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Interrogating empirical-statistical downscaling

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Introduction:
A broad range of difficult context questions hover in the background:
·Do the scientists engaged in downscaling trust the results?
·Does downscaling raise more questions than answers?
·Does downscaling add real information?
·Does the higher resolution of downscaling imply greater accuracy?
——there is a need to foster understanding of the issues between the user community and the scientists so that the data can be mutually examined in the appropriate context. Also, to raise awareness of the principal underlying assumptions, limitaitions and challenges involved in producing and interpreting downscaled products.

Context:
Predictors: large scale atmosphere drivers
Predictand: local scale variable of interest

The bulk of the downscaling literature is focused on two broad areas: the development of methods, or on applications using one or more ESD methods to providing information to end users.

——the uncertainty in weather forecasting is well characterized, making this a valuable operational activity.

Criteria of regional climate downscaling information:
—PDA
· Plausible. The results are consistent with the known dynamics of the physical system.
· Defensible. There is a physical basis that can explain the ESD results.
· Actionable.
—dependent on application, the variable in question imposes constraints(eg., downscaling by bias correcting a model's output that has too few rain days is clearly an arbitrary adjustment at best(for there is no clear basis on how to add rain days), and hence gives rise to questionable solutions).

What downscaling ideally seeks to achieve:

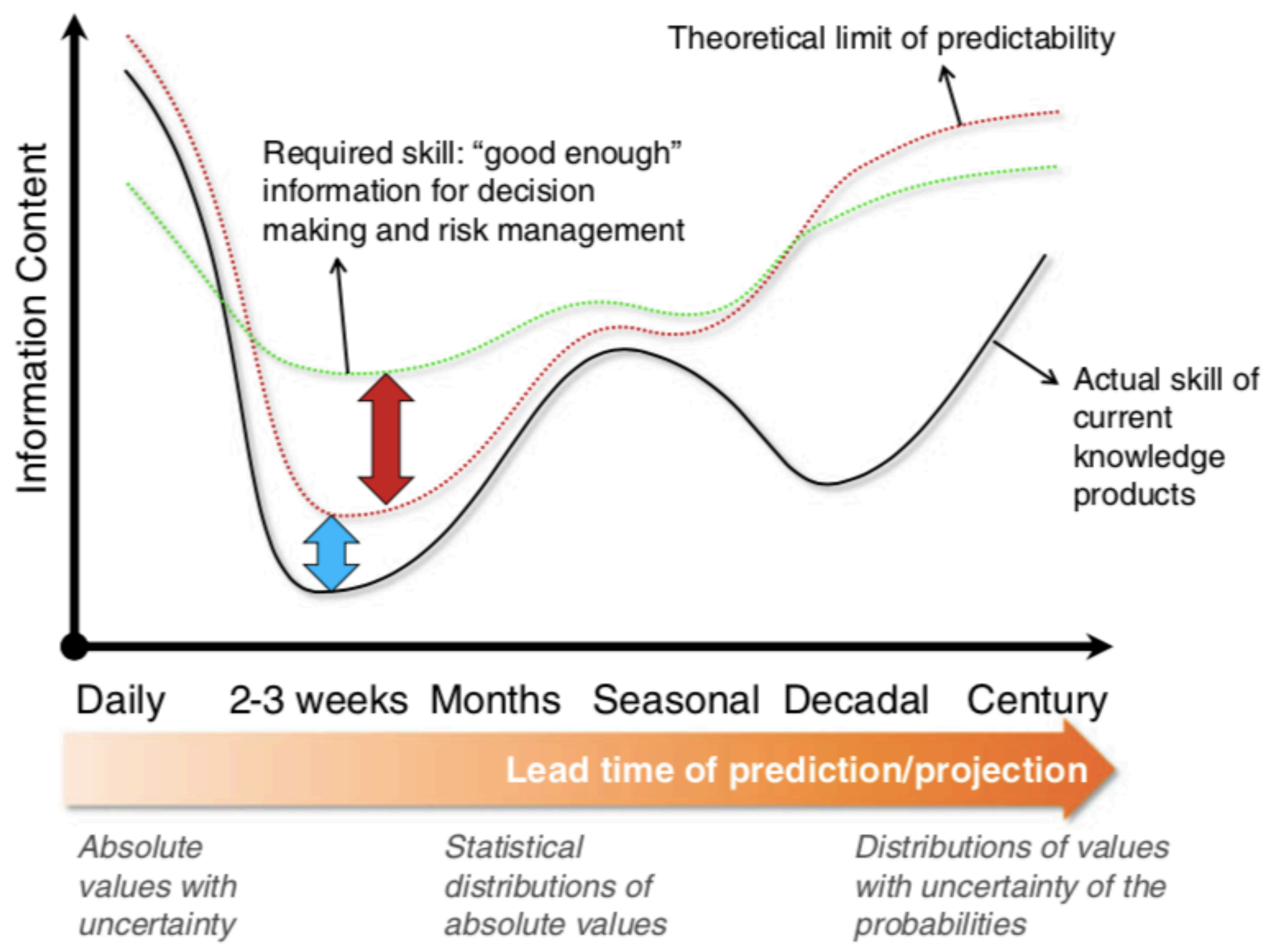


Fig. 1 Idealized representation of conceptual information issues in relation to using climate information for a given scale, variable, metric, and application. The curves are hypothetical, and in practice each line is a zone of gradation, but is represented here as a simple line for clarity (after Landman et al. 2010)

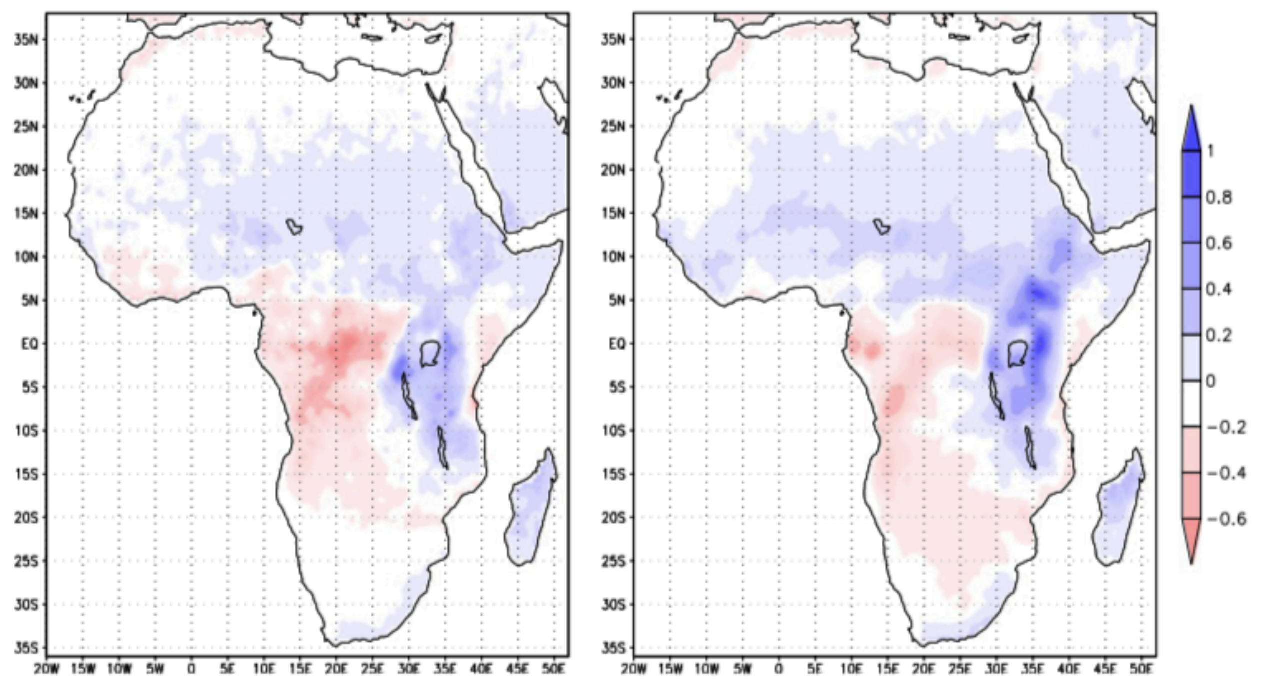


Fig. 4 Projected downscaled climate change anomaly of mean daily precipitation (mm/day) where the downscaling was trained using the CFSR (*left*) and WFDEI (*right*) gridded estimates of historical climate. The change is the difference between the mean of two 30 year periods: 2071–2100−1981–2010. The driving GCM is the CanESM2 forced by the RCP 4.5 GHG scenario from the CMIP5 archive

Table 1 General methods in approaches commonly referred to as downscaling, and important characteristics associated with each

Method	Characteristics
Weather generator	• Needs long observation time series for training. • Parameters can be conditioned by a GCM. • There are potential issues of stationarity in the model parameters. • May have issues with low frequency variability. • There are challenges in handling direct radiative forcing of enhanced GHGs.
Transfer functions	• Can use shorter time series if the data spans the full range of possible atmospheric states at that location. • There are potential stationarity issues in the transfer function parameters. • Usually underestimates extremes and high frequency variance. • There are challenges in handling direct radiative forcing of enhanced GHGs.
Index approaches	• Vulnerable to non-stationarity of the index. • Not directly tied to physically interpretable predictors. • There are challenges in handling direct radiative forcing of enhanced GHGs.
Analogue patterns	• Not strictly downscaling. • Needs a long observation time series. • The method is constrained to only reproduce historical patterns. • There are challenges in handling direct radiative forcing of enhanced GHGs. • There are possible problems with differential spatial responses to global change.
Perturbed observed (Delta method)	• Not strictly downscaling. • Reflects the signal from a GCM grid cell diagnostic variable. • Does not add additional climate change signal information; only adds observational spatial detail.
Quantile mapping / bias correction	• Not strictly downscaling. • Reflects the signal from a GCM grid cell diagnostic variable. • Does not add additional climate change signal information; only adds observational spatial detail. • Difficult to justify the bias correction of some parameters, e.g. rain-day frequency. • Bias correction is only strictly true for historical period, and is a bias adjustment for the future.
Regional climate model	• Dependent on the quality of the lateral boundary conditions (LBCs). • Develops (mostly) its own internal domain climate. • Complicated by lateral boundary effects. • Sensitive to domain size, resolution, and boundary location. • Has dependency on the model's parameterization skill and stationarity, and possible parameterization compatibility issues with the driving GCM. • Output usually requires (problematic) bias correction.
High resolution or variable resolution global model forced by Sea surface temperatures from a host AOGCM	• Not strictly downscaling, but a high resolution atmosphere-only GCM. • Forced only by sea surface temperatures from a coupled AOGCM (may include nudging). • Develops its own climate independent of the source GCM. • Has dependency on the model's parameterization skill and stationarity. • Output usually requires (problematic) bias correction.

Report

2020.09.26

張慕琪

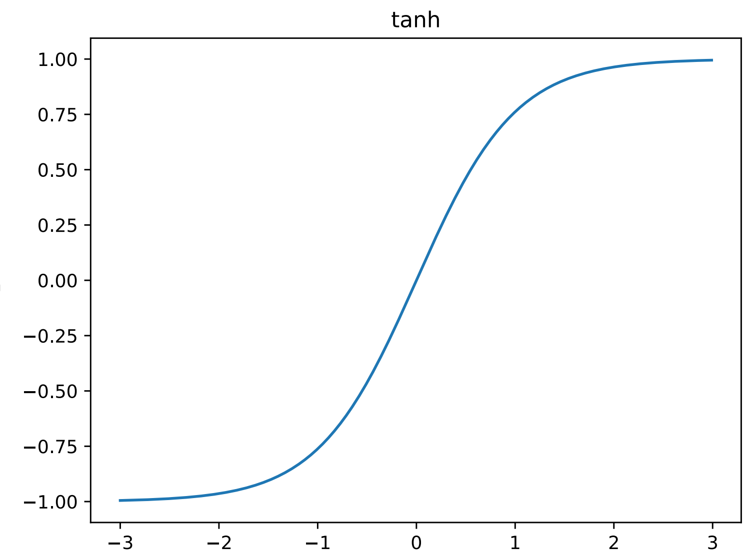
Review

∗6个GCMs: CCSM4, GFDL-CM3, BCC-CSM1.1, MIROC-ESM, MPI-LR, CNRM-CM5

∗加入Julian day: sin(x)

∗Final ANN: hidden_layer_sizes=(60, 30), solver='adam', alpha=1e-2, activation='tanh', learning_rate_init=1e-2

tanh(1) = 0.762
tanh(2) = 0.964
tanh(3) = 0.995



在[-3, +3]间，tanh比relu更有多样性

∗Normalization & Bias Correction:

ANN：标准化过程抹去了CCSM在his和future的平均值差异

CCSM future 标准化后future CCSM的平均值不应该为0！应该标准化为有偏

$\frac{x_i - \bar{x}_i}{标准差}$ his

Fifth method: $T_{BC}(t) = T_{RAW} - (\bar{T}$

thrid method:

$T_{BC}(t) = \bar{T}_{RAW} - (\bar{T}_{REF} - \bar{O}_{REF}) + \frac{\delta_{O,REF}}{\delta_{T,REF}}(T_{RAW} - \bar{T}_{RAW})$

①REF：56yr计算参数

②hist用56yr做BC参数 ⇐ 不按一年一年算，按56y一起输入：56×31（7日eg.）

③future用每10yr的31个数做BC！（15+10+10+…）← 年际和季节做BC 2006-2100

∗Plots:

- Maps
- Tmax
- Tmin

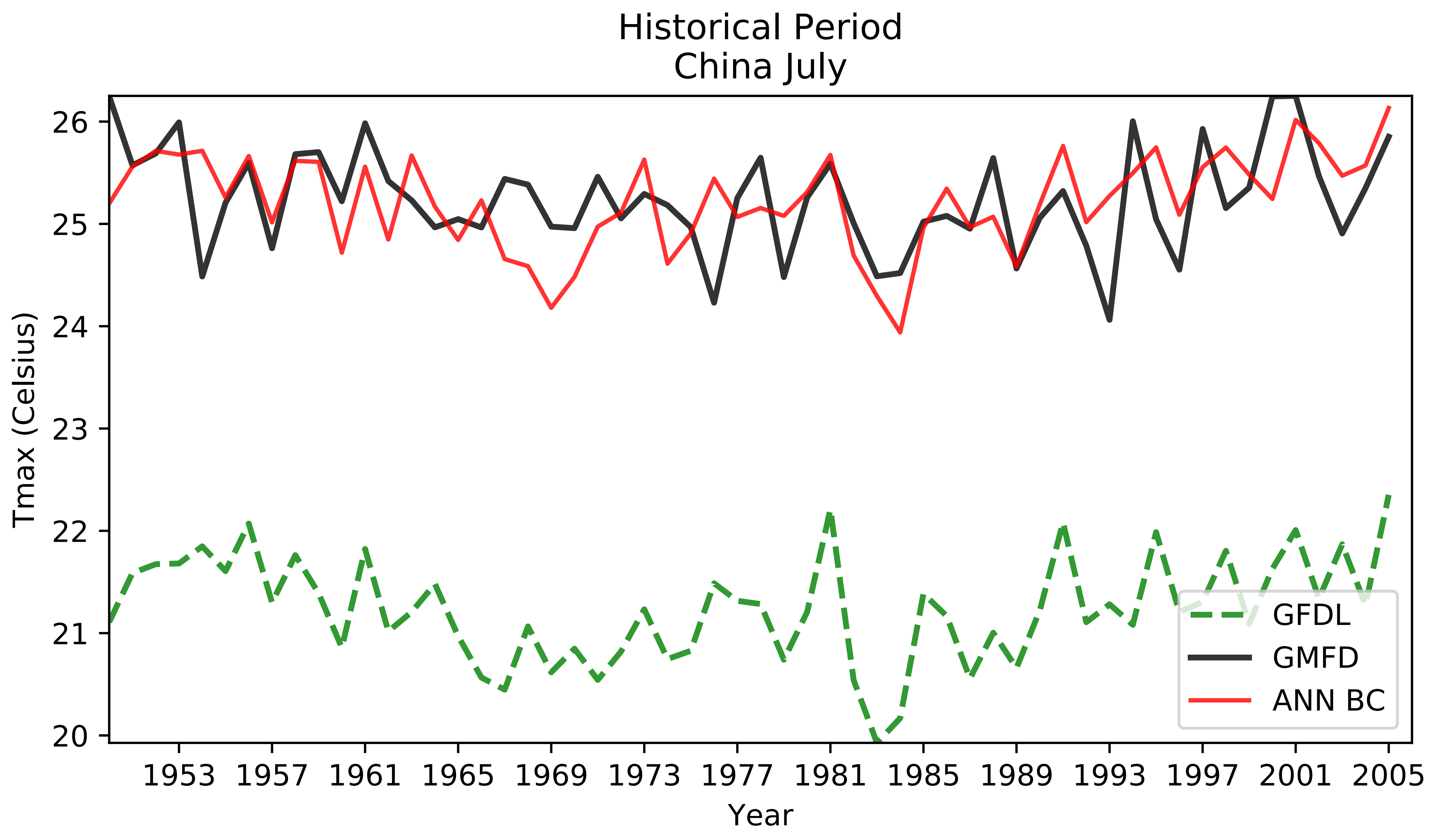
- Maps
- Taylor Diagrams
- Time series

- 气候态(CLIM)：1971-2000
- 长期气候趋势：1950-2005 & 2006-2100
- 全国加权平均

Results

China ts train+vali(1950-2005)

Tmax

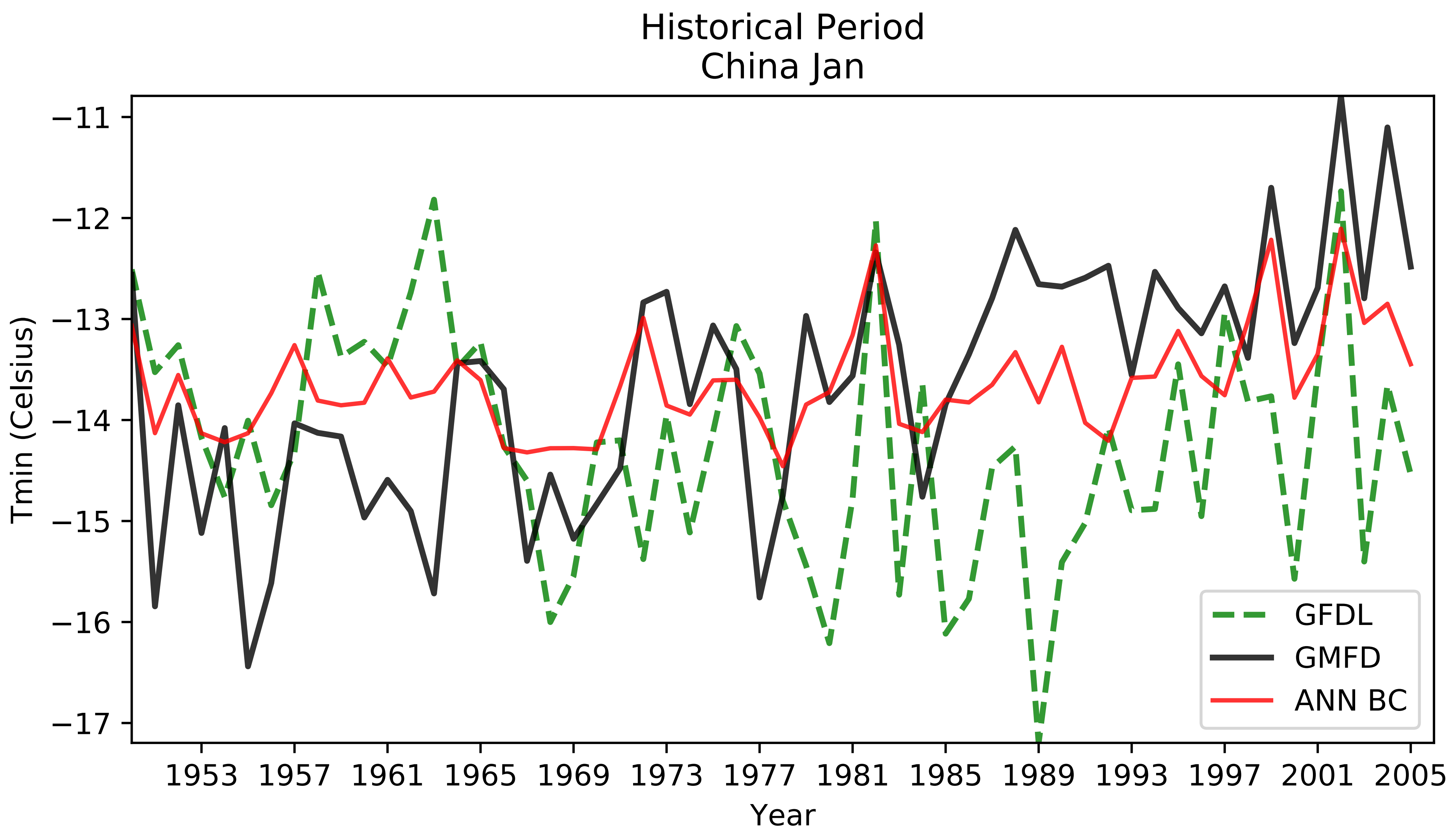



```
mean_ccsm = 21.24
mean_ground = 25.24
mean_ann_bc = 25.22

std_ccsm = 0.52
std_ground = 0.50
std_ann_bc = 0.46

rmse_ccsm = 4.04
rmse_ann_bc =  0.51
```

Tmin




```
mean_ccsm = −14.24
mean_ground = −13.64
mean_ann_bc = −13.64

std_ccsm = 1.15
std_ground = 1.20
std_ann_bc = 0.51

rmse_ccsm = 1.77
rmse_ann_bc = 0.95
```

Results

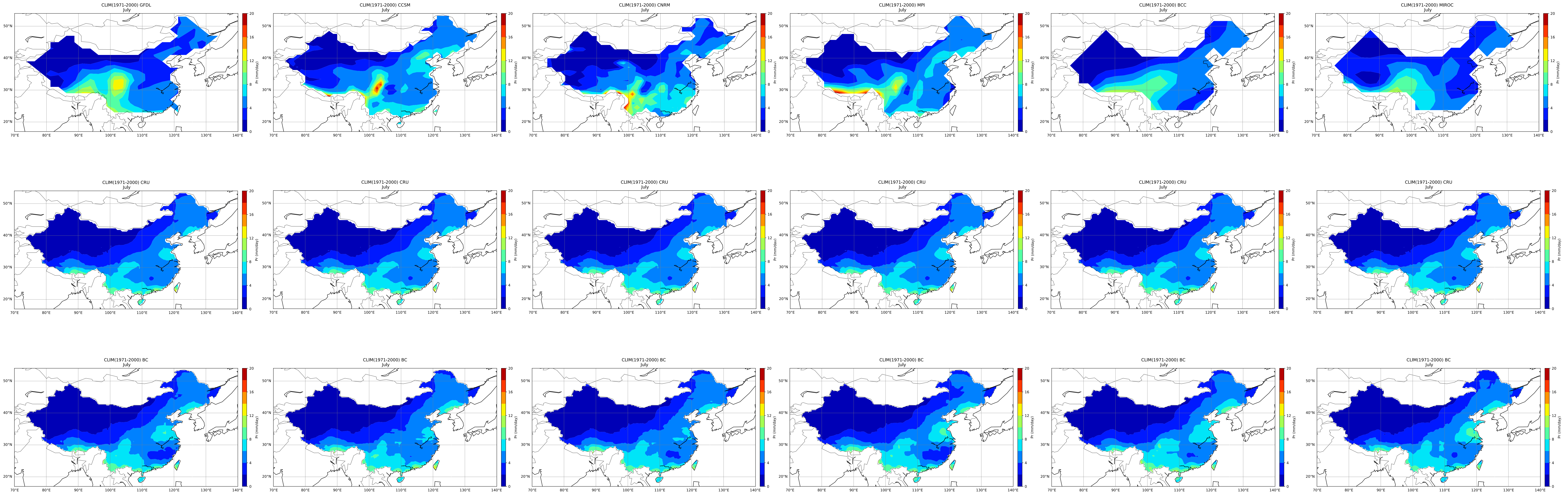
China Maps CLIM(1971-2000) Pr

GFDL CCSM CNRM MPI BCC MIROC

GCM

CRU

BC



Results

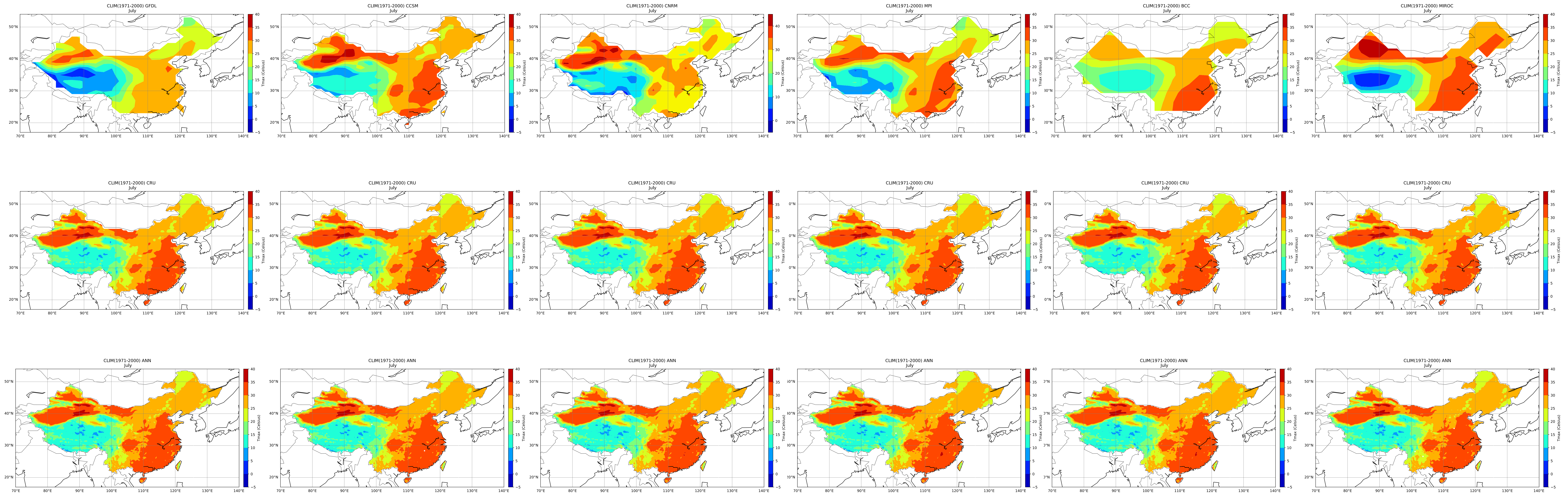
China Maps CLIM(1971-2000) Tmax

GFDL CCSM CNRM MPI BCC MIROC

GCM

CRU

ANN



Results

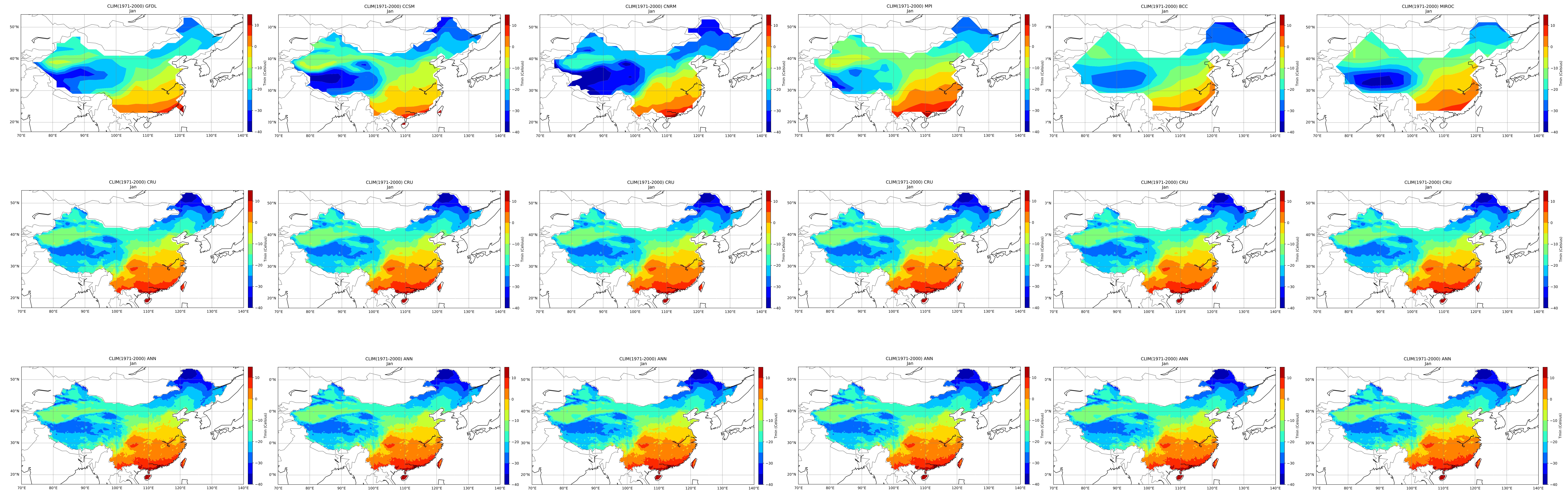
China Maps CLIM(1971-2000) Tmin

GFDL | CCSM | CNRM | MPI | BCC | MIROC

GCM

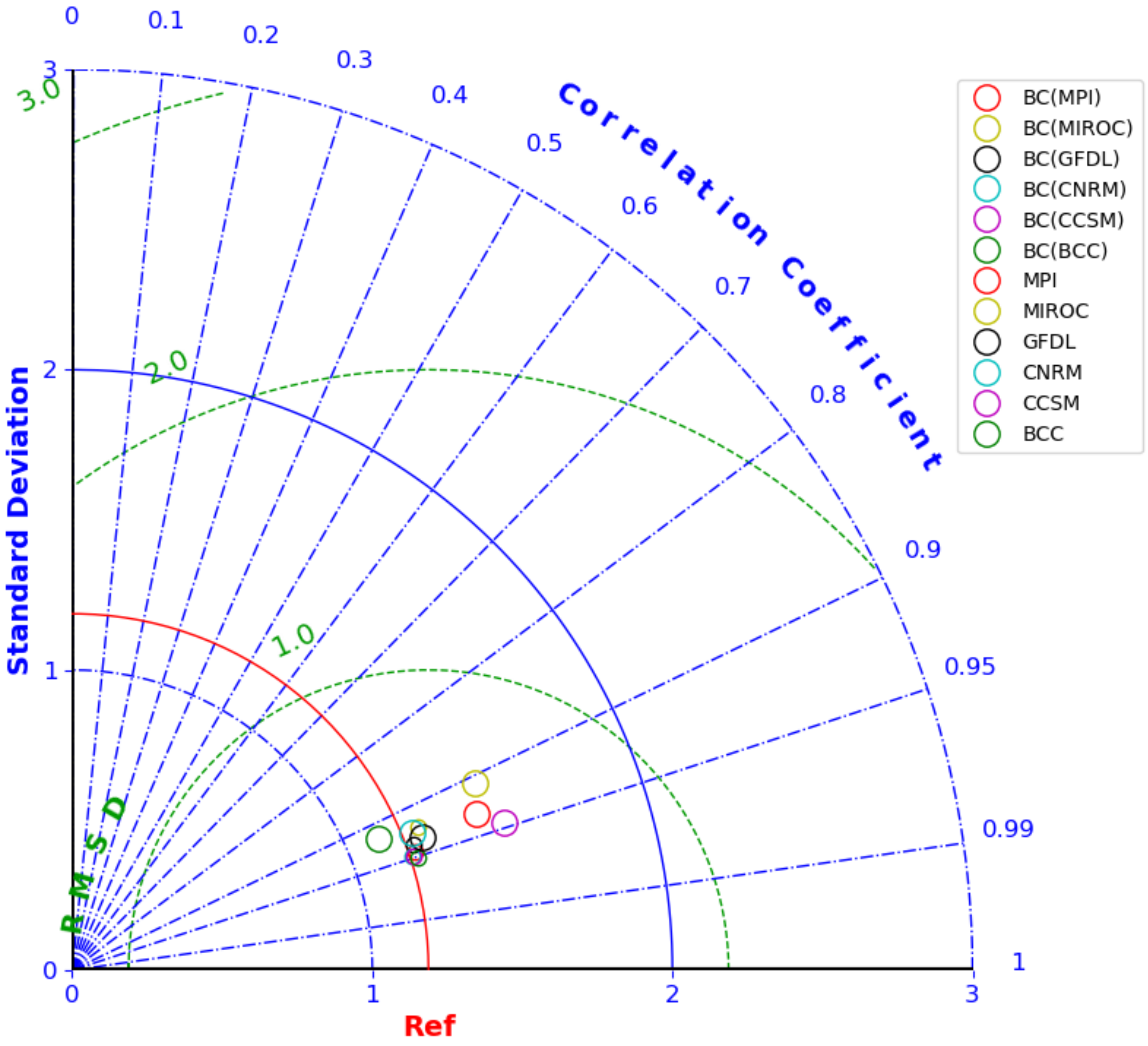
CRU

ANN

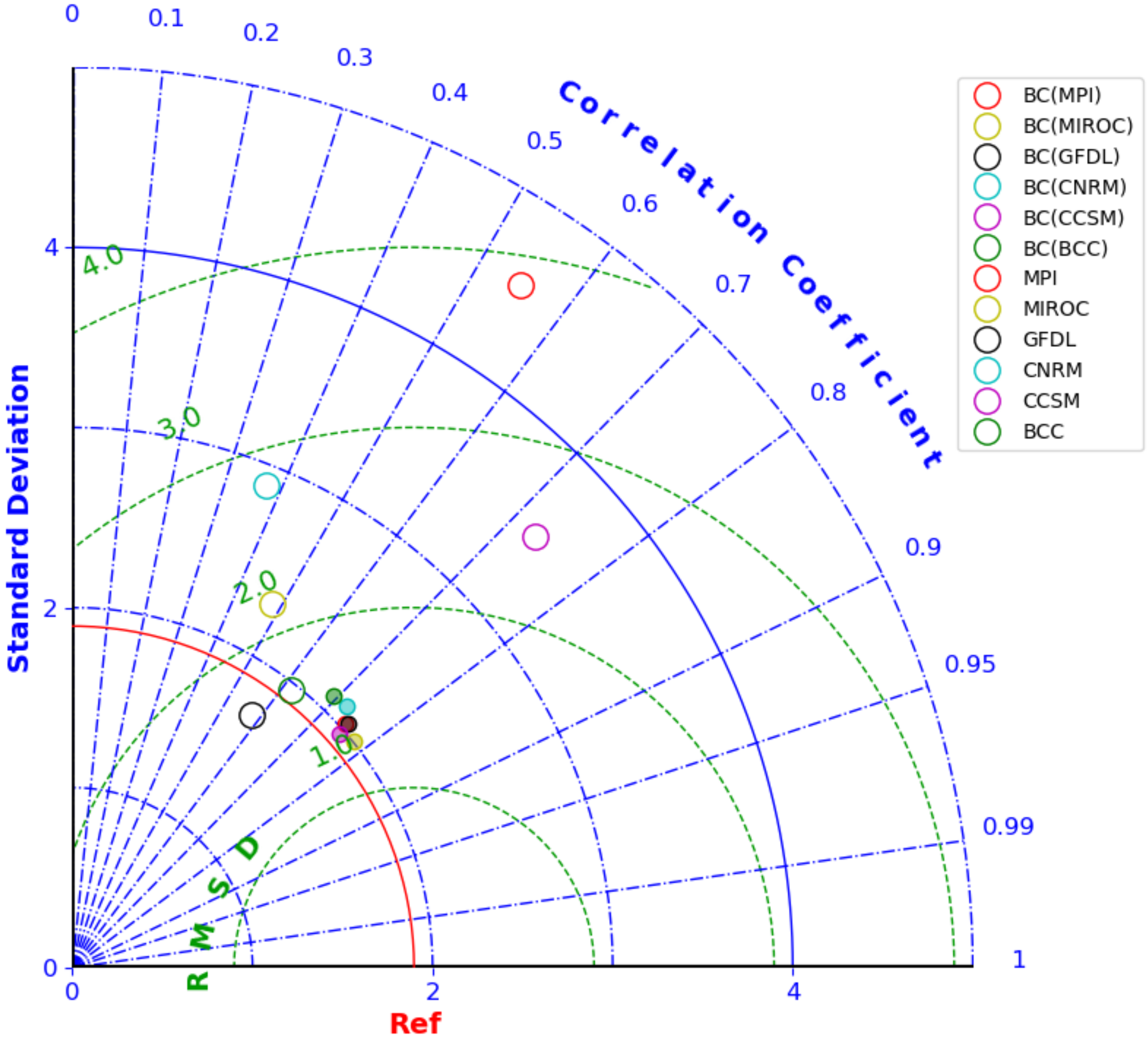


Results

Taylor Diagram CLIM(1971-2000)
Pr



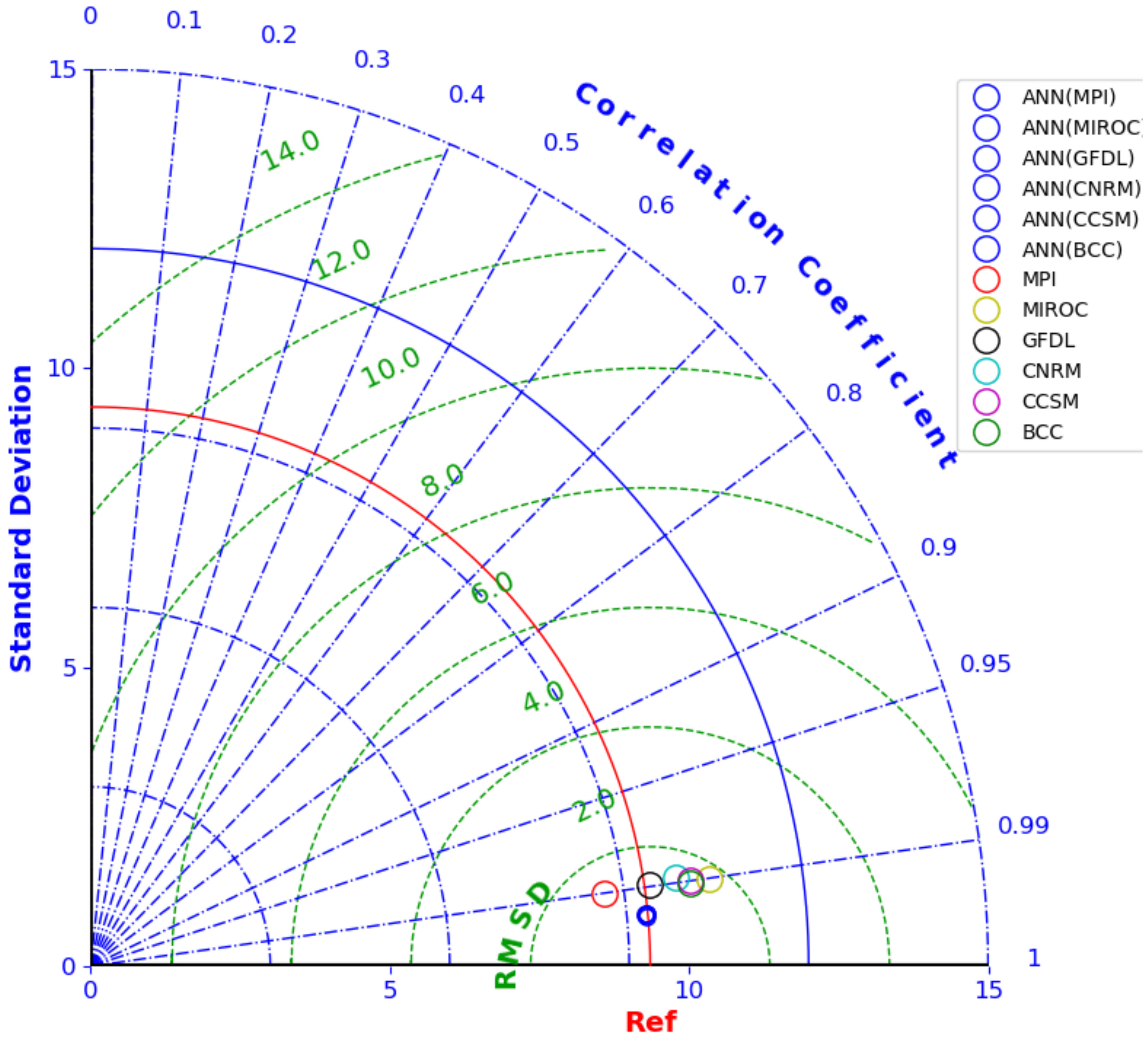
China



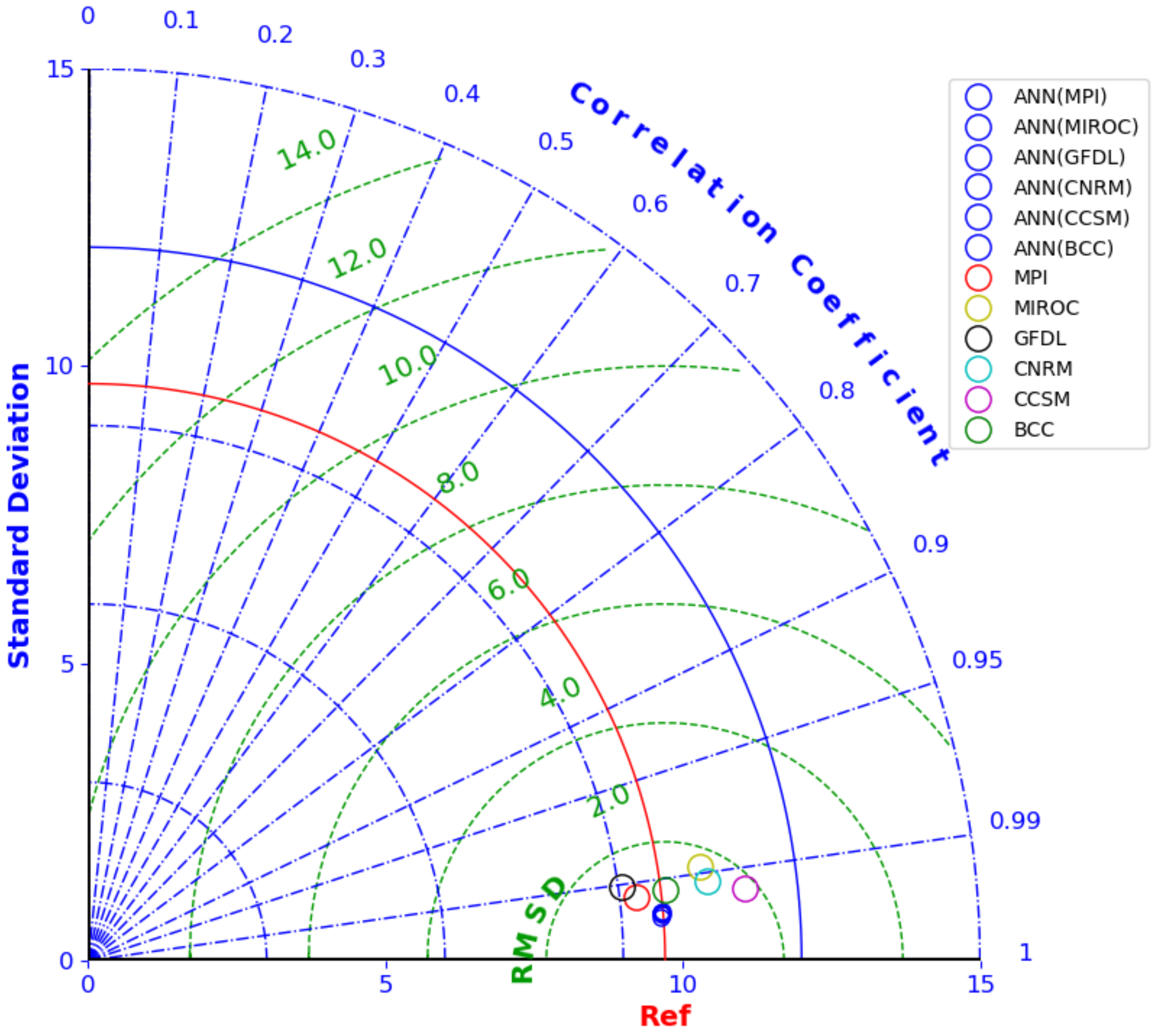
Beijing

Results

China Taylor Diagram CLIM(1971-2000)



Tmax

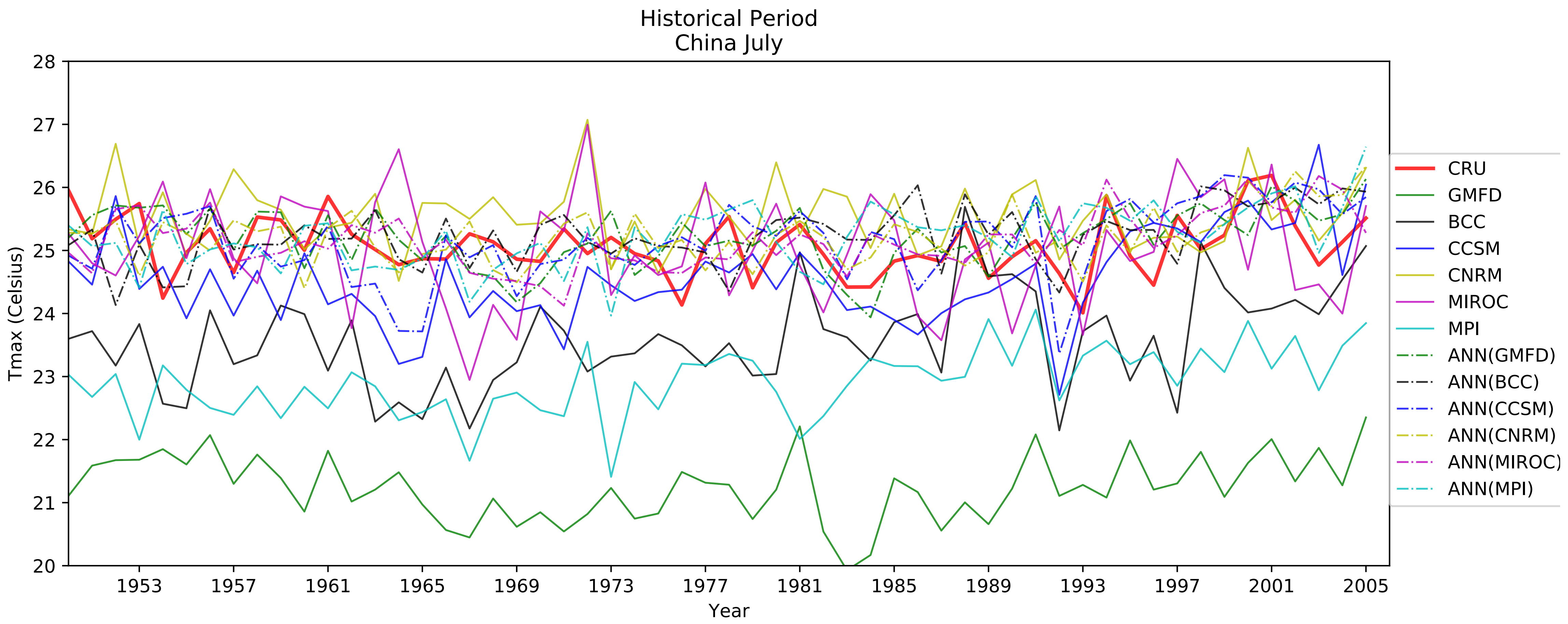


Tmin

Results

China ts ALL(1950-2005)

Tmax



mean_gfdl = 21.24
mean_bcc = 23.60
mean_ccsm = 24.55
mean_cnrm = 25.54
mean_miroc = 25.01
mean_mpi = 22.92

std_gfdl = 0.52
std_bcc = 0.77
std_ccsm = 0.72
std_cnrm = 0.52
std_miroc = 0.86
std_mpi = 0.53

rmse_gfdl = 3.88
rmse_bcc = 1.69
rmse_ccsm = 0.91
rmse_cnrm = 0.77
rmse_miroc = 0.93
rmse_mpi = 2.28

mean_gfdl_ann = 25.22
mean_bcc_ann = 25.24
mean_ccsm_ann = 25.16
mean_cnrm_ann = 25.22
mean_miroc_ann = 25.16
mean_mpi_ann = 25.22

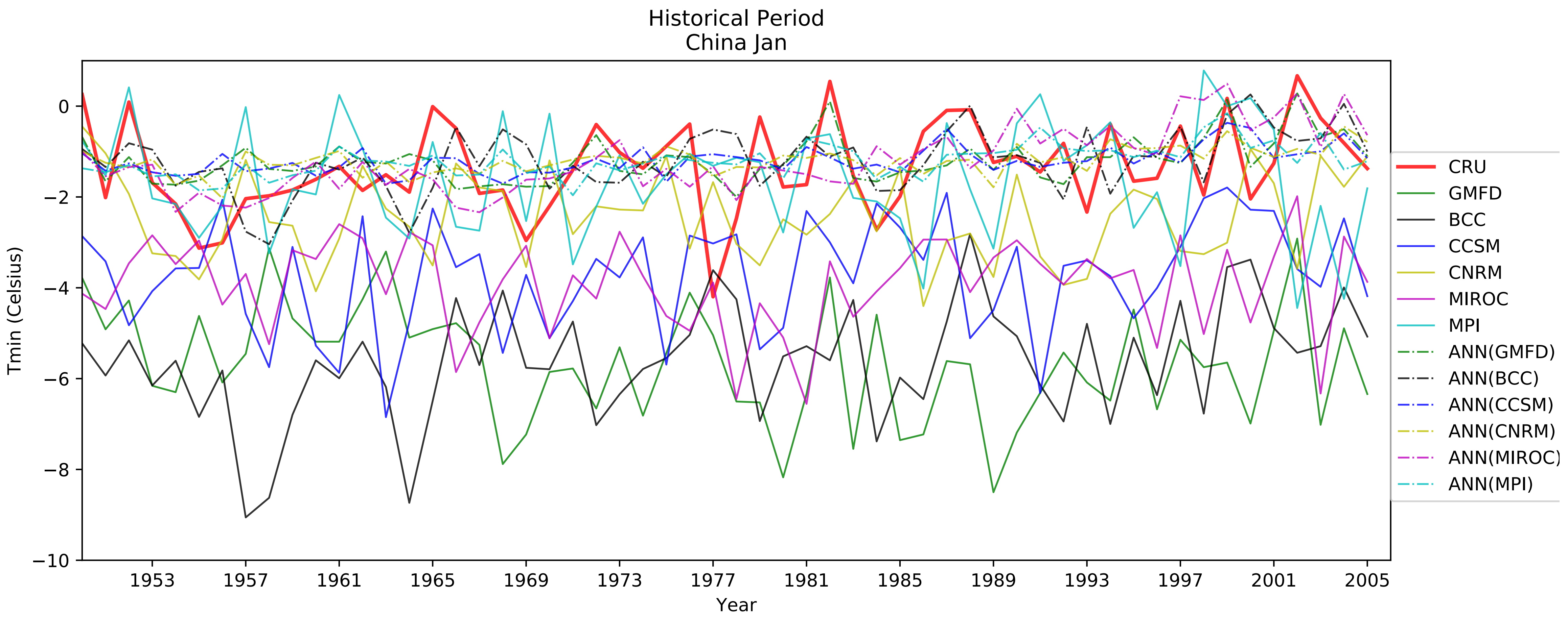
std_gfdl_ann = 0.46
std_bcc_ann = 0.46
std_ccsm_ann = 0.61
std_cnrm_ann = 0.44
std_miroc_ann = 0.44
std_mpi_ann = 0.49

rmse_gfdl_ann = 0.52
rmse_bcc_ann = 0.61
rmse_ccsm_ann = 0.63
rmse_cnrm_ann = 0.77
rmse_miroc_ann = 0.55
rmse_mpi_ann = 0.70

mean_cru = 25.08

std_cru = 0.47

Tmin



mean_gfdl = −5.67
mean_bcc = −5.62
mean_ccsm = −3.73
mean_cnrm = −2.45
mean_miroc = −3.92
mean_mpi = −1.63

std_gfdl = 1.25
std_bcc = 1.26
std_ccsm = 1.2
std_cnrm = 0.95
std_miroc = 1.00
std_mpi = 1.24

rmse_gfdl = 4.56
rmse_bcc = 4.53
rmse_ccsm = 2.84
rmse_cnrm = 1.77
rmse_miroc = 2.88
rmse_mpi = 1.59

mean_gfdl_ann = −1.20
mean_bcc_ann = −1.20
mean_ccsm_ann = −1.20
mean_cnrm_ann = −1.20
mean_miroc_ann = −1.20
mean_mpi_ann = −1.20

std_gfdl_ann = 0.48
std_bcc_ann = 0.68
std_ccsm_ann = 0.29
std_cnrm_ann = 0.29
std_miroc_ann = 0.70
std_mpi_ann = 0.35

rmse_gfdl_ann = 0.83
rmse_bcc_ann = 1.10
rmse_ccsm_ann = 0.95
rmse_cnrm_ann = 0.90
rmse_miroc_ann = 0.98
rmse_mpi_ann = 0.94

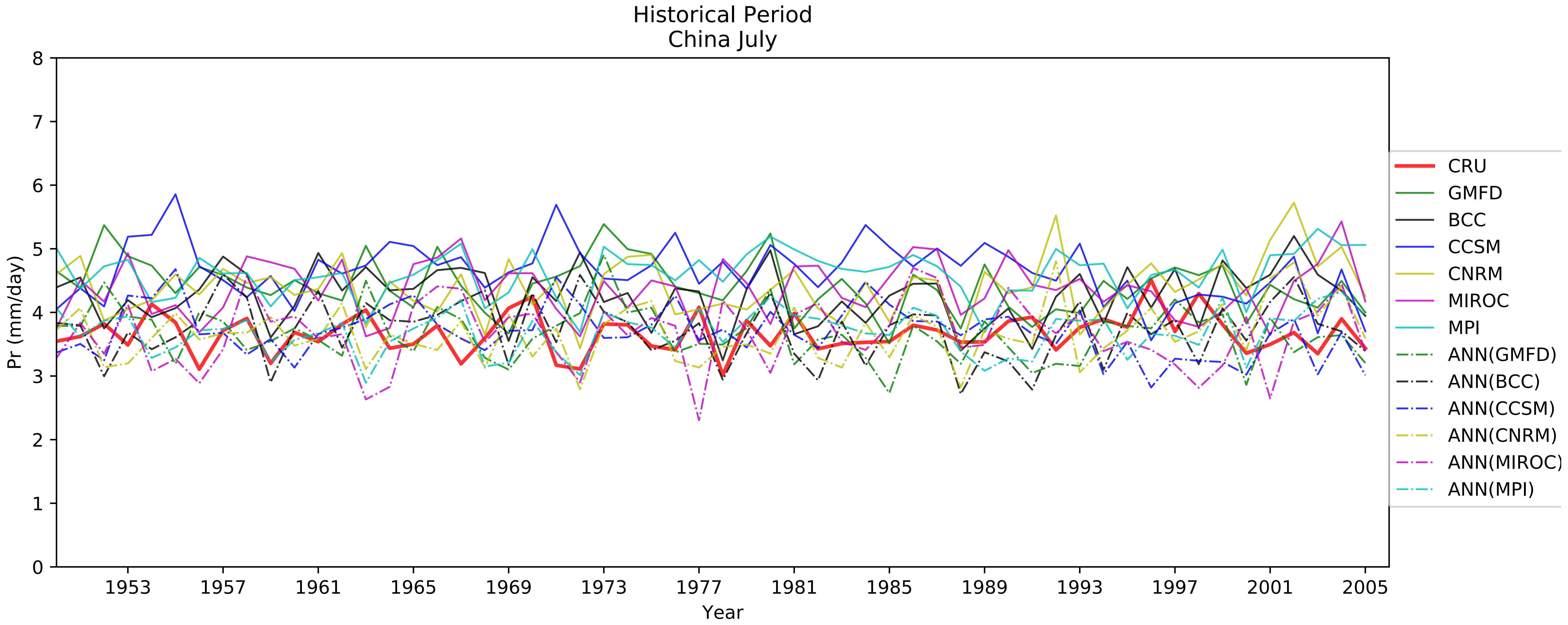
mean_cru = −1.35

std_cru = 0.99

Results

China ts ALL(1950-2005)

Pr




```
mean_gfdl = 4.42        std_gfdl = 0.41        rmse_gfdl = 0.90
mean_bcc = 4.26         std_bcc = 0.44         rmse_bcc = 0.81
mean_ccsm = 4.65        std_ccsm = 0.45        rmse_ccsm = 1.15
mean_cnrm = 4.40        std_cnrm = 0.45        rmse_cnrm = 0.90
mean_miroc = 4.36       std_miroc = 0.44       rmse_miroc = 0.88
mean_mpi = 4.62         std_mpi = 0.37         rmse_mpi = 1.06

mean_gfdl_bc = 3.66     std_gfdl_bc = 0.41     rmse_gfdl_bc = 0.50
mean_bcc_bc = 3.71      std_bcc_bc = 0.46      rmse_bcc_bc = 0.56
mean_ccsm_bc = 3.69     std_ccsm_bc = 0.40     rmse_ccsm_bc = 0.55
mean_cnrm_bc = 3.66     std_cnrm_bc = 0.43     rmse_cnrm_bc = 0.90
mean_miroc_bc = 3.65    std_miroc_bc = 0.53    rmse_miroc_bc = 0.62
mean_mpi_bc = 3.69      std_mpi_bc = 0.34      rmse_mpi_bc = 0.45

mean_cru = 3.67         std_cru = 0.31
```

Results(Lack)

China ts ALL(2006-2100)

Tmax Tmin Pr

谢谢