基于人工神经网络技术发展中国地区高分辨率统计降尺度气候预估数据

汇报人：张慕琪
指导老师：闻新宇

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目录

Part 01

研究背景和研究意义

研究背景和研究意义

GCMs分辨率粗糙

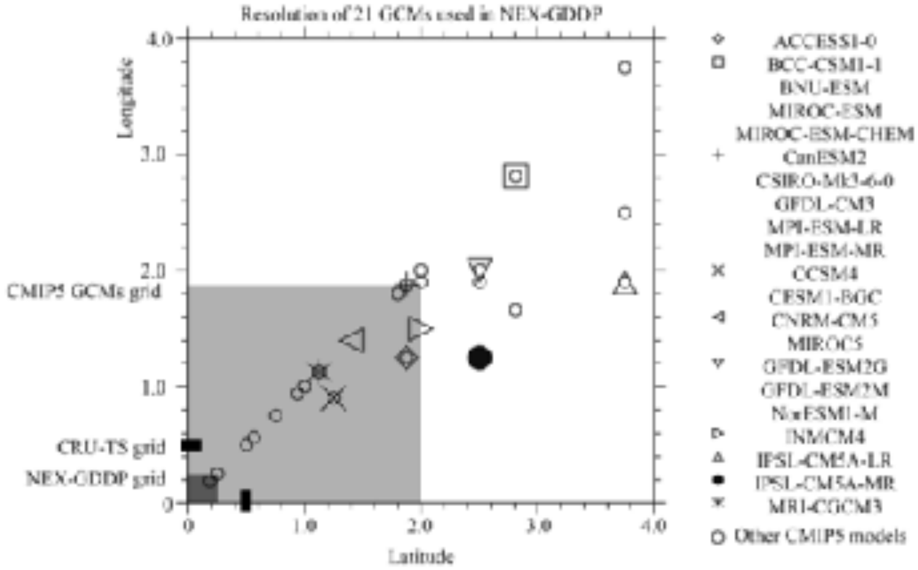


Fig. 1. Grid sizes of the 21 CMIP5 GCMs used in the NEX-GDDP (NASA Earth Exchange Global Daily Downscaled Projections) dataset (big markers) and the other 23 GCMs (small black circle), as well as the mean size of the CMIP5 2° × 2° grid (light grey box) and the NEX-GDDP 0.25° × 0.25° grid (dark grey box). The grid size of the observational dataset (CRU-TS) is also marked, as solid black axis ticks. All model names comply with IPCC-AR5 convention (Flato et al., 2013).

Bao et al., 2017

研究背景和研究意义

GCMs存在系统性偏差（空间）

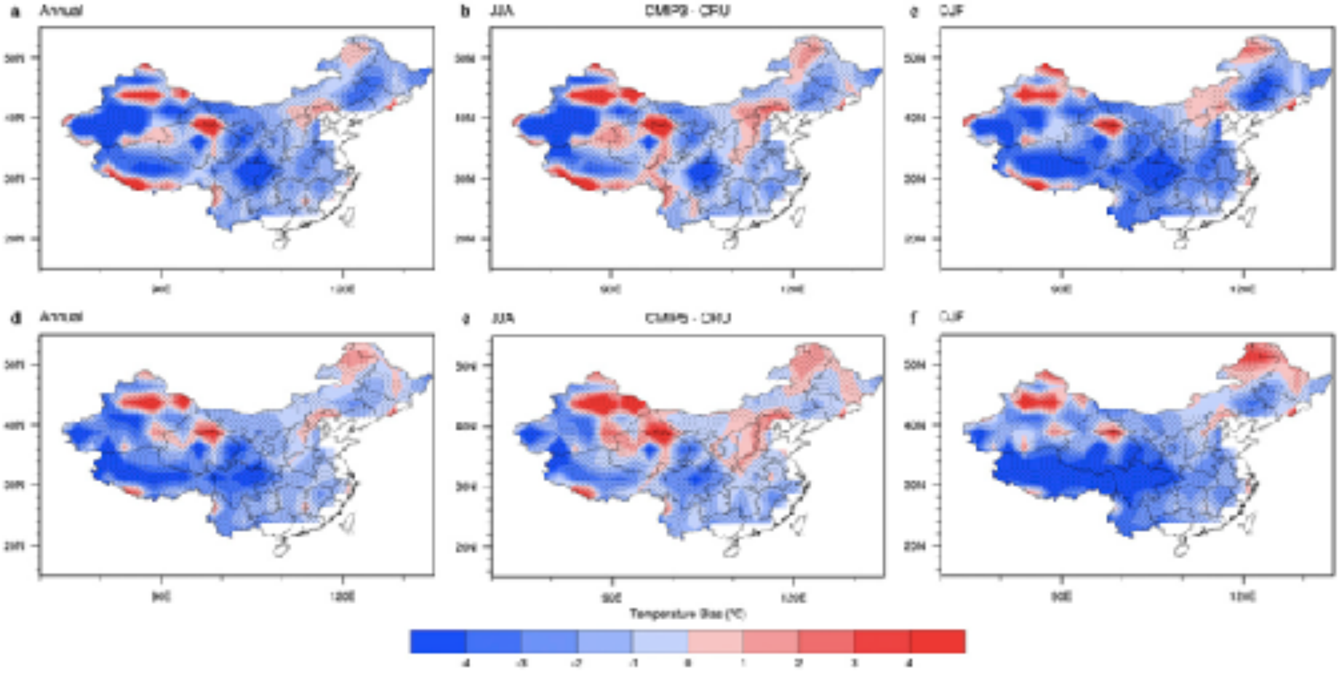
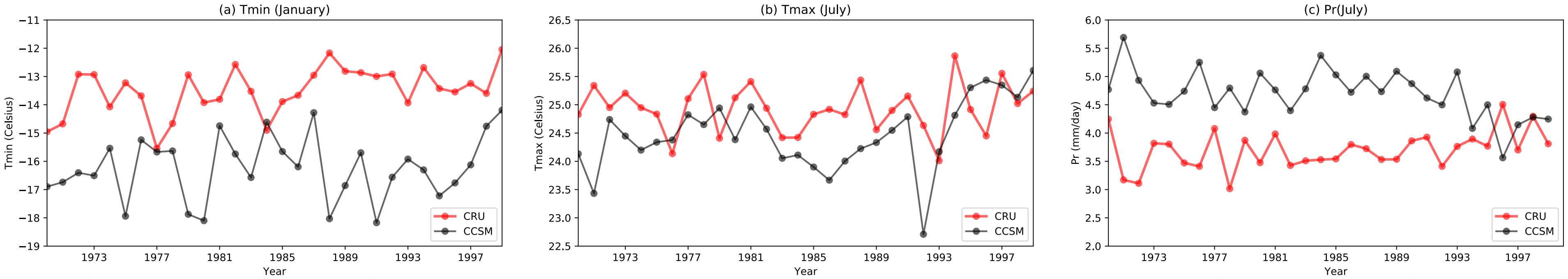


FIG. 2. Annual and seasonal temperature biases of CMIP3 and CMIP5 relative to CRU observations. (top) The difference between CMIP3 and CRU and (bottom) the difference between CMIP5 and CRU for (left) annual, (center) summer [June–August (JJA)], and (right) winter [December–February (DJF)] temperature. Stippled regions indicate statistically significant differences (95% level).

Chen et al., 2014

研究背景和研究意义

GCMs存在系统性偏差（时间）

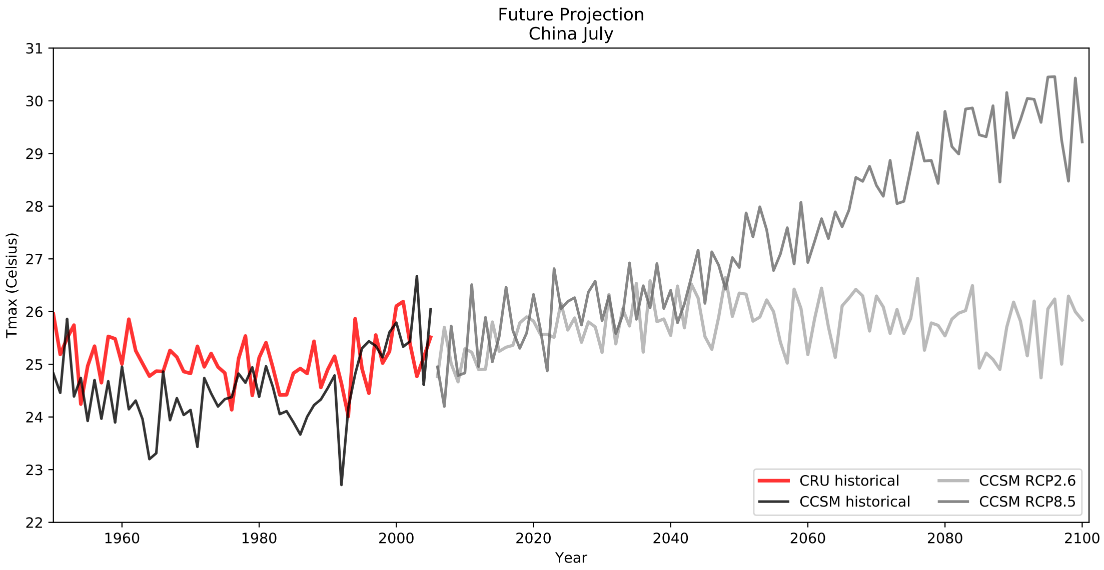


	CRU	CCSM4
Mean	-13.50	-16.23
StdDev	0.82	1.11
RMSE	N/A	3.10

	CRU	CCSM4
Mean	24.93	24.47
StdDev	0.42	0.61
RMSE	N/A	0.79

	CRU	CCSM4
Mean	3.70	4.70
StdDev	0.33	0.42
RMSE	N/A	1.20

研究背景和研究意义



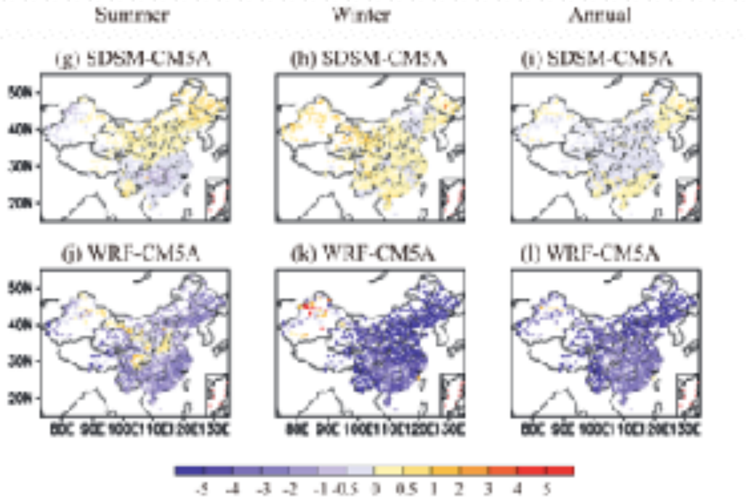
· 降尺度 (Downscaling):

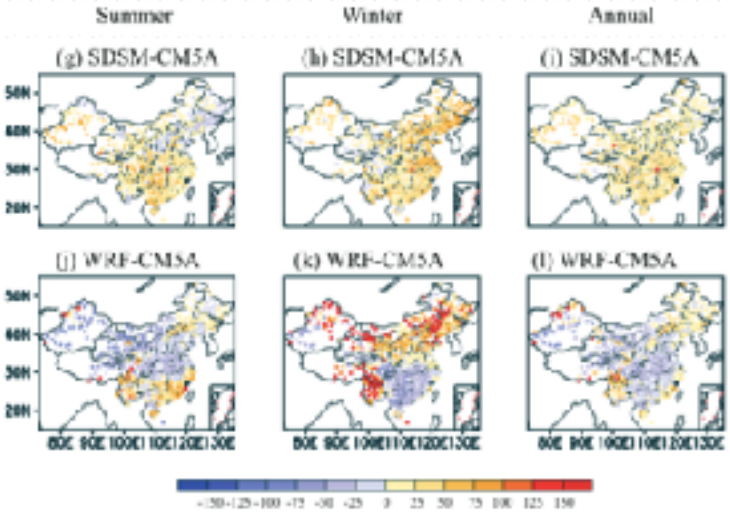
- 动力降尺度
- 统计降尺度 (线性回归、人工神经网络…)

科学问题：如何结合两种数据得到对未来更准确的气候变化预估数据?

研究背景和研究意义

动力降尺度 vs. 统计降尺度



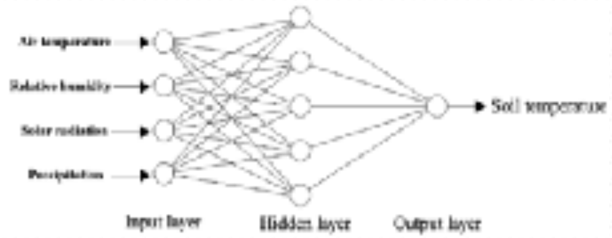


Tang et al., 2016

研究背景和研究意义

人工神经网络 vs. 多元线性回归

Fig. 3 Architecture of the neural network model used in this study



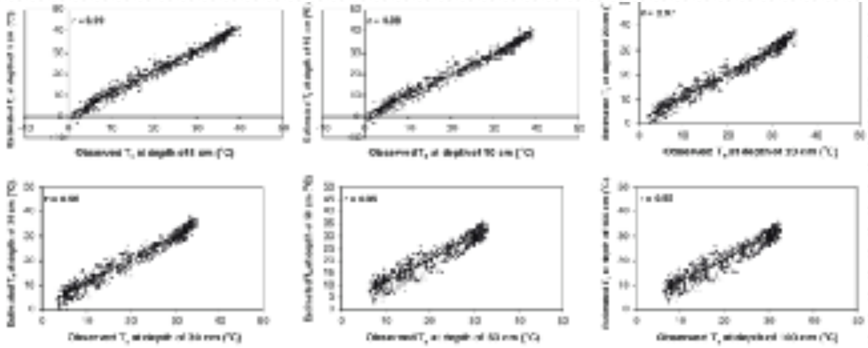


Fig. 5 Comparison of the daily T_s predicted by ANN and observed values at the testing phase

Table 5 Statistical performance evaluation criteria of MLR for all depths

Soil depth (cm)	r	RMSE	MAE	Equation
5	0.99	1.474	1.062	[illegible]
10	0.99	1.532	1.918	[illegible]
20	0.98	1.634	2.106	[illegible]
30	0.97	1.830	2.114	[illegible]
50	0.95	2.110	2.382	[illegible]
100	0.87	2.446	2.752	$T_{S,100} = 0.061T_a + 5.577RH + 7.17 \times 10^{-3}R_s - 0.244P + 7.288$

* RMSE and MAE are in ℃

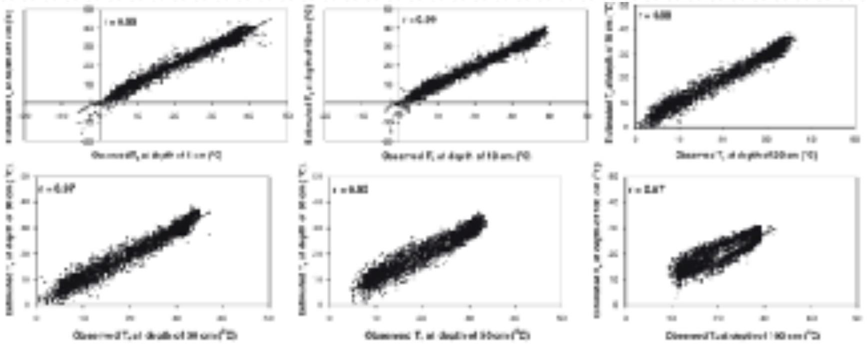


Fig. 6 Comparison of the daily Ts predicted by MLR and observed values at different depths

Part 02

数据和方法

数据和方法

研究范围： 中国地区

数据：

模式数据： CCSM4 (1° x 1.25°)

观测数据： GMFD (0.25° x 0.25°),
CRU (0.5° x 0.5°)

研究变量： 日最低温(Tmin, Jan),
日最高温(Tmax, July),
日降水量(Pr, July)

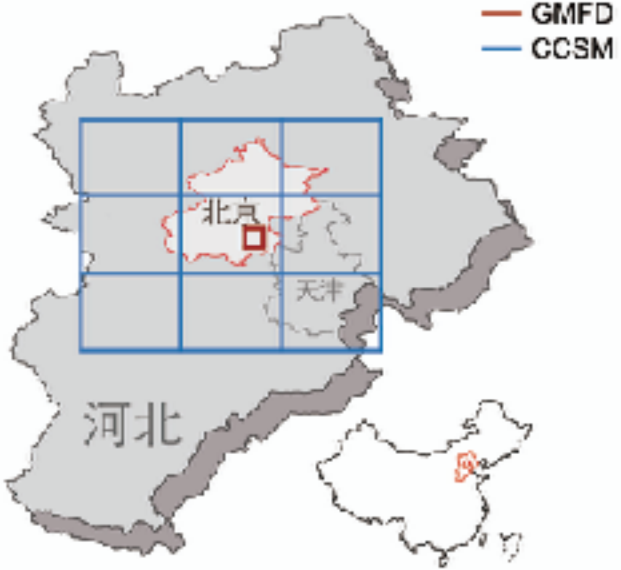


图 1 全球气候模式CCSM4和格点观测数据GMFD分辨率对比
Fig. 1 The Comparison of CCSM4 and GMFD's grids

数据和方法

研究时段：1950-2100

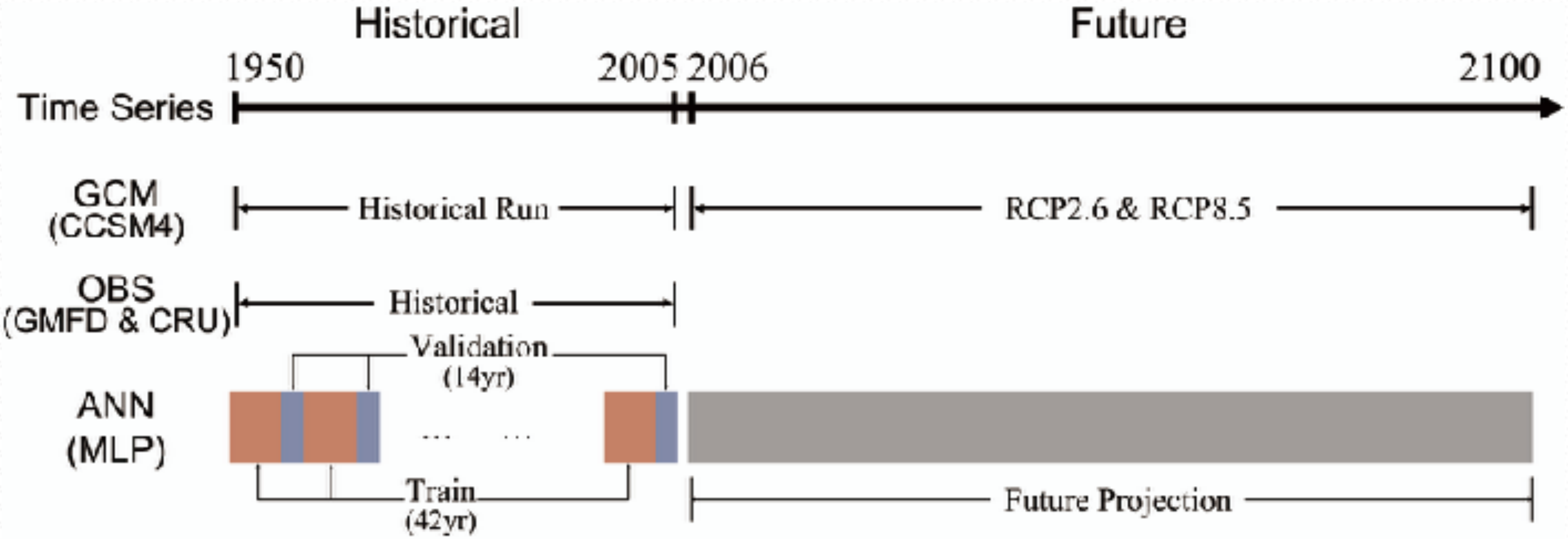
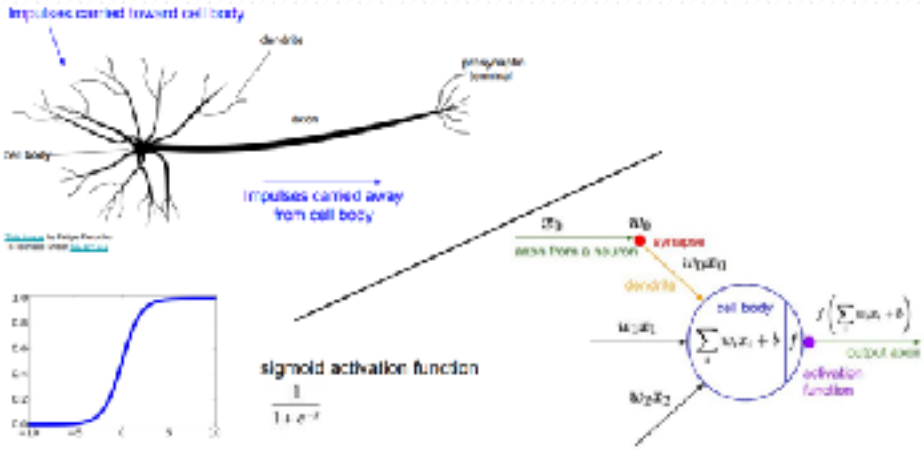


图 2 数据划分示意图

Fig. 2 Sketch map of the data

数据和方法



Fei-Fei Li CS231n

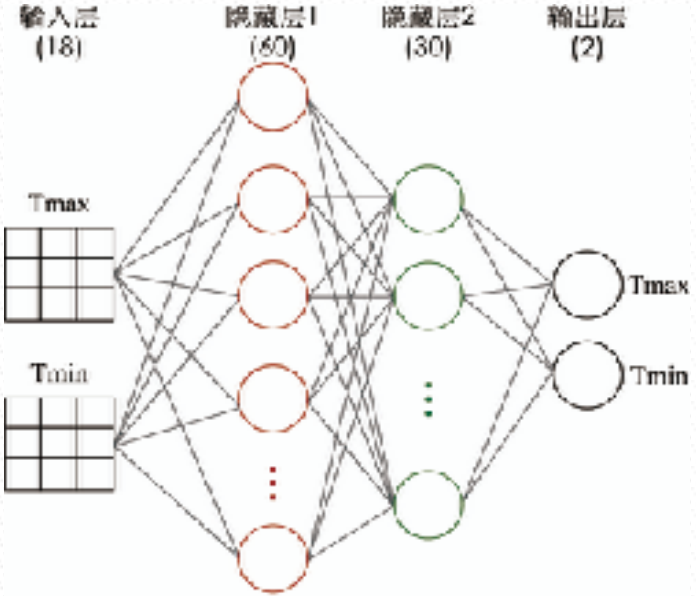
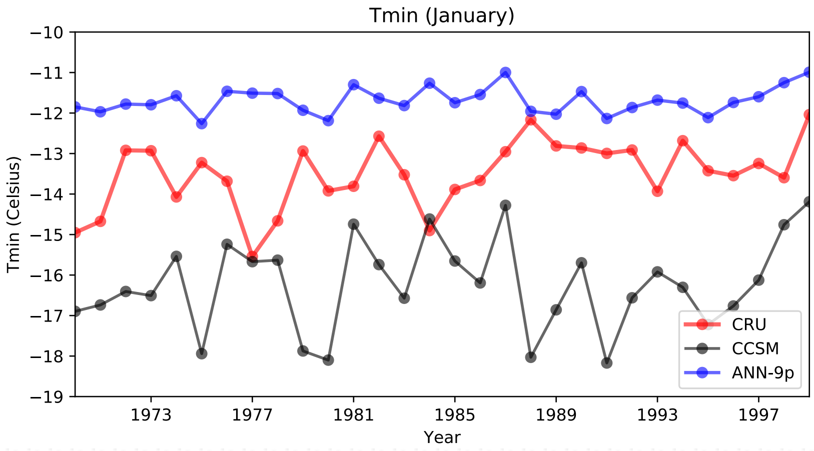
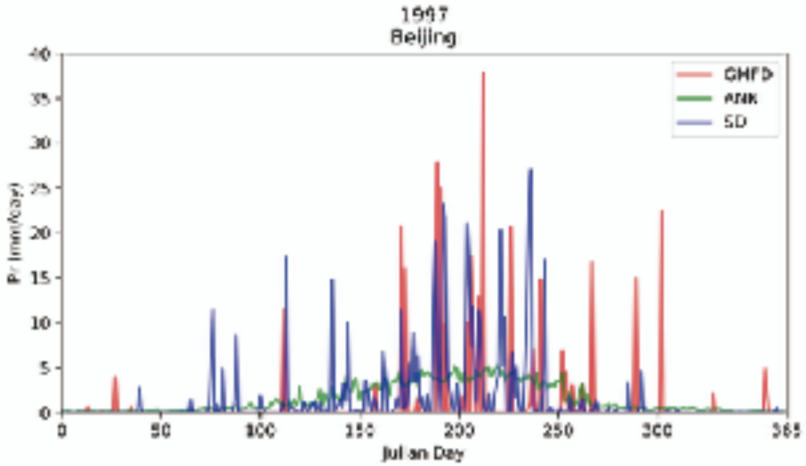


图 3 多层感知器神经网络结构
Fig. 3 The Architecture of MLP Regressor

数据和方法

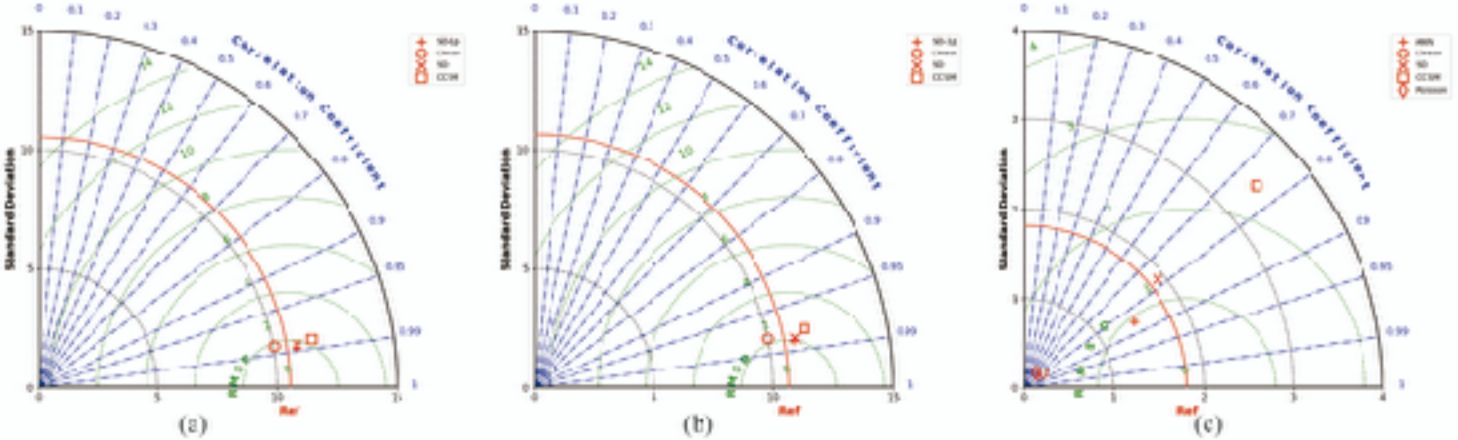




$$T_{BC}(t) = \overline{T}_{RAW} - (\overline{T}_{REF} - \overline{O}_{REF}) + \frac{\sigma_{O,REF}}{\sigma_{T,REF}}(T_{RAW}(t) - \overline{T}_{RAW})$$

$$P_{BC}(t) = \frac{\sum_{i=1}^{42} P_{Obs}}{\sum_{i=1}^{42} P_{GCM}} P_{GCM}(t)$$

数据和方法



(a) 1月日最低温；(b) 7月日最高温；(c) 7月日降水量。其中，径向坐标是标准差，角向坐标是相关系数。正十字是仅使用1个CCSM格点输入并进行偏差校正的方法，圆是多元线性回归方法，斜十字是SD方法，正方形是CCSM原始数据，菱形是泊松回归方法

图 4 日最低温、日最高温和日降水量在北京格点的不同统计降尺度方法泰勒图

Fig. 4 Taylor diagram for Tmin, Tmax, and precipitation in Beijing

Tmin

Tmax

ANN	+	BC
ANN	+	BC

SD

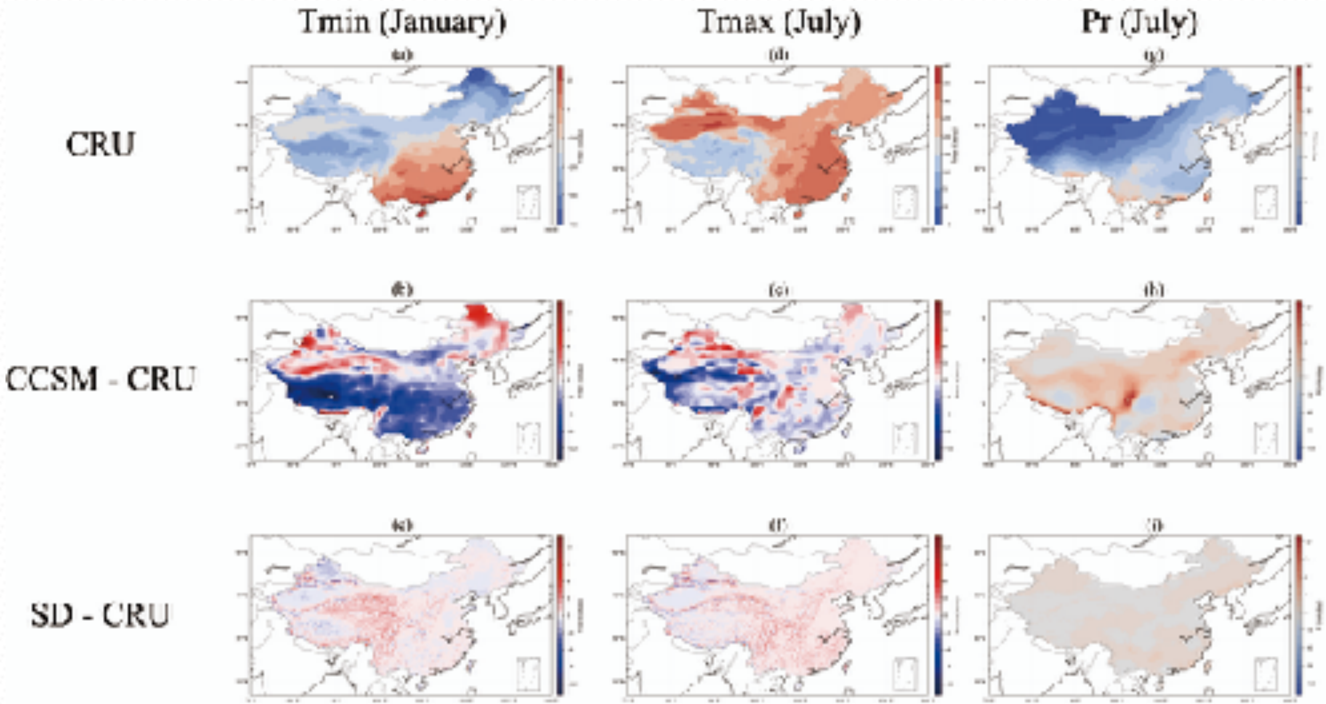
Precipitation ~~ANN~~ BC

SD

Part 03

研究结果

研究结果

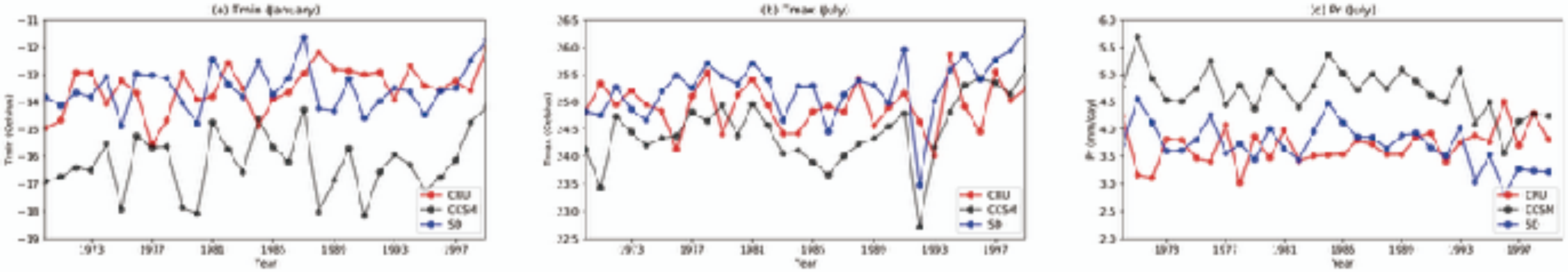


第一列(a-c)是1月日最低温，第二列(d-f)是7月日最高温，第三列(g-i)是7月日降水量。第一行(a, d, g)是1970-1999年平均CRU气候态；第二行(b, e, h)是CCSM4和CRU的差值；第三行(c, f, i)是SD和CRU的差值

图 5 1970-1999年平均日最低温、日最高温和日降水量空间分布

Fig. 5 The spatial distribution of Tmin, Tmax, and precipitaion in 1970-1999

研究结果



(a) 1970-1999年中国所有格点加权平均后1月日最低温时间序列；(b) 1970-1999年中国所有格点加权平均后7月日最高温时间序列；(c) 1970-1999年中国所有格点加权平均后7月日降水量时间序列。其中，红色实线是CRU，黑色实线是CCSM4，蓝色实线是SD

图 6 1970-1999年全中国平均日最低温、日最高温和日降水量时间序列

Fig. 6 The time series of China's Tmin, Tmax, and precipitation in 1970-1999

研究结果

表 1 全国平均日最低温、日最高温和日降水量在训练集上的表现

Table 1 The statistics of Tmin, Tmax, and precipitation of China on training samples

	Tmax			Tmin			Pr		
	OBS	CCSM	SD	OBS	CCSM	SD	OBS	CCSM	SD
Mean	25.05	24.56	**25.25**	-13.79	-16.38	**-13.62**	3.66	4.64	**3.67**
StdDev	0.43	0.73	**0.66**	1.10	**1.12**	0.86	0.33	0.47	**0.42**
RMSE	N/A	0.91	**0.73**	N/A	2.98	**1.28**	N/A	1.17	**0.59**

研究结果

表 2 全国平均日最低温、日最高温和日降水量在验证集上的表现

Table 2 The statistics of Tmin, Tmax, and precipitation of China on validation samples

	Tmax			Tmin			Pr		
	OBS	CCSM	SD	OBS	CCSM	SD	OBS	CCSM	SD
Mean	25.17	24.52	**25.21**	-13.89	-16.17	**-13.70**	3.69	4.68	**3.74**
StdDev	0.56	0.69	**0.59**	0.85	**0.88**	0.71	0.22	0.40	**0.34**
RMSE	N/A	0.89	**0.55**	N/A	2.49	**1.01**	N/A	1.09	**0.44**

Part 04

未来展望

未来展望

1. 利用现有模型对近未来时段和远未来时段的气候变化进行预估；
2. 分析中国地区未来气候变化情况。

THANK YOU

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