Projected changes of mean and extreme climate events over China under 1.5°C and 2°C based on machine learning

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Bei Jing

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Research Background

1 Research Background

- nonlinear
- high-dimensional
- hierarchical

ML → extract implicit patterns

- multi-model ensembles
- partially replacing physical processes
- bias correction
- statistical downscaling

1 Research Background

When machine learning was used in multi-model ensemble,

Comparing with MME,

How much will be improved?

Which part of area's improvement are most obvious?

What are the similarities and difference between the results projected under the 1.5℃ and 2℃ warming?

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Data and Methods

2 Data and Methods

Observations and CMIP5 models

OBS: daily gridded dataset CN05.1；

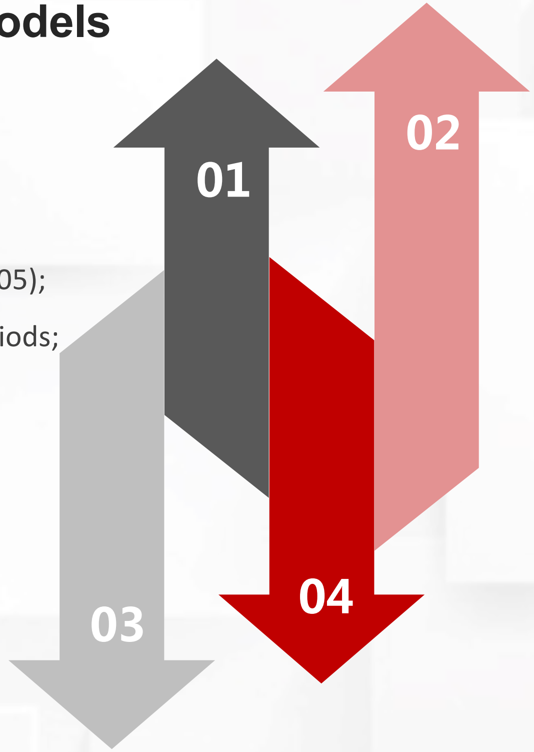
MOL: 21 CMIP5 models；

TIME: HIS: 1961—2005

(modeling: 1961– 1985; testing: 1986--2005);

RCP85: 1.5 °C / 2°C 21years window periods;

RANGE: 0 °—55 °N; 71 °-- 160 °E.



Extreme indices

TAS: The average temperature in a year;

TXx: The maximum temperature in a year;

TNn: The minimum temperature in a year;

PR: The average precipitation in a year;

R95P: The strong precipitation events in a year;

RX5DAY: The maximum 5-day precipitation in a year.

Machine leaning models

LR: Linear regression ;

ANN: Artificial neural network;

RF: Random forest;

SVR: Support vector regression

Model evaluation indices

R^2 : The square of Pearson correlation coefficient;

RMSE : The normalized root-mean-square error;

Taylor diagram;

TS: Taylor skill score.

$$TS = \frac{4(1+R_s)^2}{\left(\frac{\sigma_m}{\sigma_o} + \frac{\sigma_o}{\sigma_m}\right)^2 (1+R_0)^2}$$

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Simulation evaluation of different models during the test period

3 Simulation evaluation of different models during the test period

a. Statistical properties' simulation

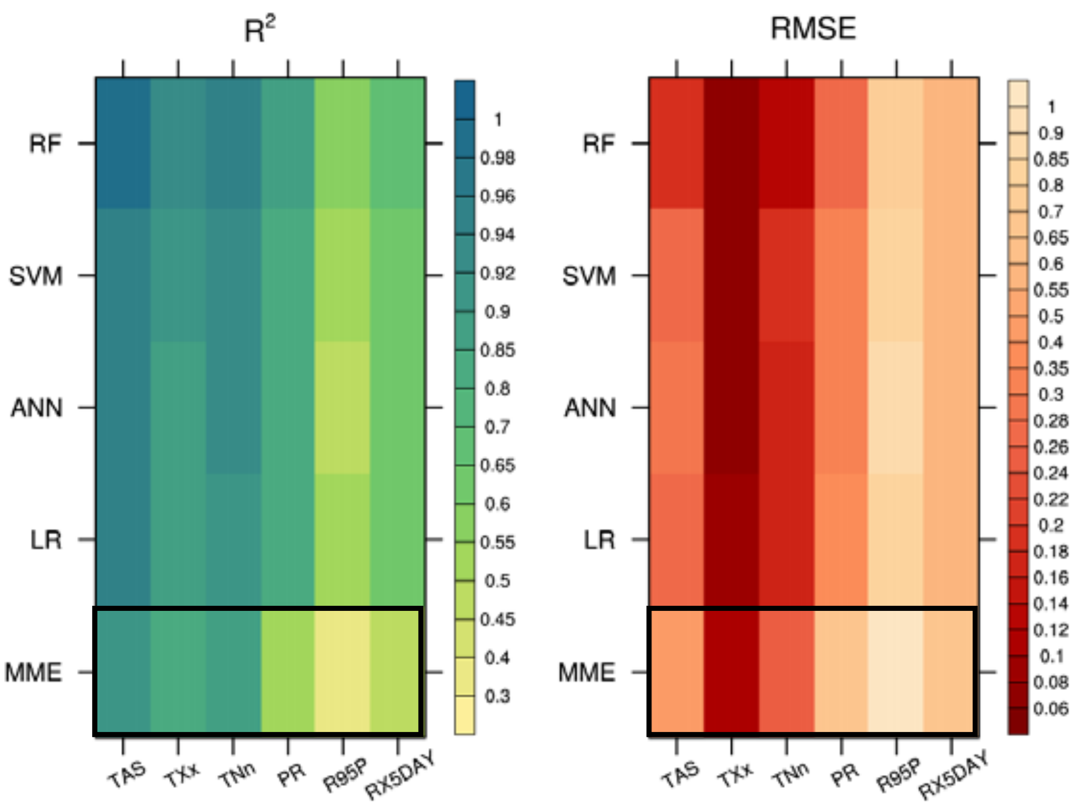


Fig1. R^2 and RMSE of four ML models and MME relative to observations for mean and extreme temperature and precipitation in the validation period 1985-2005.

Table 1. The statistical indices' relative change (%) of four ML models from MME in simulating the mean and extreme temperature and precipitation in the validation period 1985-2005.

R^2 (%)

	RF	SVR	ANN	LR
TAS	7.9	5.3	5.1	5.1
TXx	14.8	11.2	10.0	9.6
TNn	6.5	4.8	4.0	3.2
PR	64.0	55.1	54.3	50.0
R95P	55.0	39.3	31.5	40.0
RX5DAY	37.0	30.0	22.9	26.6

RMSE (%)

	RF	SVR	ANN	LR
TAS	-53.6	-34.9	-31.5	-37.9
TXx	-39.8	-31.4	-30.5	-26.6
TNn	-44.2	-25.6	-34.7	-32.4
PR	-60.6	-52.1	-51.5	-48.7
R95P	-22.6	-17.4	-14.1	-18.0
RX5DAY	-15.7	-15.7	-12.6	-10.5

3 Simulation evaluation of different models during the test period

b. Spatial simulation

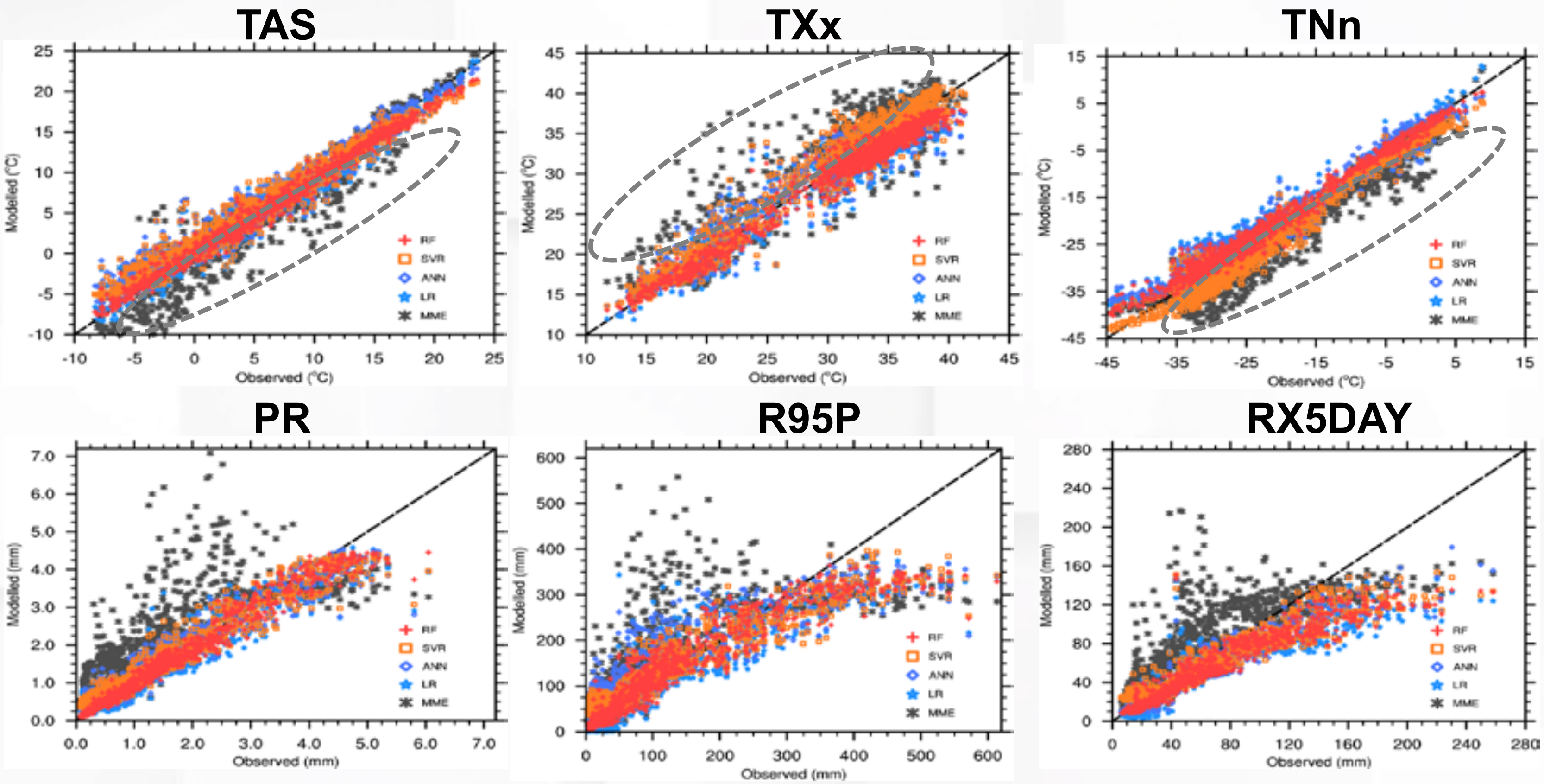


Fig 2. Quantile-Quantile plots of four machine learning ensembles and ensemble mean for mean and extreme temperature and precipitation indices in the validation period 1985-2005.

3 Simulation evaluation of different models during the test period

b. Spatial simulation

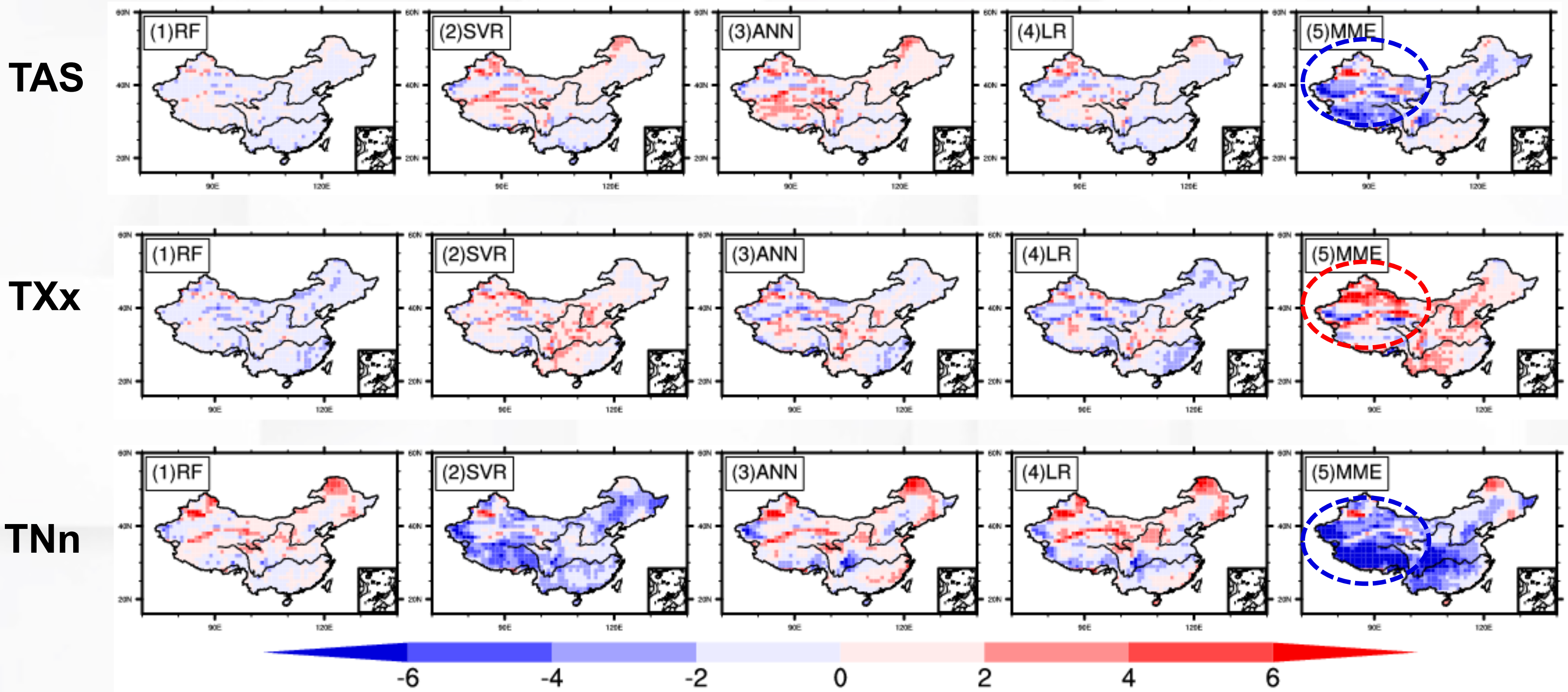
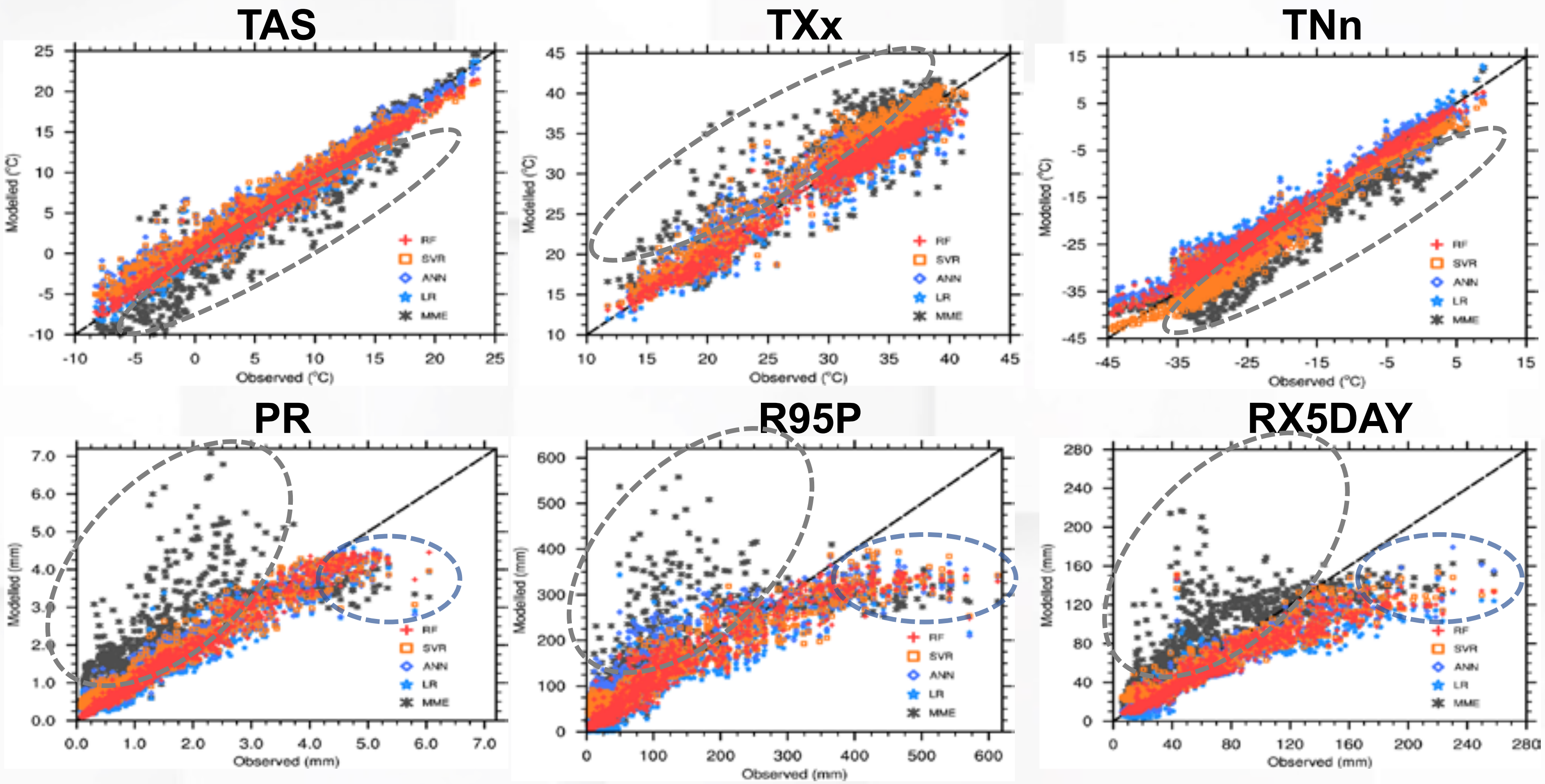


Fig 4a. The absolute bias of RF(column 1), SVR(column 2), ANN(column 3), LR(column 4), MME(column 5) for mean and extreme temperature indices in the validation period 1985-2005.

3 Simulation evaluation of different models during the test period

b. Spatial simulation



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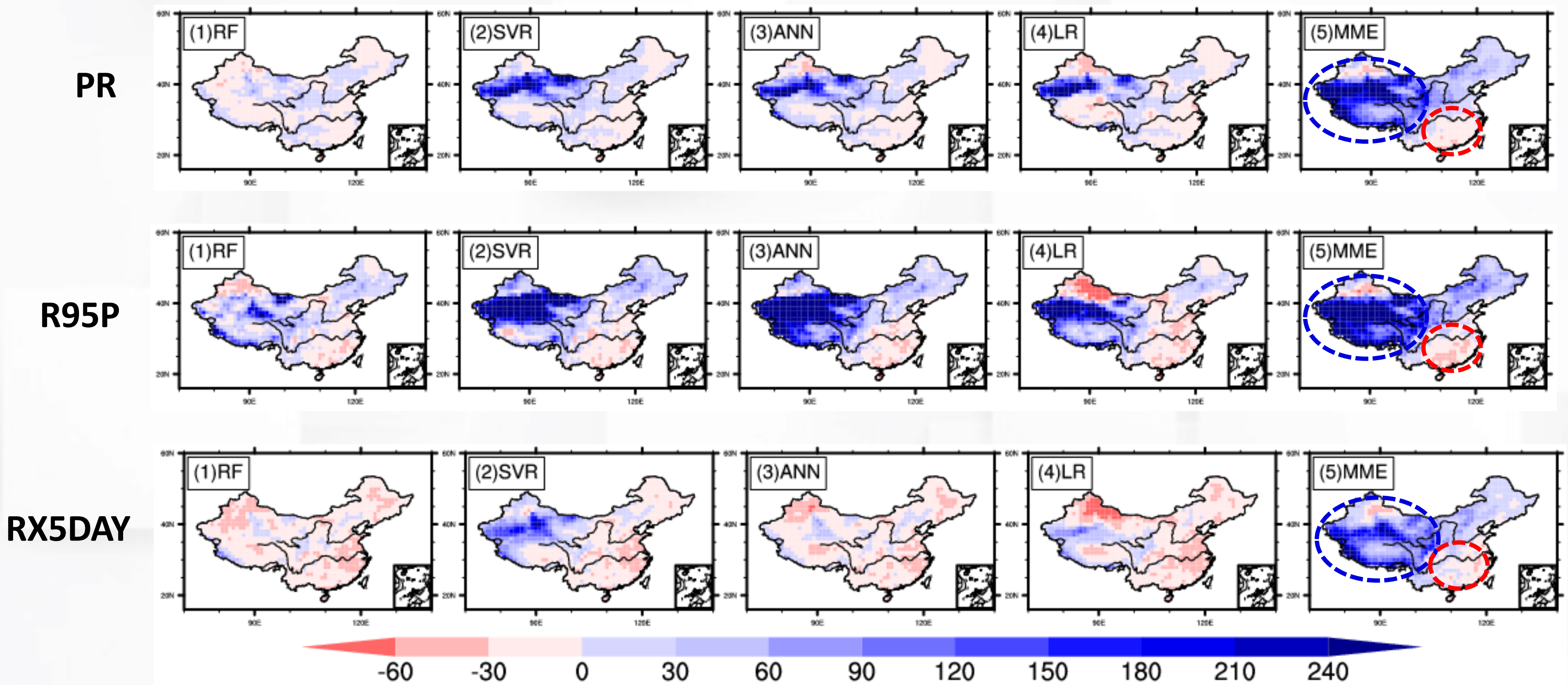


Fig 4b. The absolute bias of RF(column 1), SVR(column 2), ANN(column 3), LR(column 4), MME(column 5) for mean and extreme precipitation indices in the validation period 1985-2005.

3 Simulation evaluation of different models during the test period

b. Spatial simulation

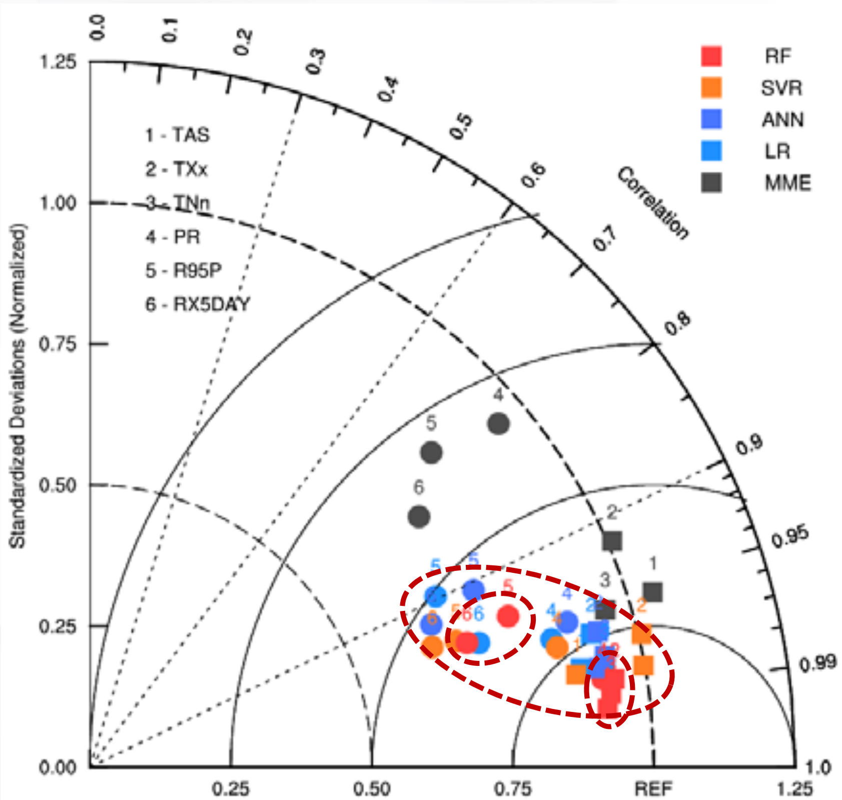
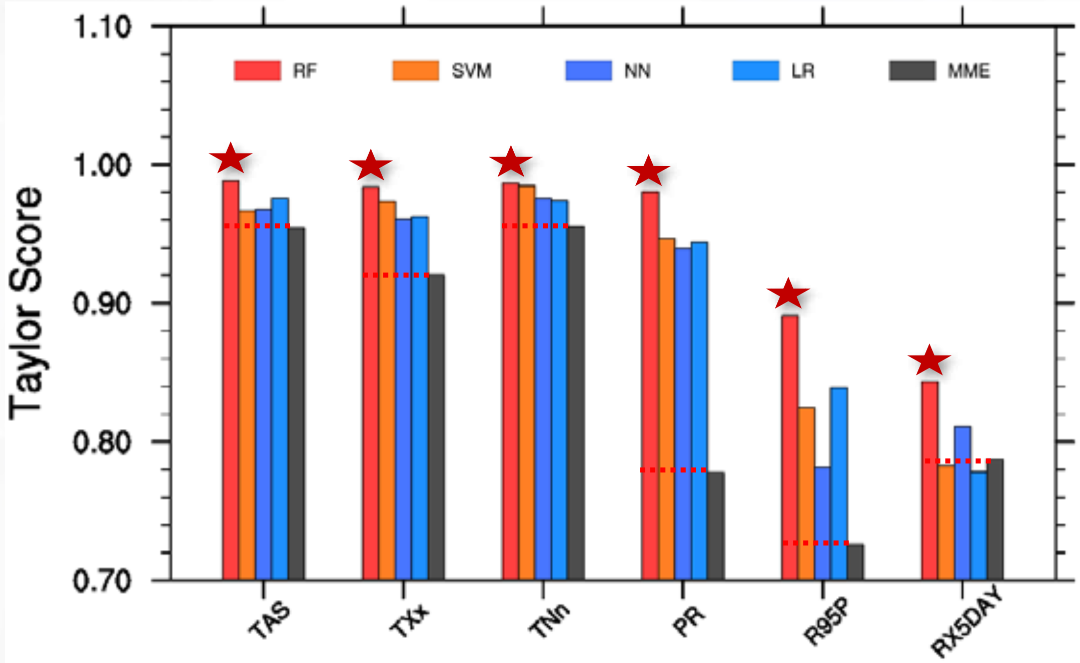


Fig 5. Taylor diagram of four machine learning ensembles and ensemble mean for mean and extreme precipitation and temperature indices in the validation period 1985-2005.

Fig 6. Four ML ensembles and ensemble mean's Taylor skill score for the mean and extreme precipitation and temperature indices in the validation period 1985-2005.



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Projections under the 1.5 °C and 2°C warming scenarios

4 Projections under the 1.5 °C and 2°C warming scenarios

a. Projected change in statistical properties

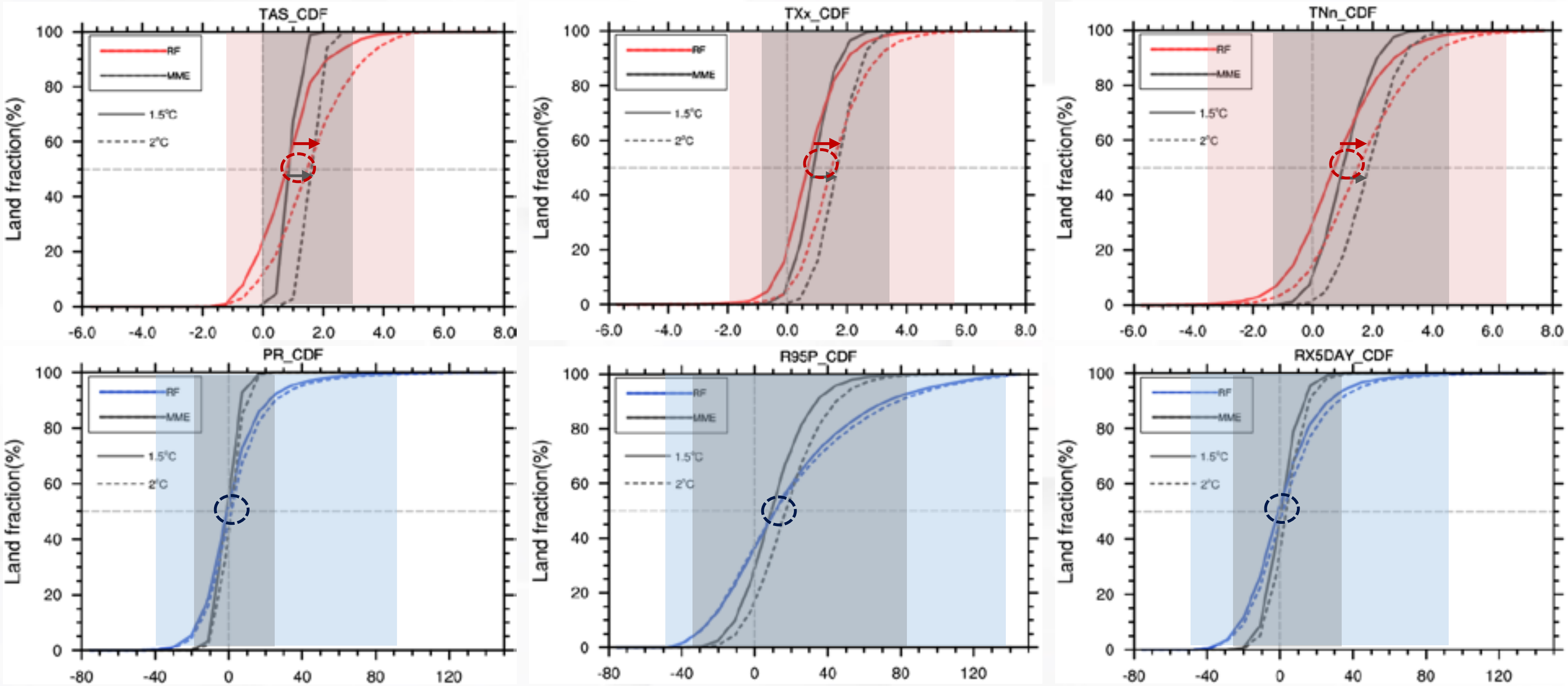
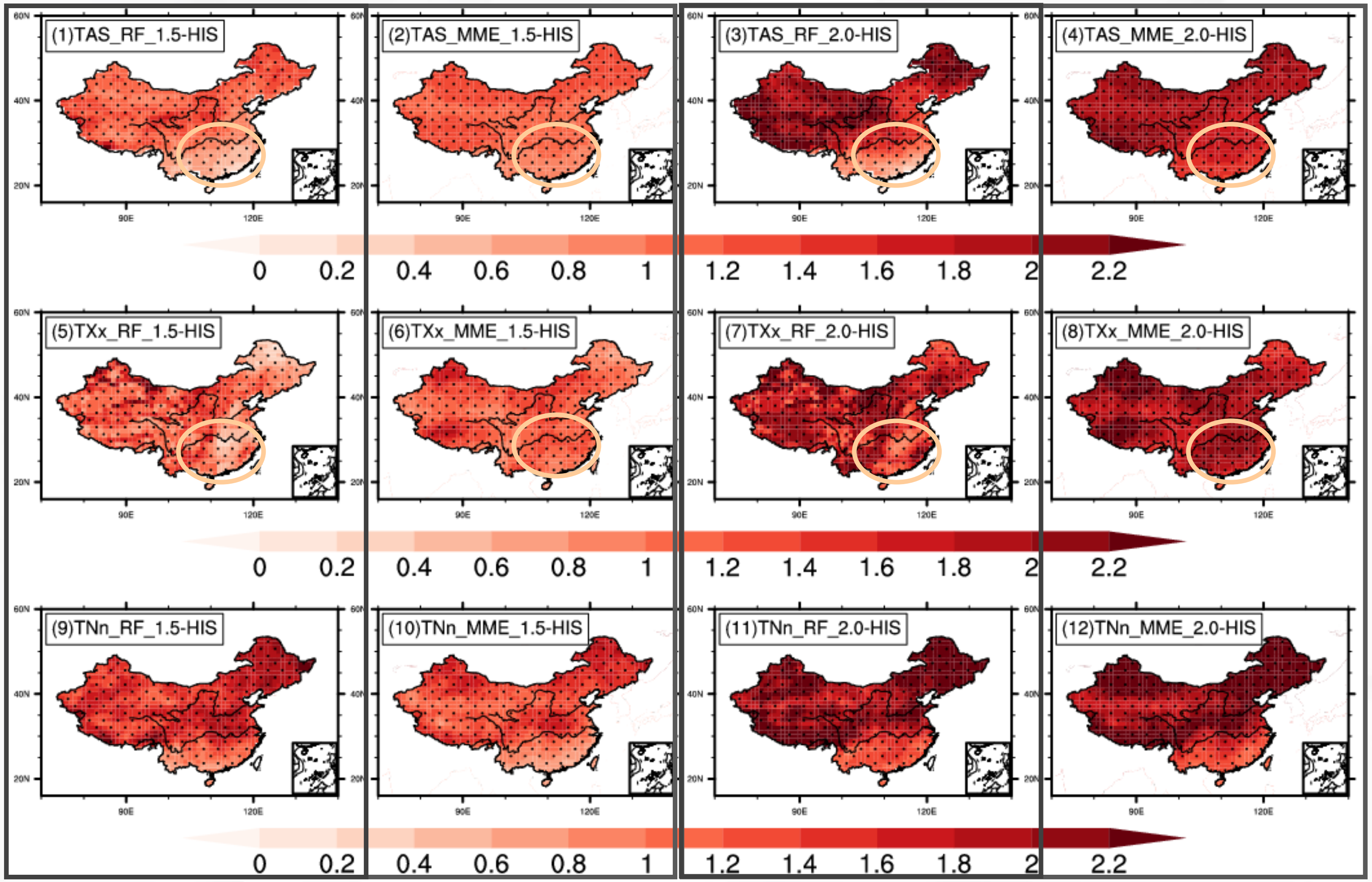


Fig 8. The spatial fraction CDFs of changes at 1.5°C and 2°C warming scenarios in mean and extreme indices for RF models and MME over China.

4 Projections under the 1.5 °C and 2°C warming scenarios

b. Projected change in spatial distribution



Hotpots:

northwestern,
southwestern,
the Hexi Corridor region

Fig 9. The changes of TAS (the first row), TXx (the second row) , TNn (the last row) under the 1.5°C and 2.0 °C warming relative to 1985—2005 reference period. Areas where with significant changes above 0.95 confidence level are marked with black dots, according to Student's t-test.

4 Projections under the 1.5 °C and 2°C warming scenarios

b. Projected change in spatial distribution

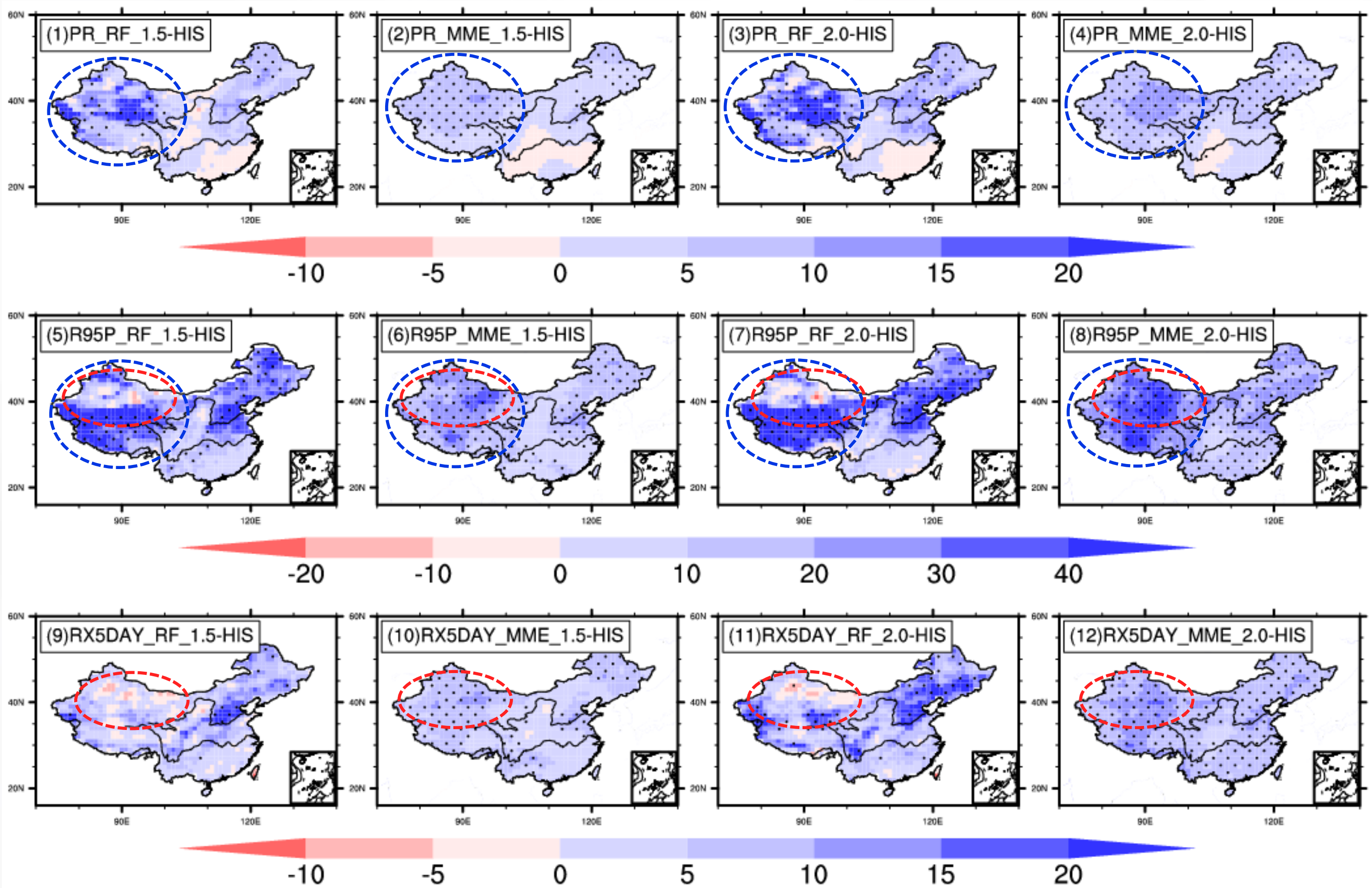


Fig 10. The same as Fig.9 but for the mean precipitation (PR), strong precipitation (R95P) and maximum five day's precipitation (RX5DAY). And the areas where with significant changes above 0.95 confidence level are marked with black dots, according to KS t-test.

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Summaries

5 Summaries

When machine learning was used in multi-model ensemble, comparing with MME,

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How much have been improved?

- R^2 : +3.2 to 64.0%; RMSE : -10.5 to 60.6%;
- The spatial pattern correlations all exceed 0.9, and the Taylor sill score have significant improvement.
- RF have the best simulation ability.

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Which part of area's improvement are most obvious?

- For the mean and lowest temperature, the low deviation in the southwestern China, especially in the Tibetan Plateau areas up to 6°C, and were corrected between -2°C and 2°C in ML ensembles.
- The wet bias exceeds 240% in the northwestern China and the Tibetan Plateau has a superior correction in machine leaning ensembles lower than 60%.

3

What is the difference between the results projected under the 1.5℃ and 2℃ warming?

- For temperature indices, the projection's spread simulated by RF ensembles are larger than MME, and the warming are slightly higher in the sensitive area and obviously lower in the southeastern region.
- For precipitation indices, the sensitive wetter area are not identical, the wetting intensity in the sensitive area are significant stronger, and for extreme precipitation, the phenomenon of getting slightly dryer is exists in the northwestern area.

THANKS

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