# GroupMeeting

2020.2.24

张慕琪

# 学期安排

本学期课程：
· 未选课
· 旁听，二外法语（二）

关于论文等工作：
· 时间安排

其他（实习等）：
· 与论文等学校工作时间相配合

# WeeklyNote

2020.02.18

張慕琪

# Bias Correction of Historical and Future Simulations of Precipitation and Temperature for China from CMIP5 Models

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# Introduction

**· 当今气候变化引起的问题**

1）全球气候变暖导致温度的升高和降水特征的变化，并在局地尺度下具有更高的多变性；
2）在这样的前提下，像中国这样农业扮演着重要角色的大国将会变得更加脆弱；
3）近年来，洪涝等灾害带来的经济损失让人们意识到更好地了解未来气候变化的重要性；

**· GCM原始输出的问题**

1）GCMs的原始输出对于人类研究问题的尺度来说太过粗糙；
2）并且由于参数化过程的不确定性，GCM的模拟在空间和时间尺度上都有偏差，这都会给研究带来巨大的影响。

# Introduction

**由于上述问题的存在：**

**· 降尺度方法的选择**

1）动力降尺度
2）统计降尺度
——为什么选择统计降尺度?
——因为统计降尺度相对快速和高效的优点；

· Bias Correction

偏差校正的方法基于一个最基本的假设：historical阶段模型输出和观测之间的统计关系始终不会改变（future period）。

# Methods

1. Datasets：

变量： Temperature and precipitation

观测数据：

· 时间： 1961-2005

· 共756个涵盖了全中国的台站信息

· 分辨率： 0.5° x 0.5°（使用双线性插值方法）

· 全中国被划分成七个气候区域：northeast China (NE), northern China (N), southeast China (SE), eastern northwest China (ENW), southwest China (SW), western northwest China (WNW), and the Tibetan Plateau (Tibet)

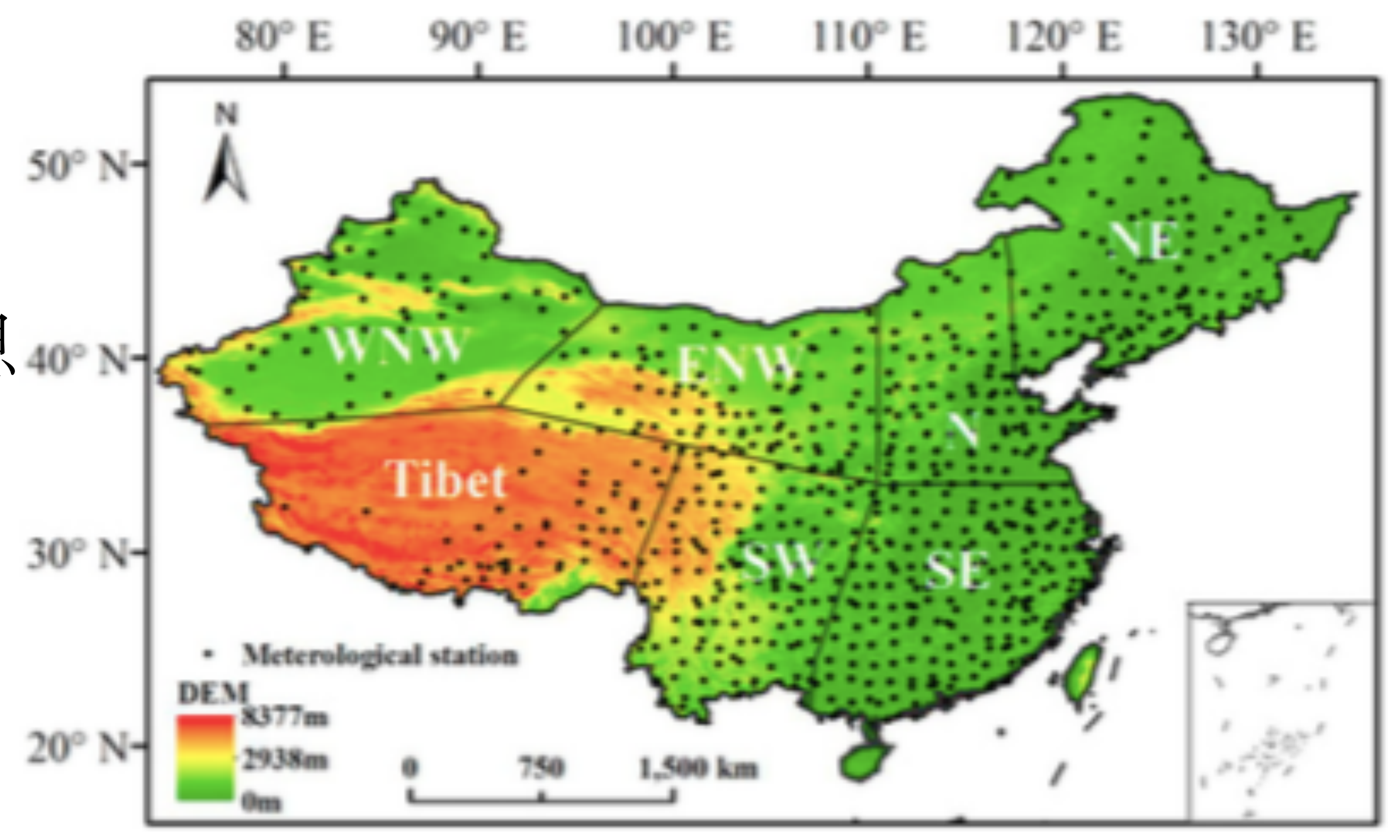


FIG. 1. Elevation map of China showing the distribution of the 756 meteorological stations and seven climatic subregions.

# Methods

TABLE 1. Information on the eight global coupled climate models.

| Model name | Country | Modeling center (or group) | Resolution (lat × lon) |
|---|---|---|---|
| BCC_CSM1.1 | China | Beijing Climate Center, China Meteorological Administration, China | 2.8° × 2.8° |
| CanESM2 | Canada | Canadian Centre for Climate Modelling and Analysis | 2.8° × 2.8° |
| CCSM4 | United States | National Center for Atmospheric Research | 1.25° × 0.9° |
| CSIRO Mk3.6.0 | Australia | Commonwealth Scientific and Industrial Research Organisation in collaboration with Queensland Climate Change Centre of Excellence | 1.875° × 1.875° |
| GISS-E2-R | United States | National Aeronautics and Space Administration | 2.5° × 2° |
| MRI-CGCM3 | Japan | Meteorological Research Institute | 1.125° × 1.125° |
| MPI-ESM-LR | Germany | Max Planck Institute for Meteorology | 1.875° × 1.875° |
| NorESM1-M | Norway | Norwegian Climate Centre | 2.5° × 1.875° |

1. Datasets:

模式：共八个

RCP情景：RCP2.6(lower), RCP4.5(medium), RCP8.5(high)

使用月平均的时间尺度

时间段：1961-1990(training period), 1991-2005(validation period), future projections[2031-2060(near-term), 2061-2090(long-term)]

# Methods

2. Quantile-based mapping method：
1) traditional quantile-based matching method(CDF method)

$$x_{m-p}=F_{o-c}^{-1}[F_{m-c}(x_{m-c})]$$

传统CDF方法都是基于模式模拟和观测数据在历史阶段上的关系始终保持不变的前提下，但是，IPCC（2007）指出该假设并不一定是正确的（因为气候变化过程具有非稳定性）；

2) equidistant quantile-based mapping method(EDCDF)——temperature

$$x_{m-p\_adjust}=x_{m-p}+F_{o-c}^{-1}[F_{m-p}(x_{m-p})]-F_{m-c}^{-1}[F_{m-p}(x_{m-p})]$$

$$x_{m-p\_adjust}=x_{m-p}\frac{F_{o-c}^{-1}[F_{m-p}(x_{m-p})]}{F_{m-c}^{-1}[F_{m-p}(x_{m-p})]}$$

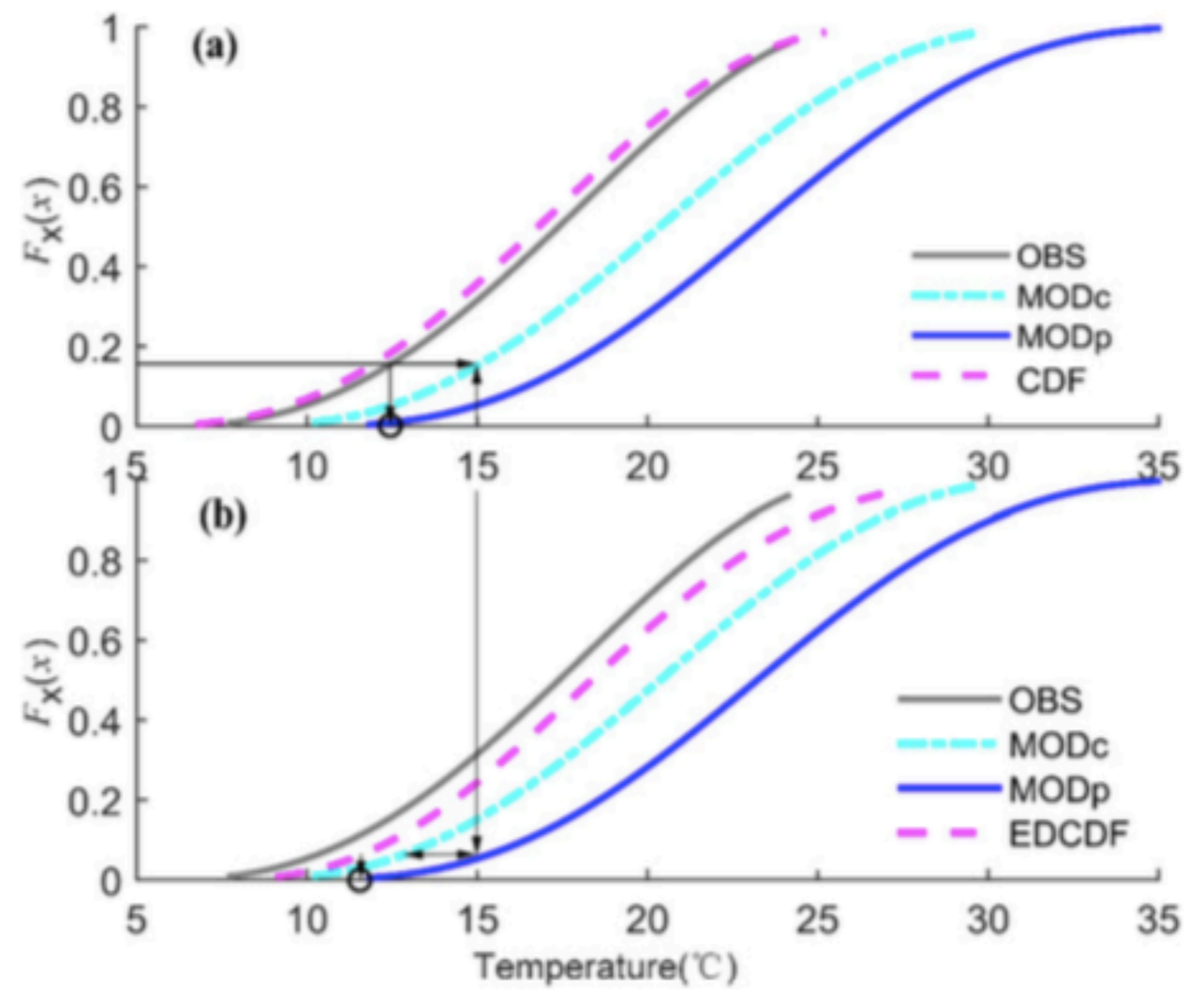


FIG. 2. Illustration of the methodology of the (a) CDF and (b) EDCDF methods (pink dashed lines) using synthetically generated temperature data for a grid point. The solid gray line shows the observations (OBS). The cyan dotted–dashed line shows the model simulation for current climate (MODc). The blue solid line shows the model simulation for the future projection (MODp). See text for details.

# Methods

3. 模型的选择：

- 使用jackknife method的交叉验证方法（Bessel首次提出）
- 滚动式重复16次（30yr+15yr）

**Idea #4**: **Cross-Validation**: Split data into **folds**, try each fold as validation and average the results

| Historical Period | | | | | Future Period |
|---|---|---|---|---|---|
| fold 1 | fold 2 | fold 3 | fold 4 | fold 5 | test |
| fold 1 | fold 2 | fold 3 | fold 4 | fold 5 | test |
| fold 1 | fold 2 | fold 3 | fold 4 | fold 5 | test |

Useful for small datasets, but not used too frequently in deep learning

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

# Results

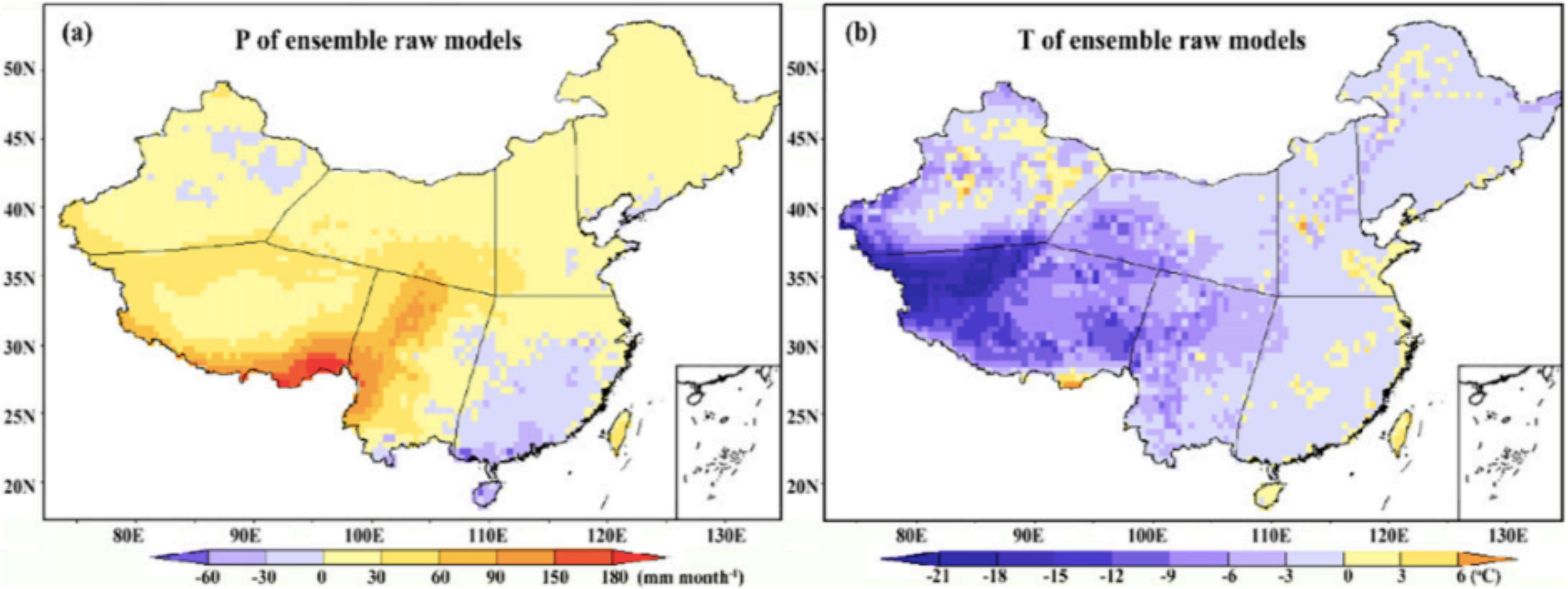


FIG. 3. The spatial distribution of mean biases between the observed and uncorrected ensemble of eight CMIP5 models (modeled minus observed) in monthly mean (a) precipitation $P$ and (b) temperature $T$.

· 原始的CMIP5模式输出低估了青藏高原地区的温度，并高估了沿海地区、西北和东北地区的温度；

· 降水变量则有90%都被高估；这可能是因为想对那些降水丰富的地区，这些地区较低的降水总量导致了较高的偏差。

# Results

CDF和EDCDF方法对于降水和温度变量效果很相似；
对于降水变量，EDCDF方法在西北和北部地区的偏差比CDF方法低了1mm/month；
对于温度变量，EDCDF方法最低的偏差出现在WNE, ENW, N和NE地区。

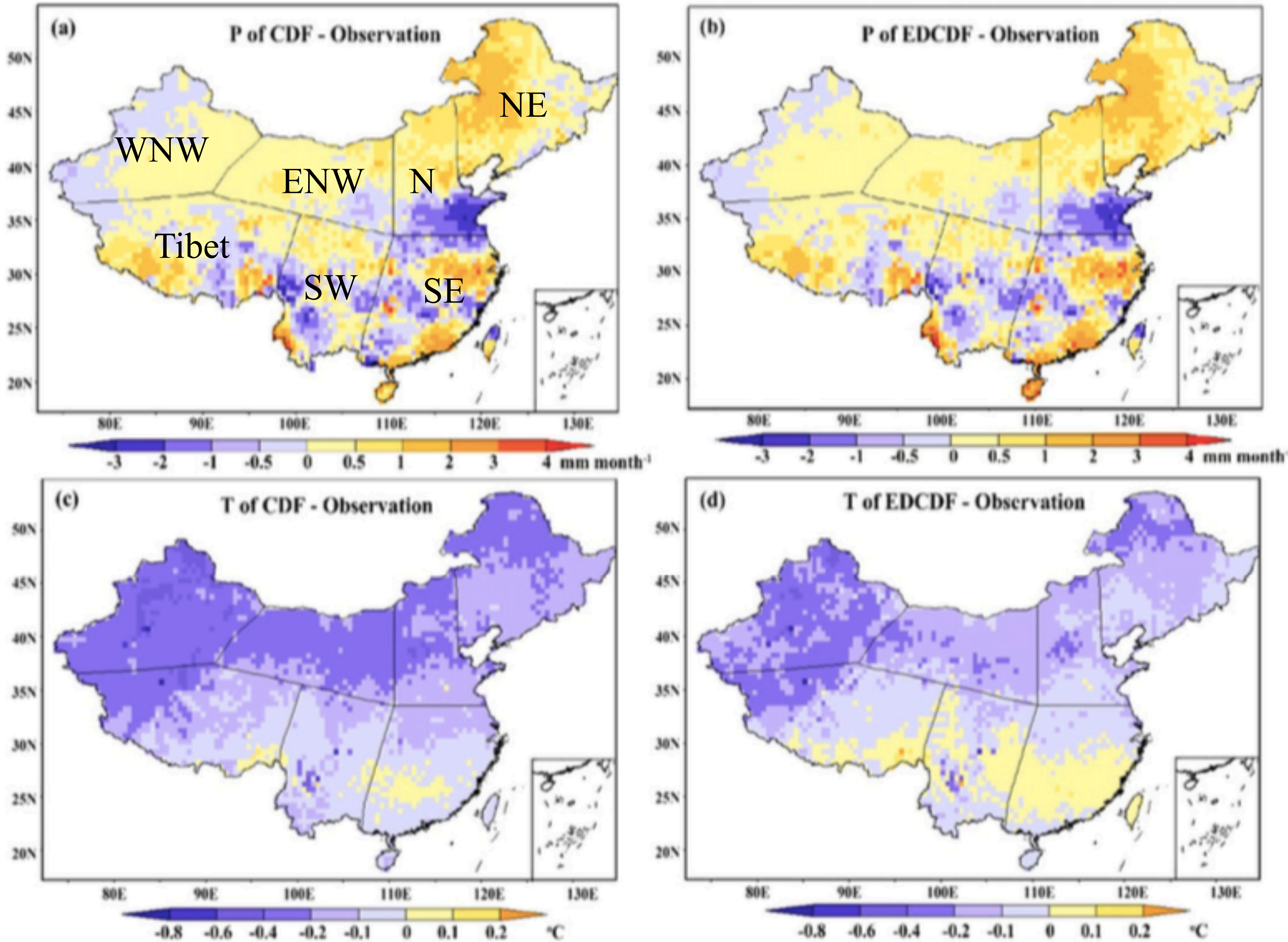


FIG. 4. The spatial distribution of mean biases for the two bias-correction methods (CDF and EDCDF) (modeled minus observed) for monthly mean (a),(b) precipitation *P* and (c),(d) temperature *T*.

# Results

对于降水变量，偏差校正方法在冬季表现优于夏季，EDCDF方法在WNW和ENW地区表现最好（10.72, 17.92mm）；

对于温度变量，EDCDF方法的RMSEs在0.9-4.5$^{o}$C之间，而原始输出的RMSEs在01.52-16.3$^{o}$C之间；同时SW和SE在所有季节的RMSEs都最小。

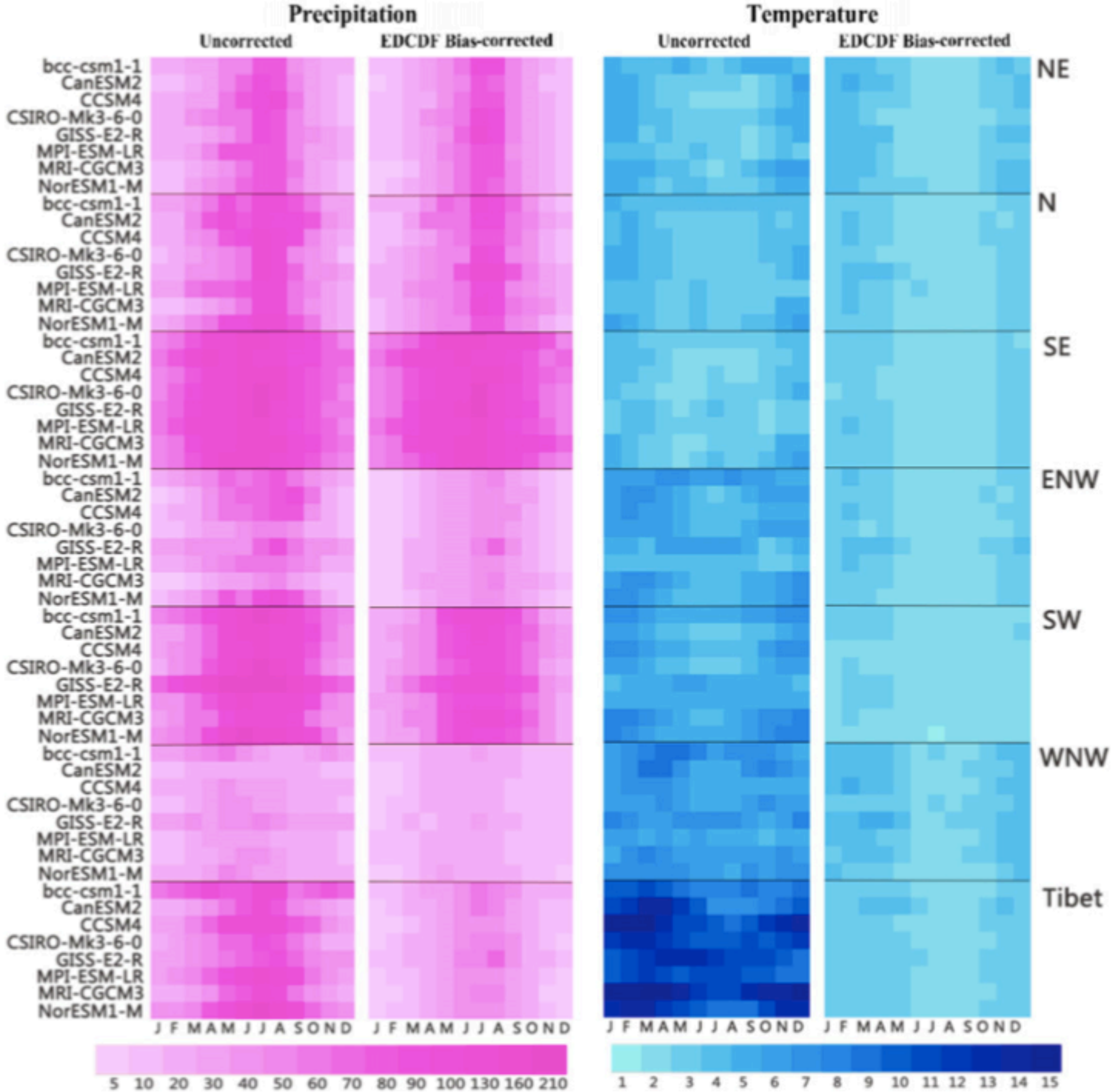


FIG. 5. The RMSE of (left) precipitation (mm month$^{-1}$) and (right) temperature (°C) of eight CMIP5 models against observations for seven subregions (for each pair of plots, the left panel shows the results for the raw models and the right panel shows the results for the EDCDF bias-corrected models).

# Results

为什么training阶段也会有bc后的数据？？？

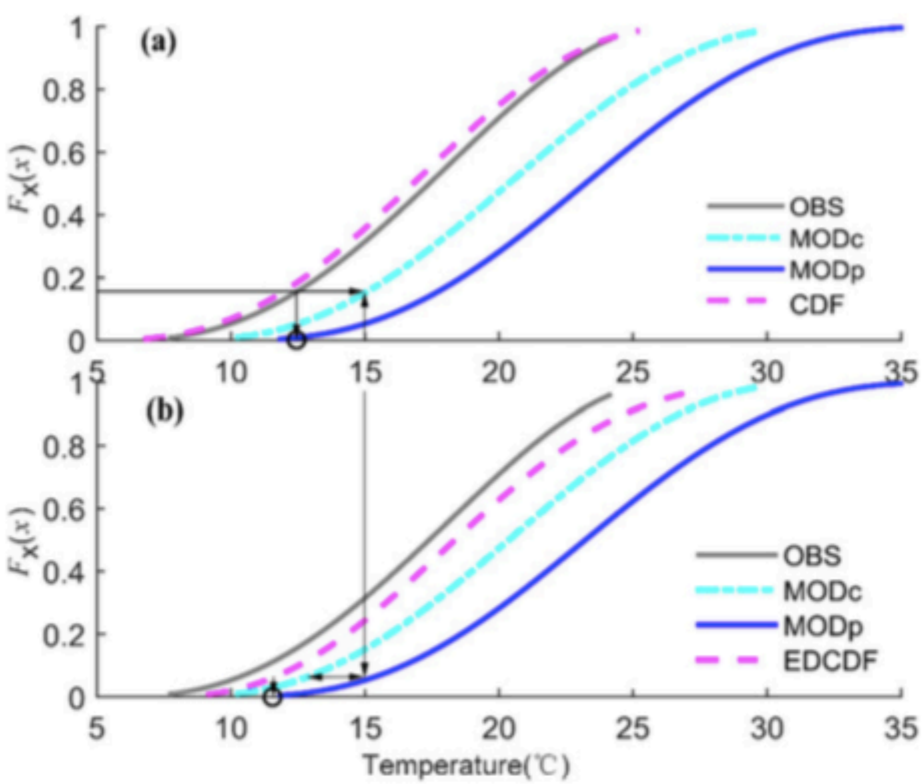


FIG. 2. Illustration of the methodology of the (a) CDF and (b) EDCDF methods (pink dashed lines) using synthetically generated temperature data for a grid point. The solid gray line shows the observations (OBS). The cyan dotted–dashed line shows the model simulation for current climate (MODc). The blue solid line shows the model simulation for the future projection (MODp). See text for details.

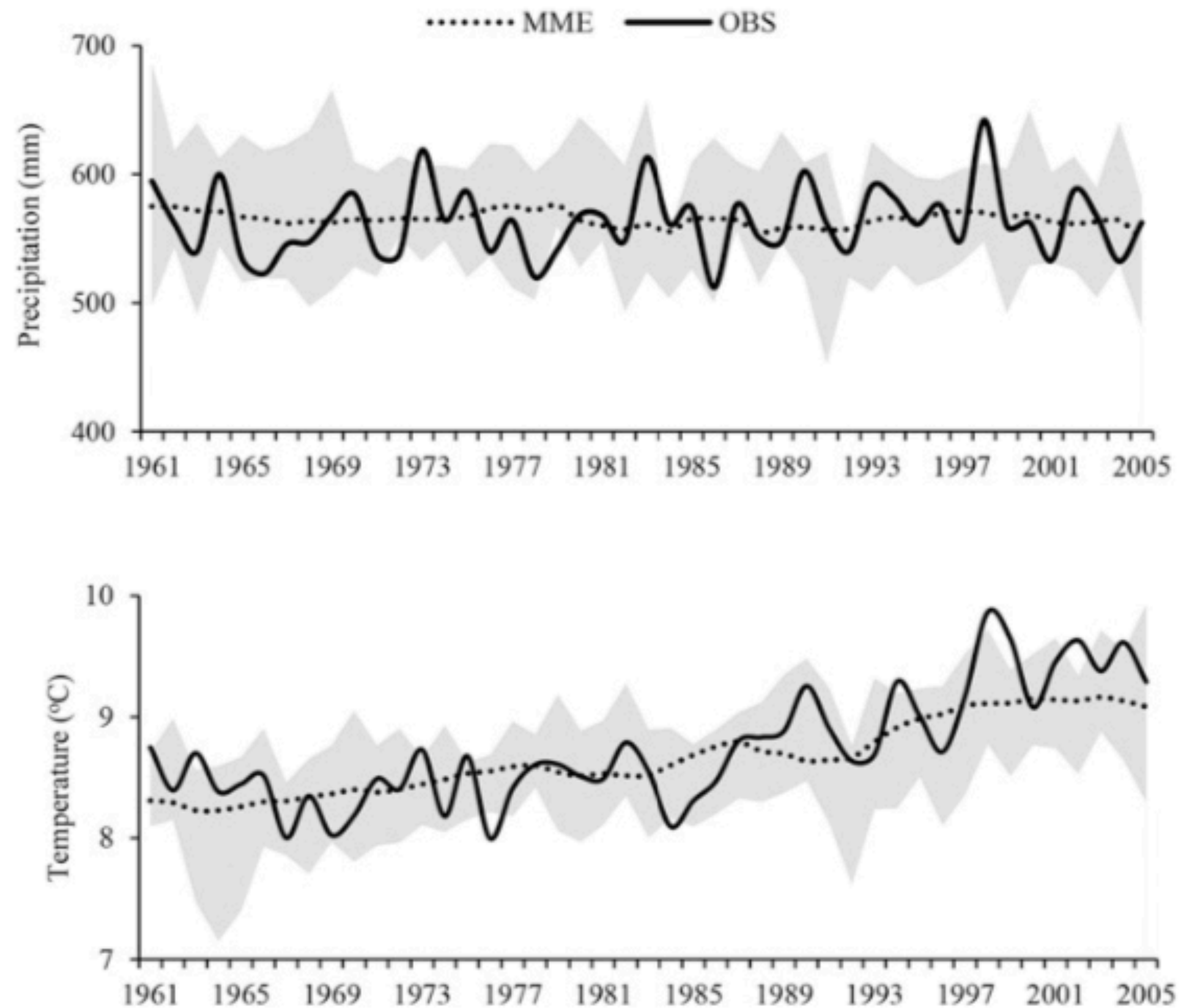


FIG. 7. Time series of the domain-averaged precipitation and temperature of the observations (black solid line) and EDCDF bias-corrected ensemble (black dotted line). The gray shading represents the uncertainty of the individual models.

# Results

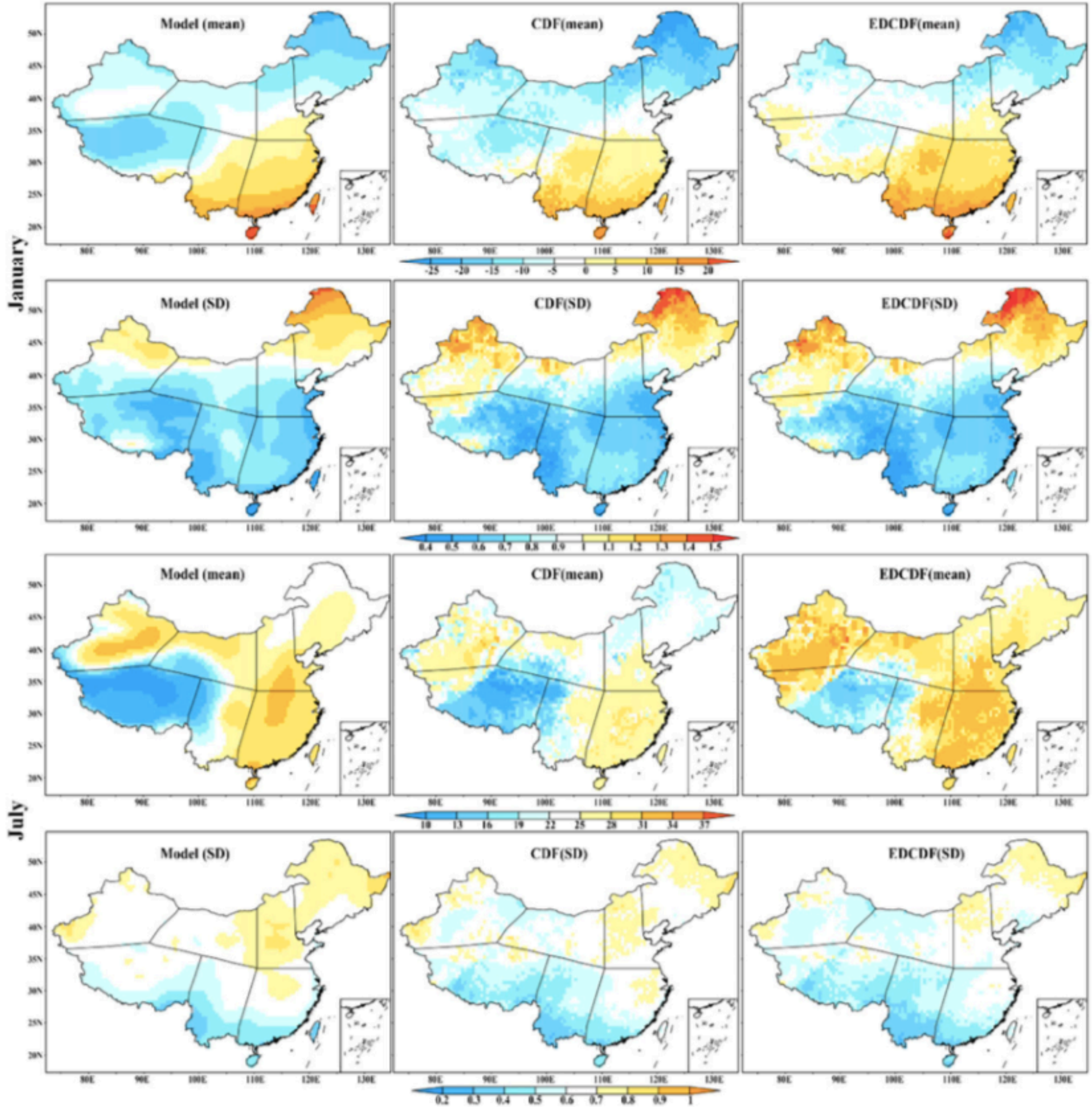


FIG. 9. Mean and standard deviation of the raw model temperature projection (2061–90) and after bias correction using the EDCDF and CDF methods in (top) January and (bottom) July.

# Conclusions

1. CDF和EDCDF方法都可以成功对CMIP5的温度和降水进行降尺度，但后者在减少极端数值上更有优势；
2. EDCDF在减少NE和N地区的降水偏差上更有优势；
3. EDCDF方法在温度变量上，在WNW，ENW，N和NE都能更好的校正偏差。

谢谢

# 附录：主要参考页面

jackknife cross-validation method：

1. https://www.jstor.org/stable/pdf/2987663.pdf?refreqid=excelsior%3A42959be0829e1f37e63f052a75506053

The Jackknife-Toy, Tool or Two-edged weapon?

bias correction的其他方法：

1. Downscaling RCP8.5 daily temperatures and precipitation in Ontario using localized ensemble optimal interpolation (EnOI) and bias correction

2. Calibration and bias correction of climate projections for crop modelling: An idealised case study over Europe （http://ccafs-climate.org/bias_correction/）

# Report

2020.2.19

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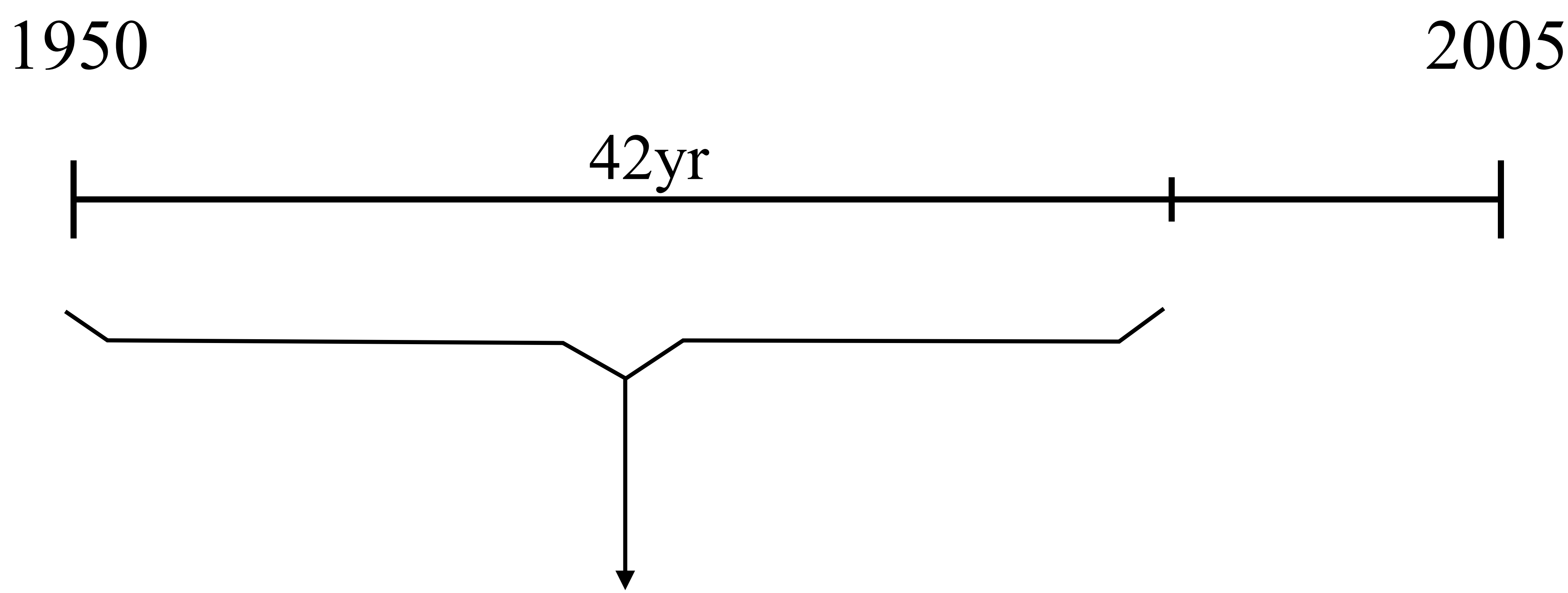
# 回顾

## Bias Correction: std

Historical Period



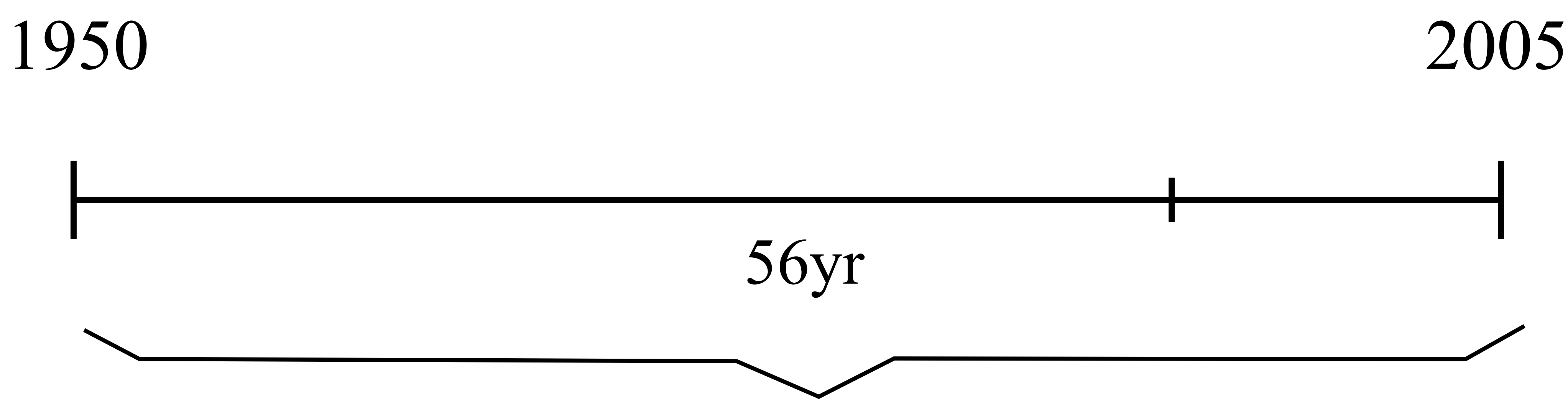

$$\frac{\sigma_{O,\ \mathrm{train}}}{\sigma_{T,\ \mathrm{train}}} \sim \alpha$$

size = 12

# 回顾

## Bias Correction: std

Historical Period

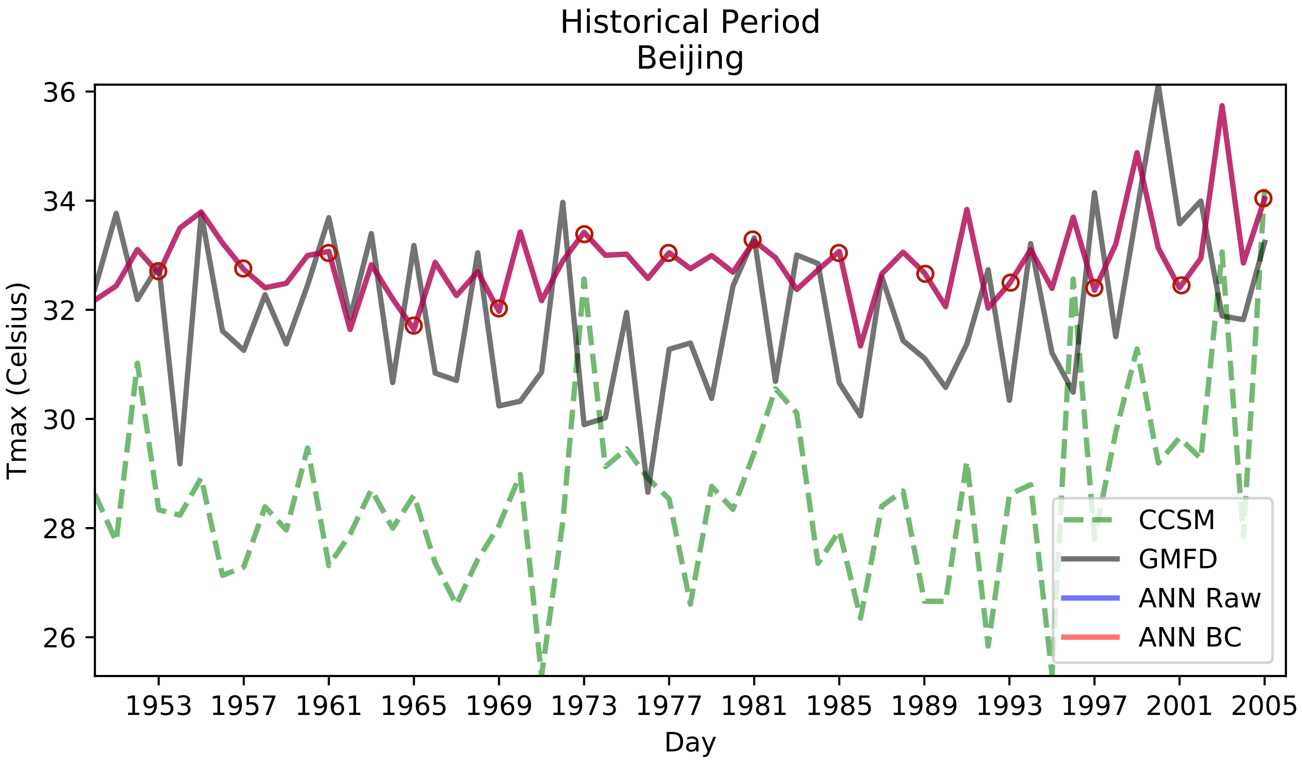



$$T_{\mathrm{BC}}(t) = \overline{T_{\mathrm{his}}} + \alpha \cdot \left( T_{\mathrm{his}}(t) - \overline{T_{\mathrm{his}}} \right)$$

# 回顾

Beijing Tmax

```
mean_ccsm =  28.612423
mean_ann_raw =  32.856594
mean_ann_bc =  32.856598
mean_ground =  31.921953

std_ccsm =  1.7578304
std_ann_raw =  0.7223801
std_ann_bc =  0.72237813
std_ground =  1.4520789

rmse_ccsm =  3.949551
rmse_ann_raw =  1.8095402
rmse_ann_bc 1.8095444
```



# Reference About Bias Correction


Figure 1. Schematic of the bias correction methodology. BC uses raw model output for the future period, and corrects it using the differences (Δ) between historical reference data from the model and observations. ($O_{REF}$ = observations in the historical reference period; $T_{REF}$ = GCM output from the historical reference period; $T_{RAW}$ = raw GCM output for the historical or future period; $T_{BC}$ = bias-corrected GCM output.)

If we assumed the variability as equal both for GCMs and observations, the daily data is simply shifted by the mean bias in the reference period (**Hawkins et al., 2013**), thus:

$$T_{SH}(t) = T_{RAW}(t) + (\overline{O_{REF}} - \overline{T_{REF}}), \qquad (1)$$

# Reference About Bias Correction

However, it is possible to apply a more general form of this bias-correction method that corrects not only the mean values but also the temporal variability of the model output in accordance with the observations (**Hawkins et al., 2013; Ho et al., 2012**):

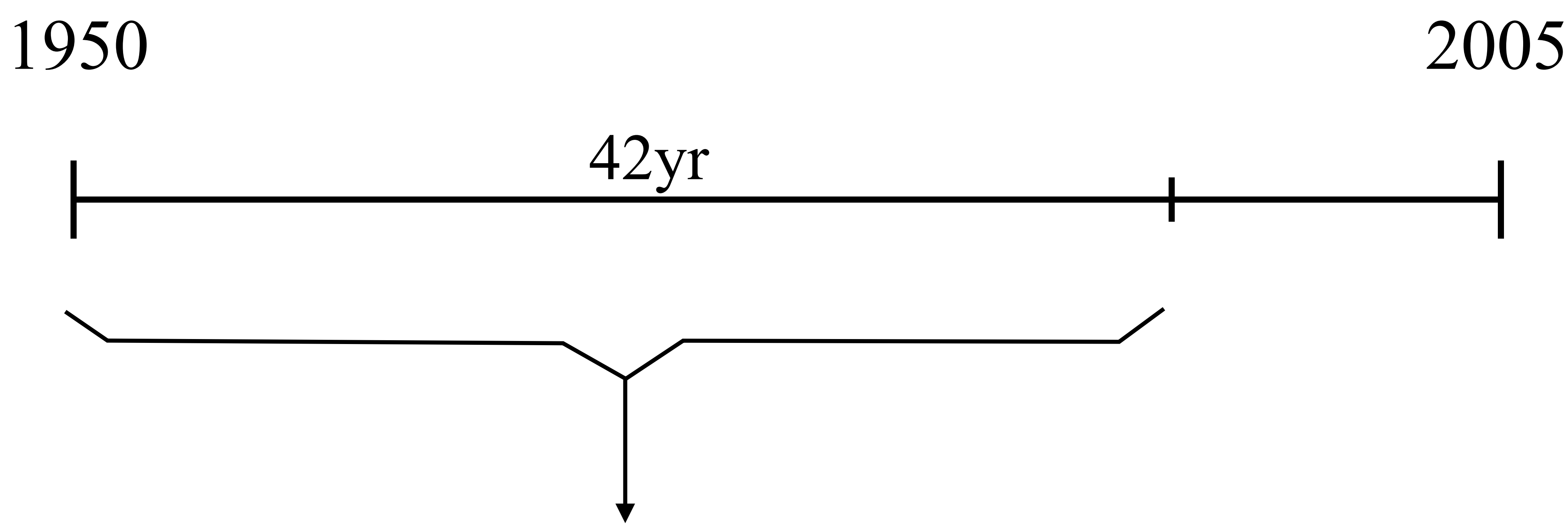
$$T_{BC}(t) = \overline{O_{REF}} + \frac{\sigma_{O,REF}}{\sigma_{T,REF}}(T_{RAW}(t) - \overline{T_{REF}}), \qquad (2)$$

where $\sigma_{T,REF}$ and $\sigma_{o,REF}$ represent the standard deviation in the reference period of the daily GCM output and observations, respectively. Note that this bias-correction procedure for the GCM output could be applied to correct both the historical and future periods.

# 回顾

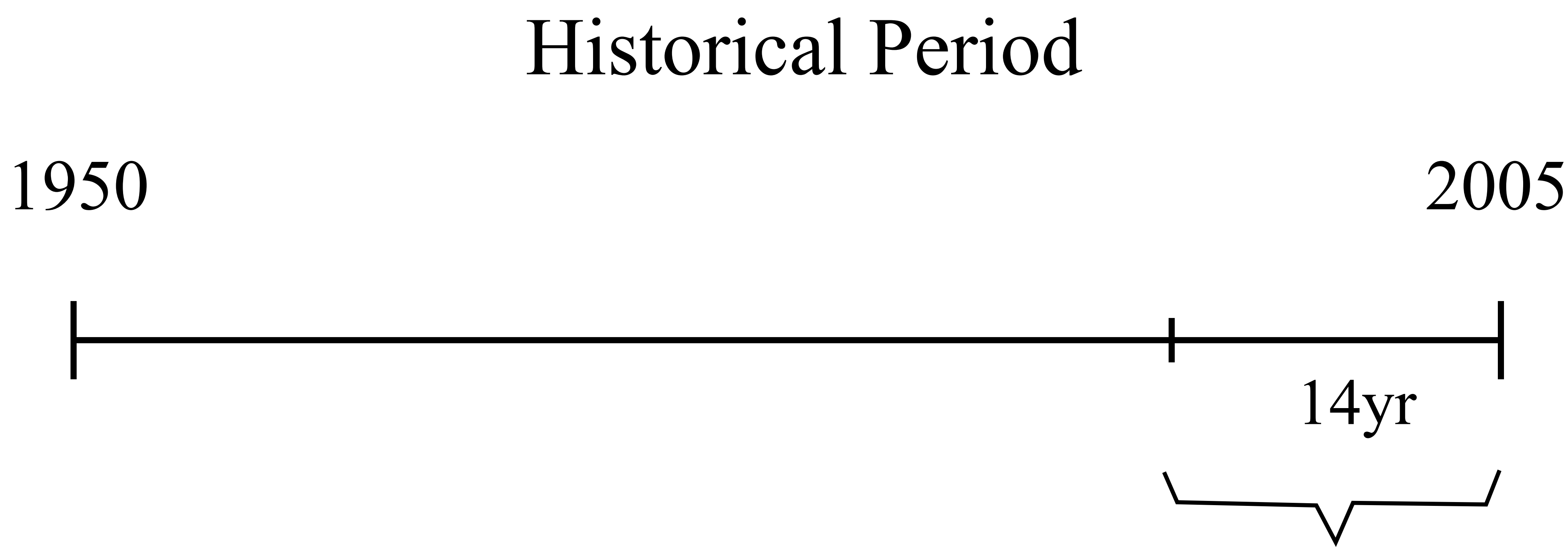
## Bias Correction: std

### Historical Period




$$\left\{\begin{array}{l} \dfrac{\sigma_{O,\ \text{train}}}{\sigma_{T,\ \text{train}}} \\ \overline{O_{\text{REF}}} \\ \overline{T_{\text{REF}}} \end{array}\right. \sim \quad \alpha \qquad \text{size} = 12$$

# Reference



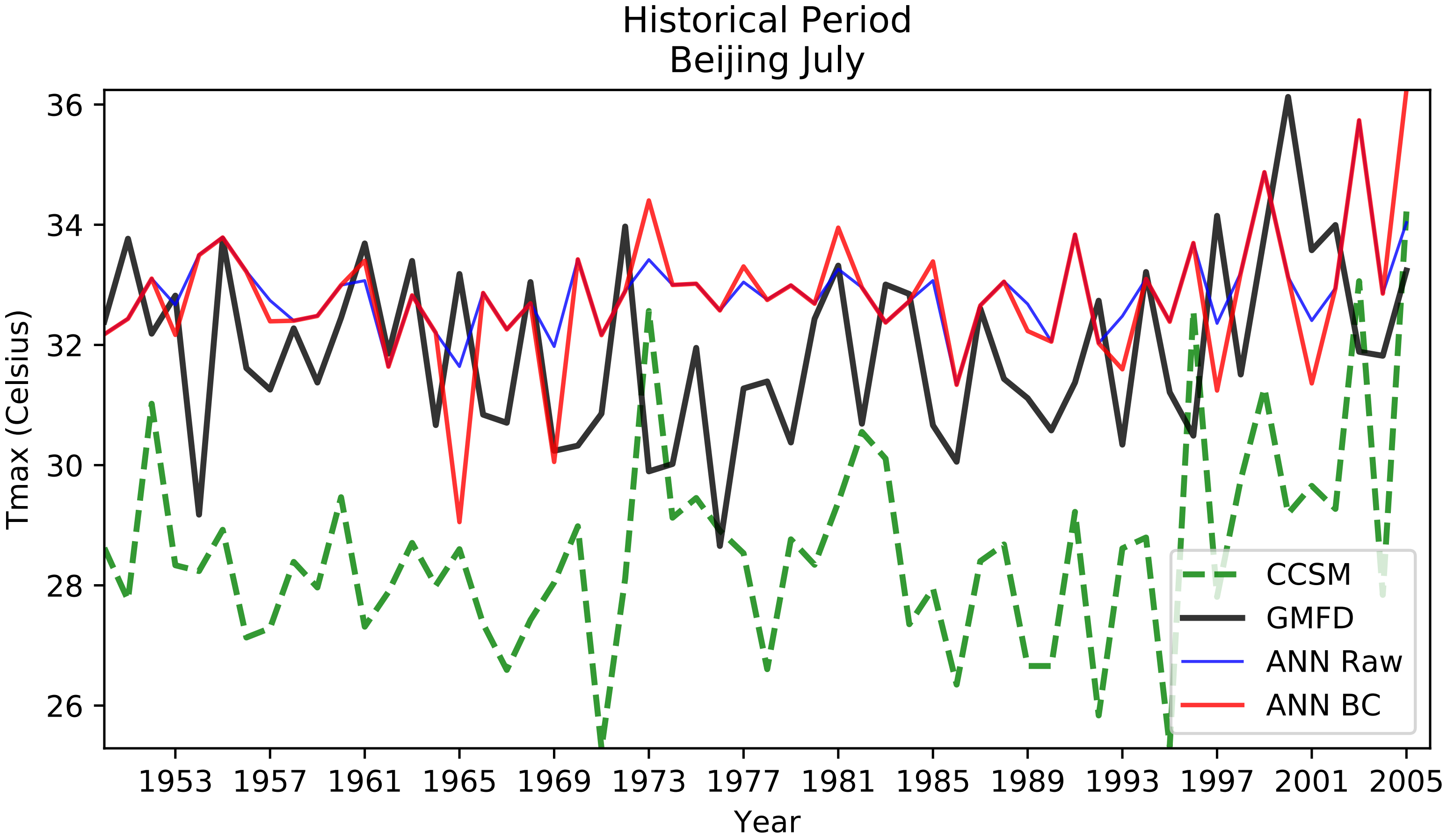

$$T_{\mathrm{BC}}(t) = \overline{O_{\mathrm{REF}}} + \frac{\sigma_{O,\mathrm{REF}}}{\sigma_{T,\mathrm{REF}}}\left(T_{\mathrm{RAW}}(t) - \overline{T_{\mathrm{REF}}}\right)$$

# Results

Beijing Tmax

Monthlymean

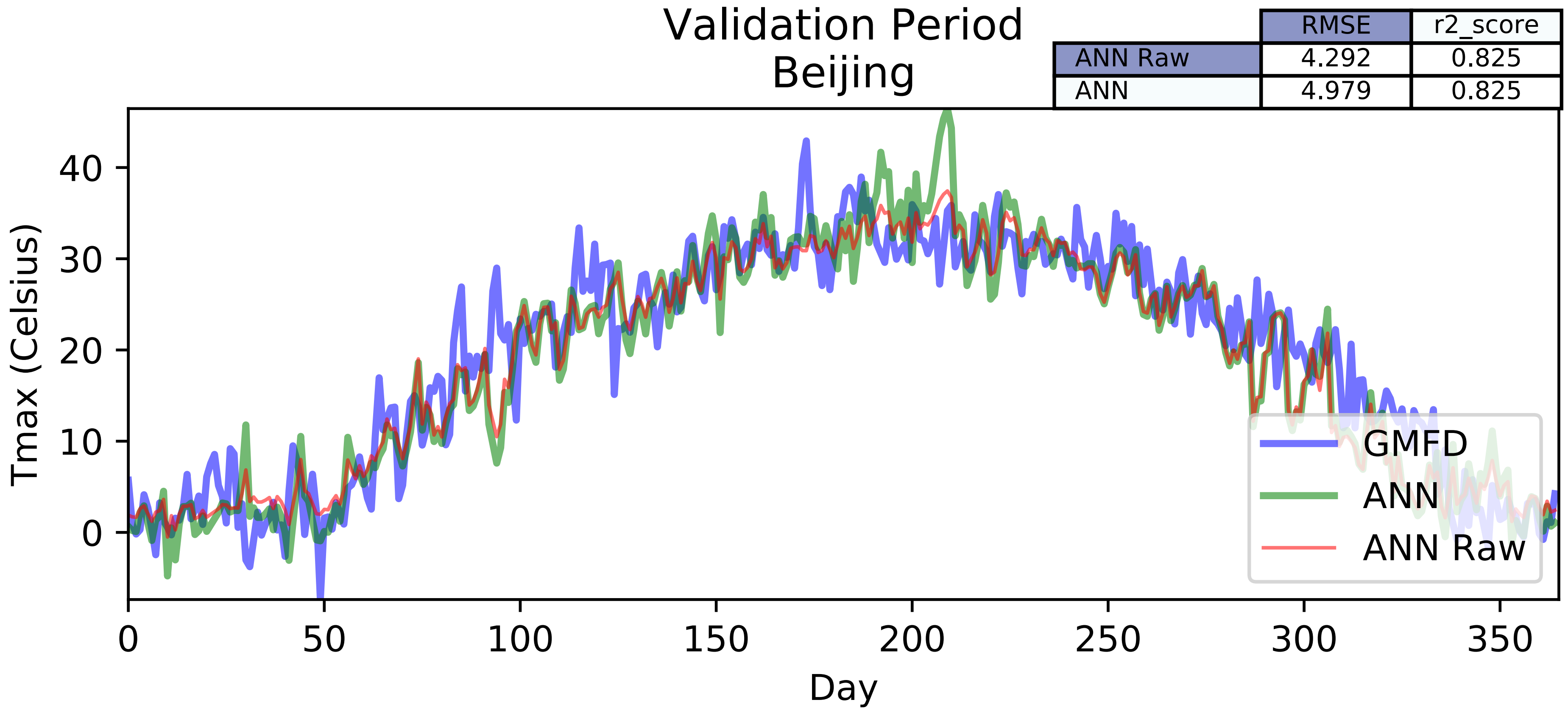
```
mean_ccsm =  28.612423
mean_ground =  31.921953
mean_ann_raw =  32.856594
mean_ann_bc =  32.781597

std_ccsm =  1.7578304
std_ground =  1.4520789
std_ann_raw =  0.7223801
std_ann_bc =  1.1150203

rmse_ccsm =  3.949551
rmse_ann_raw =  1.8095402
rmse_ann_bc 1.9722866
```



# Results

Beijing Tmax

Daily

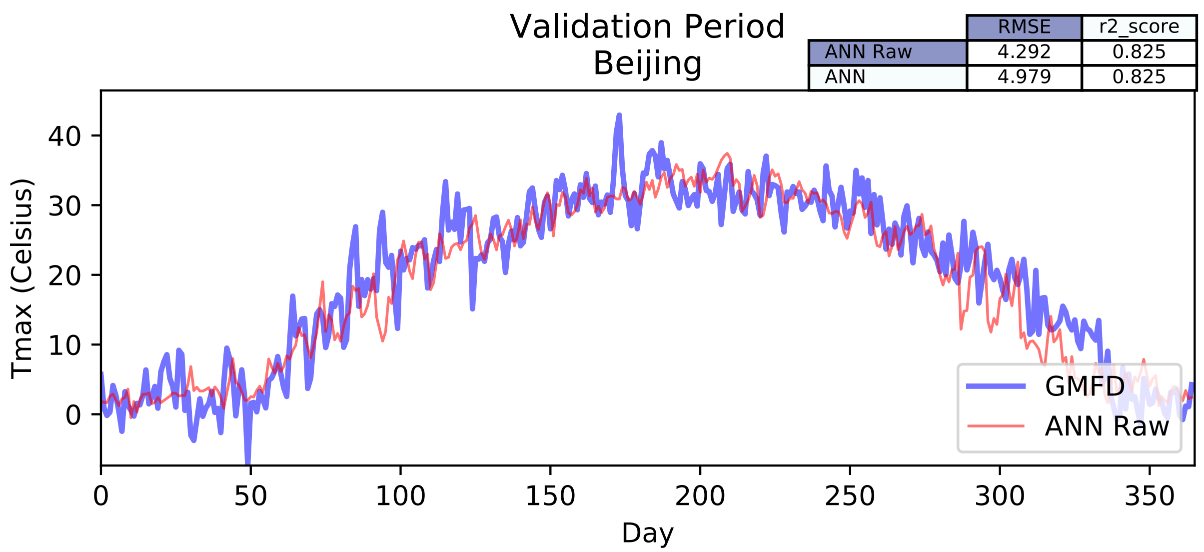


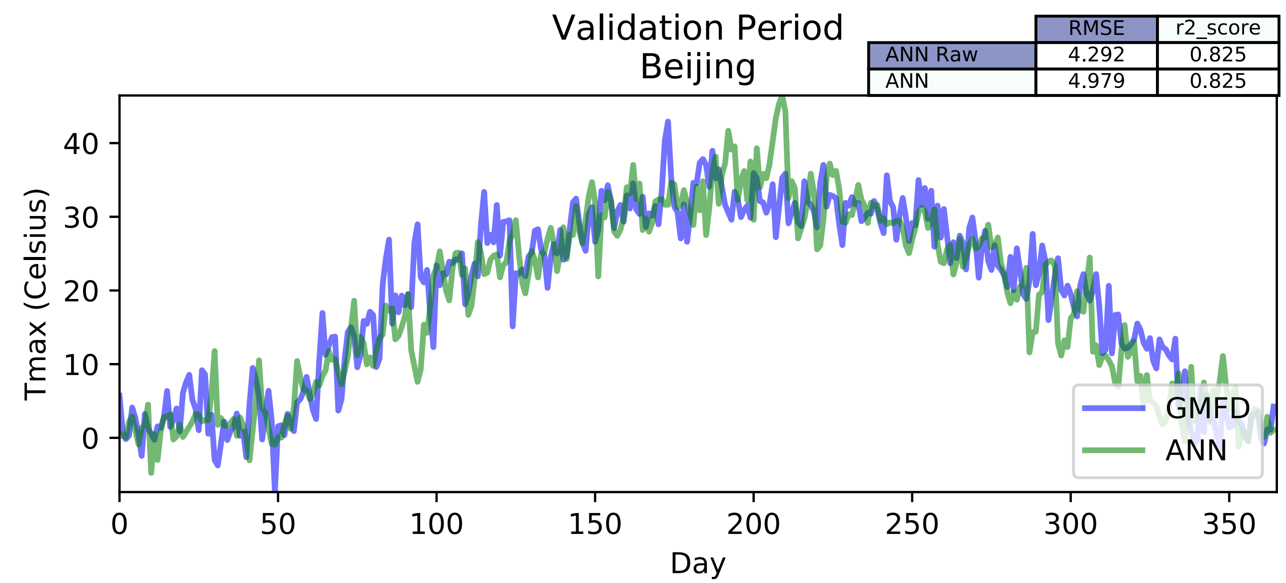
谢谢

# 附录

Beijing　Tmax

Daily



# 附录

Reference：

1. http://ccafs-climate.org/bias_correction/

2. Calibration and bias correction of climate projections for crop modelling: An idealised case study over Europe

（https://www.sciencedirect.com/science/article/pii/S0168192312001372）