near surface
hurs	Relative_humidity	Near surface
vas	Meridional wind speed	Near surface
uas	Zonal wind speed	Near surface
huss	Specific humidity	Near surface
tas	Air temperature	Near surface
sfcwind max	Daily max near surface wind speed	Near surface
sfcwind	Wind speed	Near surface
wap	Lagrangian tendency of air pressure	Various pressure levels[(a)]
ta	Air temperature	Various pressure levels[(a)]
zg	Geopotential height	Various pressure levels[(a)]
ua	Zonal wind	Various pressure levels[(a)]
va	Meridional wind	Various pressure levels[(a)]
hur	Relative humidity	Various pressure levels[(a)]
hus	Specific humidity	Various pressure levels[(a)]

[(a)] 10 hpa, 20 hpa, 30 hpa, 50 hpa, 70 hpa, 100 hpa, 200 hpa,300 hpa, 400 hpa, 500 hpa, 600 hpa, 700 hpa, 850 hpa, 1000 hpa

Method

1951-2016月平均降水和温度

Method

Fig. 3 Schematic figure of the proposed methodology. (It is noted that dominant predictors in this figure belong to Can-ESM2 model as an example)

Results

Table 3 Appropriate GCM selecting according to CC and MI measures

		Precipitation		Temperature	
	Model	CC*	MI*	CC*	MI*
CMIP5	ACCESS1.0	0.41	0.51	0.55	0.71
	CSIRO-MK3.6.0	0.39	0.48	0.51	0.70
	Can-ESM2	0.62	0.86	0.75	0.98
	BNU-ESM	0.58	0.79	0.70	0.91
	FIO-ESM	0.26	0.32	0.47	0.66
	IPSL-CM5B-LR	0.43	0.24	0.57	0.74
	HadGEM2-AO	0.37	0.43	0.50	0.69
	GISS--E2-R-CC	0.33	0.41	0.50	0.67
CMIP3	CSIRO-MK3.0	0.25	0.34	045	0.65
	CGCM3(T47)	0.49	0.70	0.60	0.82
	CGCM3(T63)	0.16	0.21	0.37	0.59
	FGOALS-g1.0	0.19	0.28	0.39	0.60
	Had-CM3	0.21	0.30	0.40	0.62
	GFDL-CM2.1	0.30	0.39	0.47	0.65
	NCAR-CCSM3	0.32	0.40	0.51	0.67

*The result of grid point with high relevancy with observed data

Results

Table 4 Selection of the dominant predictors according to three screening methods

Model	Feature extraction method	Dominant predictors for precipitation[(i)]	Dominant predictors for temperature[(i)]
Can-ESM2	CC	Pr(1),Prc(1),Prc(3),evspsbl(3)	ta(200)(3),ta(200)(4),ta(500)(1),ta(500)(3)
	MI	ta(500)(1),ta(500)(3),tas(3),ua(200)(2)	zg(500)(1),ua(500)(3),zg(500)(4),hurs(3)
	Decision tree	Prc(2),hus(850)(2),tas(1),ta(500)(1)	zg(200)(2),tas(1),zg(200)(1),hur(200)(2)
BNU-ESM	CC	prw(2),evspsbl(3),huss(1),prc(1)	ta(500)(1),ta(500)(2),ta(500)(3),ta(500)(4)
	MI	ua(850)(1),ta(850)(3),ua(200)(3),ta(850)(1)	hur(850)(1),ua(850)(3),ua(850)(3),zg(200)(3)
	Decision tree	ta(200)(2),ts(1),ta(1000)(1),pr(3)	zg(500)(2),zg(200)(1),ta(200)(2),evspsbl(1)
CGCM3	CC	Pr(1), evspsbl (3),hurs(2),pr(2)	tas(1),tas(2),tas(3),tas(4)
	MI	tas(2),tas(1),ts(1),ua(500)(2(	zg(200)(2),ua(200)(1),psl(4),huss(2)
	Decision tree	Pr(3),Pr(1),ts(1), tas(2)	tas(1),zg((500)(3),psl(3),huss(3)

[(i)] The number of GCMs grid points based on Fig. 1 ($i = 1, 2, 3, 4$)

Results

解释方差

Table 5 The results of precipitation downscaling by ANN and MLR models using dominant inputs extracted by CC, MI, and decision tree

Feature extraction method	Inputs	GCM	Downscaling model	NSE training	NSE testing	RMSE* training	RMSE* testing
CC	Pr(1),Prc(1),Prc(3),evspsbl(3)	Can-ESM2	ANN	0.56	0.53	0.52	0.53
CC	Pr(1),Prc(1),Prc(3),evspsbl(3)	Can-ESM2	MLR	0.47	0.44	0.57	0.60
MI	ta(500)(1),ta(500)(3),tas(3),ua(200)(2)	Can-ESM2	ANN	0.69	0.65	0.34	0.37
MI	ta(500)(1),ta(500)(3),tas(3),ua(200)(2)	Can-ESM2	MLR	0.40	0.36	0.64	0.68
Decision tree	Prc(2),hus(850)(2),tas(1),ta(500)(1)	Can-ESM2	ANN	0.85	0.83	0.19	0.23
Decision tree	Prc(2),hus(850)(2),tas(1),ta(500)(1)	Can-ESM2	MLR	0.61	0.58	0.39	0.47
CC	prw(2),evspsbl(3),huss(1),prc(1)	BNU-ESM	ANN	0.52	0.49	0.55	0.57
CC	prw(2),evspsbl(3),huss(1),prc(1)	BNU-ESM	MLR	0.44	0.40	0.62	0.66
MI	ua(850)(1),ta(850)(3),ua(200)(3),ta(850)(1)	BNU-ESM	ANN	0.65	0.61	0.35	0.41
MI	ua(850)(1),ta(850)(3),ua(200)(3),ta(850)(1)	BNU-ESM	MLR	0.40	0.37	0.61	0.69
Decision tree	ta(200)(2),ts(1),ta(1000)(1),pr(3)	BNU-ESM	ANN	0.79	0.77	0.25	0.30
Decision tree	ta(200)(2),ts(1),ta(1000)(1),pr(3)	BNU-ESM	MLR	0.55	0.53	0.50	0.54
CC	Pr(1), evspsbl (3),hurs(2),pr(2)	CGCM3	ANN	0.41	0.37	0.67	0.69
CC	Pr(1), evspsbl (3),hurs(2),pr(2)	CGCM3	MLR	0.34	0.32	0.72	0.73
MI	tas(2),tas(1),ts(1),ua(500)(2(	CGCM3	ANN	0.51	0.46	0.55	0.59
MI	tas(2),tas(1),ts(1),ua(500)(2((	CGCM3	MLR	0.32	0.29	0.75	0.78
Decision tree	Pr(3),Pr(1),ts(1), tas(2)	CGCM3	ANN	0.62	0.59	0.39	0.45
Decision tree	Pr(3),Pr(1),ts(1), tas(2)	CGCM3	MLR	0.45	0.41	0.63	0.65

*indicates normalized RMSE values

Results

Table 6 The results of temperature downscaling by ANN and MLR models using dominant inputs extracted by CC, MI, and decision tree

Feature extraction method	Inputs	GCM	Downscaling model	NSE calibration	NSE validation	RMSE* calibration	RMSE* validation
CC	ta(200)(3),ta(200)(4),ta(500)(1),ta(500)(3)	Can-ESM2	ANN	0.61	0.57	0.30	0.37
CC	ta(200)(3),ta(200)(4),ta(500)(1),ta(500)(3)	Can-ESM2	MLR	0.67	0.61	0.27	0.31
MI	zg(500)(1),ua(500)(3),zg(500)(4),hurs(3)	Can-ESM2	ANN	0.75	0.71	0.15	0.20
MI	zg(500)(1),ua(500)(3),zg(500)(4),hurs(3)	Can-ESM2	MLR	0.59	0.53	0.35	0.43
Decision tree	zg(200)(2),tas(1),zg(200)(1),hur(200)(2)	Can-ESM2	ANN	0.94	0.91	0.06	0.08
Decision tree	zg(200)(2),tas(1),zg(200)(1),hur(200)(2)	Can-ESM2	MLR	0.75	0.69	0.16	0.22
CC	ta(500)(1),ta(500)(2),ta(500)(3),ta(500)(4)	BNU-ESM	ANN	0.59	0.56	0.33	0.39
CC	ta(500)(1),ta(500)(2),ta(500)(3),ta(500)(4)	BNU-ESM	MLR	0.66	0.59	0.27	0.33
MI	hur(850)(1),ua(850)(3),ua(850)(3),zg(200)(3)	BNU-ESM	ANN	0.72	0.71	0.20	0.23
MI	hur(850)(1),ua(850)(3),ua(850)(3),zg(200)(3)	BNU-ESM	MLR	0.57	0.50	0.38	0.45
Decision tree	zg(500)(2),zg(200)(1),ta(200)(2),evspsbl(1)	BNU-ESM	ANN	0.95	0.89	0.06	0.11
Decision tree	zg(500)(2),zg(200)(1),ta(200)(2),evspsbl(1)	BNU-ESM	MLR	0.75	0.67	0.15	0.24
CC	tas(1),tas(2),tas(3),tas(4)	CGCM3	ANN	0.49	0.45	0.47	0.50
CC	tas(1),tas(2),tas(3),tas(4)	CGCM3	MLR	0.54	0.51	0.38	0.47
MI	zg(200)(2),ua(200)(1),psl(4),huss(2)	CGCM3	ANN	0.58	0.56	0.35	0.38
MI	zg(200)(2),ua(200)(1),psl(4),huss(2)	CGCM3	MLR	0.49	0.44	0.48	0.52
Decision tree	tas(1),zg((500)(3),psl(3),huss(3)	CGCM3	ANN	0.79	0.77	0.15	0.16
Decision tree	tas(1),zg((500)(3),psl(3),huss(3)	CGCM3	MLR	0.63	0.59	0.28	0.32

*indicates normalized RMSE values

Results

Fig. 5 Observed and simulated precipitation values with ANN and MLR during the base period (1951–2000). ANN model for **a** Can-ESM2, **b** BNU-ESM, and **c** CGCM3. MLR model for **d** Can-ESM2, **e** BNU-ESM, and **f** CGCM3

Results

Fig. 6 Observed and simulated temperature values with ANN and MLR during the base period (1951–2000). Simulated temperature with ANN respectively for three GCMs, **a** Can-ESM2, **b** BNU-ESM, and **c** CGCM3. Simulated temperature with MLR model respectively for three GCMs, **d** Can-ESM2, **e** BNU-ESM, and **f** CGCM3

Results

Fig. 7 Monthly precipitation variation according to projected and baseline periods for **a** Can-ESM2, **b** BNU-ESM, and **c** CGCM3 models

Fig. 8 Monthly temperature variation according to projected and baseline periods for Can-ESM2, **b** BNU-ESM, **c** CGCM3 models

Results

Fig. 9 The change percentage of annual observed and simulated **a** precipitation and **b** temperature

(a)

(b)

Conclusions

1. 使用非线性的决策树方法且基于ANN方法的降尺度模型比使用CC和MI（线性方法）更加准确；
2. 使用非线性的决策树方法且基于ANN方法的降尺度模型在降水和温度两个变量上比MLR方法准确率提高了31%和25%；
3. 未来的降水和温度既有增加的时候也有减少的时候。这暗示了全球变暖正在发生，全球温度上升、海平面上升都会使降水的特征和总量发生变化；
4. 本文认为未来降水将减少10.35-29.78%，而温度将上升0.06-2.49%。

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ORIGINAL PAPER

Projected temperature and precipitation changes on the Tibetan Plateau: results from dynamical downscaling and CCSM4

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Introduction

青藏高原由于有广泛的冰覆盖面积以及巨大的淡水储库，因此被世人称为世界的“第三极”，其250万平方公里以及平均海拔4000m的平均高度是世界上最大、海拔最高的高原。

青藏高原对于大气循环和局地气候都扮演着重要的作用，青藏高原近十几年的气候变化已经导致冰川削减、雪覆盖率的降低以及多年冻土的减少。

Method

Data

WRF version 3.7.1;

时间:

1. 1979-2005(conducted using ERA-Interim reanalysis and CCSM4 GCM initial and Lateral boundary conditions)、

2. 2020-2060(used CCSM4 and explored high and low emission scenarios using the representative concentration pathways(RCP) 8.5 and 4.5, respectively)

Method

Domain 01: centered at 34° N, 88° E, 75*48个网格，精度为75km；

Domain 02: centered within the outer domain, 157*82个网格，精度为25km。

Fig. 1 Locations of the WRF domains (**a**). The horizontal resolutions of domains 01 and 02 are 75 (**b**) and 25 km (**c**), respectively, and elevation resolutions are shown in (**d**) and (**e**), respectively

Results

Fig. 2 Spatial distribution of annual and seasonal mean temperature (**a**) and precipitation (**c**) over the Tibetan Plateau (1979–2016) determined from observations and ERA-Interim reanalysis data. Difference between the observation and reanalysis data: **b** temperature, unit: °C; **d** precipitation, unit: mm day^{-1}

ERA-Interim 的温度通常偏冷，特别是在西部偏差最大（5°C）；

EAR-Interim的降水偏差主要发生在春季，夏季和秋季最大，而在冬季可以忽略不计。

Results

Fig. 3 Time series of temperature and precipitation anomalies (**a**) and changes in annual and seasonal mean temperature and precipitation (**b**) over the Tibetan Plateau (1979–2016) determined from observations and ERA-Interim reanalysis data, units: °C and mm day^{-1}

冬季（春季）温度升高最大（最小）；

降水最多（最少）的季节为夏季（冬季）；

ERA-Interim在分析资料的时空特征和观测相对一致；但是，温度（降水）的增加往往被低估（高估）。

Results

由ERA-Interim驱动的历史模拟称为'WRFE'；

由CCSM驱动的历史模拟称为'WRFC'。

Fig. 4 Observed and simulated (WRFE, WRFC, and CCSM4) spatial distribution of annual and seasonal mean temperatures **a** over the Tibetan Plateau (1980–2005) and **b** their associated difference plots, unit: °C

温度普遍表现为偏冷，该偏差在冬季和春季最为显著，而在夏秋季节则不明显；

这有可能由于对积雪的高估导致地表反照率更强以及地表吸收短波辐射减少导致的；

季节性温度差异更为明显。

Results

Fig. 5 Time series of temperature anomalies (**a**) and changes in annual and seasonal mean temperature (**b**) over the Tibetan Plateau (1980–2005) for observations, WRFE, WRFC, and CCSM4, unit: °C

TP温度明显呈现上升趋势，在1980－2006年期间，年平均温度升高超过1.0° C，高于全球变暖的平均温度，该现象与最近的研究一致。

相对于观测，WRFE在年平均温度和季节平均温度方面表现出更强的变暖趋势；

WRFC则显示年、夏季和春季的温度升高趋势较强，而秋季的趋势较弱，其中冬季趋势接近观测值；

与观测值相比，CCSM4在冬季表现出较弱的趋势，在春季和夏季表现出较强的趋势，与观测值相反，秋季表现出下降趋势；

因此，WRFC是预测TP未来温度变化的更可靠方法。

Results

Fig. 6 Same as Fig. 4 but for precipitation, unit: mm day^{-1}

WRFE和WRFC均可再现TP降水的空间分布，特别是在东南TP区域高降水方面。相比之下，CCSM4表现较差；

与WRFE相比，WRFC和CCSM4的相关系数明显较低。

Results

Fig. 7 Same as Fig. 5 but for precipitation, unit: mm day^{-1}

与观测结果相比，WRFE，WRFC和CCSM4的趋势明显不同；

在WRFC中，温度和降水的偏差很明显，在降水方面，WRFC的性能比WRFE差。但是，WRFC通常能够在TP上再现温度的时空分布，并且明显优于CCSM4；

因此，使用WRFC预测TP上的未来温度和降水变化是可行的。

Results

Fig. 8 Spatial distribution of projected trends (WRFC and CCSM4) in annual and seasonal mean temperatures over the Tibetan Plateau (2006–2050) under the RCP4.5 and RCP8.5 emission scenarios, unit: °C decade^{-1}

Results

Fig. 9 Time series of projected (WRFC and CCSM4) temperature anomalies (**a**) and warming patterns (**b**) for annual and seasonal mean temperatures over the Tibetan Plateau (2006–2050) under the RCP4.5 and RCP8.5 emission scenarios, unit: °C

Results

Fig. 10 Same as Fig. 8 but for precipitation, unit: mm day^{-1} decade^{-1}

Results

Fig. 11 Same as Fig. 9 but for precipitation, unit: mm day^{-1}

Conclusions

1. 观测表明，1979-2016年间TP的温度平均升高了2°C，降水也有所增加，其中夏季（冬季）降水量最高（最低），而ERA-Interim能够很好的反应温度和降水在年和季节上的时空特征，WRFE和WRFC也很好的再现了温度的空间分布，CCSM则在中部和西部普遍偏冷，特别是在冬季和春季；
2. 1980-2005年间观测降水表明，夏季降水较大，东南（西北）的降水通常较高（较低），而WRFE和WRFC都可再现该地区降水的时空分布，相反，CCSM出现明显的高估；
3. 未来，TP的温度会继续升高，且RCP8.5情景升高的温度大于RCP4.5，在RCP4.5情境下，预计到2050年，温度升高1.5°C，夏季和秋季（冬季和春季）的变暖幅度更大（更小），在RCP8.5情境下，预计到2050年，温度升高2.5°C；
4. 排放情景对WRFC的未来降水预测没有明显影响，而CCSM4预测降水将会明显增加，特别是在冬季和春季。

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Probabilistic precipitation and temperature downscaling of the Twentieth Century Reanalysis over France

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Introduction

Figure 1. Evolution of the monthly averaged number of available precipitation and temperature stations in the Météo-France database (as of March 2015) since 1871.

Method

Data:

1. NOAA Twentieth Century Reanalysis: Version 2 of 20CR(Compo et al., 2011), 2.0° spatial resolution and 6 hourly temporal resolution from the 1 January 1871 to present.

(temperature at 925 and 600 hPa, geopotential height at 1000 and 500 hPa, vertical velocity at 850 hPa, precipitable water content and relative humidity at 850 hPa)

2. NOAA Extended Reanalysis sea surface temperature version 3b(ERSST, Smith and Reynolds, 2003; Smith et al., 2008), 2.0° spatial resolution since the 1 January 1854.

(SST)

3. Safran: a meteorological reanalysis available at an 8 km spatial resolution and at the hourly temporal resolution from the 1 August 1958 to present.

(daily precipitation and temperature)

Method

SANDHY method:

1. First Predictor domain selection
2. Calendar selection
3. Stepwise selection

Results

1. 所有方法的偏差在年尺度上表现都很小；
2. First domain selection方法在冬季（夏季）存在较大的正偏差（负偏差）；
3. 后两种方法在季节上的偏差都得到了改进，冬季法国北部地区的偏差在0.5°C以下。

Figure 6. Median of annual and seasonal temperature bias between Safran and the three subselection methods for the 1959–2007 period. Red corresponds to an overestimation of the reconstructed temperature. Minimum bias of −1.0 °C for the first domain selection in summer and maximum bias of 1.7 °C for the first domain selection in winter.

Results

1. 在年尺度上，降水的偏差大概在-10%（-20%～+5%）；
2. First domain selection方法在四季均存在较大的正偏差（负偏差）；
3. 后两种方法在季节上的偏差并未得到显著改进。

Figure 7. As for Fig. 6, but for precipitation. Red corresponds to an underestimation for precipitation. Minimum bias of −34 % for the first domain selection in autumn and maximum bias of 41 % for the first domain selection in spring.

Results

1. 相关系数最低发生在夏季（特别是东部地区）；
2. 使用Calendar selection方法并没有使相关系数有所提升；
3. 同时，stepwise selection却能得到相当高的相关系数（几乎大于0.9）。

Figure 8. Median of the annual and seasonal temperature rank correlation between Safran all subselection methods for the 1959–2007 period. Minimum value of 0.35 for the first domain selection (year) and maximum value of 0.97 for the stepwise selection (year).

Results

1. 相关系数最高的时节是在冬季（大部分地区均大于0.9）；
2. 三种方法的相关系数十分接近。

Figure 9. As for Fig. 8, but for precipitation. Minimum value of 0.19 for the first domain selection in summer and maximum value of 0.92 for the first domain selection in winter.

Results

Figure 14. Paris Montsouris temperature homogenized time series, corresponding Safran data and reconstructed series from the stepwise selection at the annual and seasonal timescales over the 1871–2012 time period. Grey and blue ribbons define the range and the interquartile range, respectively, of values from all 25 realizations from the stepwise selection. Note the different scales for the *y* axes.

Results

Year
Spring
Summer
Autumn
Winter
Precipitation (mm)
1873
1883
1893
1903
1913
1923
1933
1943
1953
1963
1973
1983
1993
2003
2013
Safran
Hom
Median
Minimum and maximum
First and third quartiles

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Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America

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Introduction

在山区地区，由于降水以及温度变量依赖高度的特性无法由GCM表现出来，高精度的信息经常需要和粗糙的GCM进行合并。

特别的，由于难以模拟对流型降水，相较于秋季和冬季，RCM对于降水的精度在夏季最差。

因此，本文使用6中方法，对四个原始RCM的最高温、最低温以及降水量进行统计降尺度并进行比较。

Method

Figure 1. Location of the 10 selected river basins over North America. Different typefaces on watershed name represent different performances of bias correction approaches for hydrological modeling: roman = good, italic = bad, and bold = very bad.

Method

Table 1. Basic Information of the Selected 10 River Basins Over North America and the Nash-Sutcliffe Coefficient (NSE) of the Calibration and Validation of Hydrological Model HSAMI[a]

Country	Province or State	Basin Name	Area (km^2)	Precip (mm)	Tmax (°C)	Tmin (°C)	Calibration Period	NSE Calibration	Validation Period	NSE Validation
Canada	BC	Nation	6790	612	5.9	−4.3	1981–1993	0.932	1994–2003	0.905
	SK	Carrot	12,600	409	6.1	−5.4	1967–1980	0.822	1981–2000	0.719
	QC	Manic 5	24,610	902	2.5	−7.9	1966–1980	0.917	1981–2000	0.856
USA	OR	Umpqua	9535	1270	16.7	4.4	1948–1980	0.907	1981–2000	0.889
	MT	Yellowstone	6791	688	8.5	−5.3	1948–1980	0.897	1981–2000	0.701
	CO	Yampa	8828	598	12.5	−3.4	1948–1980	0.815	1981–2000	0.728
	MO	Grand	5825	872	16.9	4.9	1948–1980	0.754	1981–2000	0.778
	WI	Wolf	5851	769	12.0	0.7	1948–1980	0.847	1981–2000	0.744
	MS	Chickasawhay	6967	1428	24.7	11.1	1948–1980	0.861	1981–2000	0.851
	NY	Sacandaga	1271	1215	11.7	−0.5	1948–1980	0.798	1981–2000	0.807

[a]Precip = precipitation, Tmax = maximum temperature, and Tmin = minimum temperature.

1. 10个盆地覆盖了北美地区5中气候区域（基于Koppen天气划分法）；
2. 这10个盆地还通过不同的地形条件进行了挑选（从西部的多山地形到中部和东部的平原地区）；
3. 位于加拿大的3种盆地坐落于Quebec, Saskatchewan和British Columbia三个地区，尽管它们都是降雪覆盖型盆地，但它们同样具有不同的气候条件。

Method

Data set：

1. 观测得到的日降水，日最高温和日最低温以及RCM模拟得到的日降水；
2. 位于加拿大的3个盆地的数据取自National Land and Water Information Service(www.agr.gc.ca/nlwis-snite) data set;
3. 四个由NCEP在北美地区根据再分析资料驱动的RCMs（Canadian Regional Climate Model (CRCM), Hadley Regional Model 3 (HRM3), Regional Climate Model version 3 (RCM3), and Weather Research & Forecasting model (WRFG)）；
4. Spatial resolution: 50km;
5. Period: 1981-2000.

Method

mean-based approaches

distribution-based approaches

Table 2. The Advantages (or Characteristics) and Disadvantages of the Six Bias Correction Methods

Method	Advantage	Disadvantage	Reference
1. Linear scaling (LS)	*Mean-based*	The daily precipitation sequence is the same as that of the RCM-simulated data (usually too many wet days compared to the observation).	*Lenderink et al.* [2007] and *Teutschbein and Seibert* [2012]
	A mean monthly correction factor is applied to the RCM-simulated daily precipitation in a month. It is the simplest bias correction method.	It does not account for the changes in the frequency distribution of precipitation.	
		No adjustment is made to the temporal structure of daily precipitation occurrence.	
2. Local intensity scaling (LOCI)	*Mean-based*	It does not account for the different changes in the frequency distribution of precipitation.	*Schmidli et al.* [2006]
	The wet-day frequency is corrected. A mean monthly correction factor is applied to the RCM-simulated daily precipitation in a month.	No adjustment is made to the temporal structure of daily precipitation occurrence.	
3. Daily translation (DT)	*Distribution-based*	The daily precipitation sequence is the same as that of the RCM-simulated data (usually too many wet days compared to the observation).	*Mpelasoka and Chiew* [2009]
	Different correction factors (differences in percentiles between observed and RCM-simulated data at the calibration period) are applied to correct the frequency distribution of RCM-simulated daily precipitation.	No adjustment is made to the temporal structure of daily precipitation occurrence.	
4. Daily bias correction (DBC)	*Distribution-based*	No adjustment is made to the temporal structure of daily precipitation occurrence.	*Schmidli et al.* [2006] and *Mpelasoka and Chiew* [2009]
	Combines the DT and LOCI approaches to take into account the different changes in frequency distributions of daily precipitation, and corrects the wet-day frequency of precipitation.		
5. Quantile mapping based on an empirical distribution (QME)	*Distribution-based*	No adjustment is made to the temporal structure of daily precipitation occurrence.	*Themeßl et al.* [2010, 2011]
	Corrects the RCM-simulated precipitation based on point-wise daily constructed empirical cumulative distribution functions (ecdfs). The frequency of precipitation occurrence is corrected at the same time.		
6. Quantile mapping based on a gamma distribution (QMG)	*Distribution-based*	The performance depends on whether the observed and RCM-simulated precipitation follows the gamma distribution (or not).	*Ines and Hanson* [2006], *Piani et al.* [2010], and *Teutschbein and Seibert* [2012]
	Corrects the RCM-simulated precipitation based on a gamma distribution. The frequency of precipitation occurrence is corrected using the LOCI method.	No adjustment is made to the temporal structure of daily precipitation occurrence.	

Method

Evaluation of bias correction methods is based on a split-sample cross-validation approach：

1. 1981-2000(20yr)的冠词和RCM降水模拟值分为两部分——10年的基数年和10年的偶数年；
2. 10年的偶数年被用作训练，10年的基数年被用作测试；
3. 10年的基数年被用作训练，10年的偶数年被用作测试；
4. 1981-2000(20yr)全部被用作测试集。

Results

1. 和观测降水数据比较，原始的RCM平均值偏差较大，特别是HRM3和WRFG；
2. LS和DT方法对于降水并未表现出较好的提高；
3. 其他四种方法的确对于降水平均值的偏差的纠正有所改进。

Figure 3. Boxplot of the absolute relative error (ARE) of raw RCM-simulated (RCM) and six bias correction method-corrected daily mean precipitation (precip) values for all four RCMs. Each boxplot is constructed using 10 mean values from 10 river basins.

ARE：0.7%-3.4%(LOCI)，1.7%-2.6%(DBC)，1.2%-4.4%(QME)以0.4%-2.0%(QMG)

Results

1. 和观测降水数据比较，原始的RCM标准差偏差较大；
2. 所有方法均对CRCM的标准差偏差校正有效果；
3. 然而，对于其他三种RCMs，LS和LOCI方法并为是标准差的偏差有所降低。

Figure 4. Boxplot of the ARE of standard deviation (std) of raw RCM-simulated (RCM) and six bias correction method-corrected daily precipitation (precip) values for all four RCMs. Each boxplot is constructed using 10 standard values from 10 river basins.

Results

Table 3. Nash-Sutcliffe Coefficient (NSE) of the Calibration (CAL) and Validation (VAL) of Hydrological Model HSAMI Using RCM-Simulated Precipitation Combining With Observed Temperature (Odd Year for Calibration and Even Year for Validation)[a]

Model	Source	Nation	Carrot	Manic5	Umpqua	Yellowstone	Yampa	Grand	Wolf	Chickasawhay	Sacandaga	Mean
CRCM	CAL	0.84	*0.58*	0.86	0.75	0.92	0.85	**0.27**	*0.48*	**0.39**	*0.54*	0.65
	VAL	0.85	*0.37*	0.77	0.70	0.78	0.73	**−0.11**	*0.46*	**0.33**	*0.18*	0.51
HRM3	CAL	0.91	*0.73*	0.78	0.64	0.88	0.72	**0.07**	*0.28*	**0.29**	*0.39*	0.57
	VAL	0.89	*−0.95*	0.76	0.61	0.79	0.41	**0.06**	*0.30*	**0.00**	*0.34*	0.32
RCM3	CAL	0.81	*0.38*	0.78	0.55	0.89	0.80	**0.09**	*0.24*	**−0.07**	*0.51*	0.50
	VAL	0.81	*0.18*	0.76	0.58	0.75	0.68	**0.02**	*0.23*	**−0.14**	*0.31*	0.42
WRFG	CAL	0.79	*0.34*	0.69	0.61	0.87	0.77	**0.04**	*0.26*	**0.22**	*0.47*	0.51
	VAL	0.86	*0.06*	0.73	0.39	0.78	0.73	**0.03**	*0.05*	**0.14**	*0.35*	0.41
Mean		0.84	*0.21*	0.77	0.60	0.83	0.71	**0.06**	*0.29*	**0.15**	*0.39*	

[a]Different typefaces on watershed name represent different performances of bias correction approaches for hydrological modeling: roman = good, italic = bad, and bold = very bad.

10个偶数年作为训练集，10个基数年作为验证集；

Results

1. 总体而言，原始RCM模拟的降水无法重现大多数流域的观测结果；
2. 但是，除Nation和Carrot，雪山覆盖型盆地的结果通常比无雪覆盖型盆地效果好；
3. Nation和Carrot的峰值被远远高估。

Figure 6. Mean annual hydrographs simulated using observed (OBS), raw RCM-simulated (RCM), and six bias correction methods' corrected precipitation time series from the CRCM simulation for all 10 river basins. The simulated hydrograph using RCM-simulated precipitation (RCMC) but with the specific hydrological model calibration is also plotted.

Conclusions

本文评估了六种偏差较种方法对北美地区10个盆地流域的降水的再现能力:

1. RCM模拟的日降水总是有偏差的，有时甚至偏差较大，因此无法用于水文研究，对RCM进行校正可以改善其模拟，克服部分偏差;
2. 所有的偏差校正方法都对RCM模拟的降水有所改进;
3. 其中，基于分布的方法的效果总是优于基于均值的方法。

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