A Bayesian Hierarchical Model for Statistical Downscaling of Climate Extremes Using Monthly Output from CMIP5 Models

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Motivation

- Currently, statistical downscaling of climate extremes is achieved indirectly, i.e.
  - Daily outputs from GCMs are downscaled first,
  - Local information about climate extremes is then extracted from downscaled daily series.
- This is necessary to derive some indices such as those from the CLIMDEX project, but seems too expensive if only some annual extremes such as annual maximum daily precipitation (P_{max}), maximum and minimum temperatures (T_{max}, T_{min}) are desired.

Motivation

- However, it is not easy to downscale annual extremes straightforwardly, because in general observed and GCM-simulated annual extremes do not correspond to each other at the daily time scale.
- Here we present a Bayesian hierarchical approach to downscale annual extremes using observed annual extremes and monthly GCM output only, without a large space for data storage and a heavy computational burden.

Model Assumptions

- (A1) The annual maxima follow the GEV distribution having the following CDF

$$G(y;\, \mu,\, \sigma,\, \xi) = \exp\{-[1+\xi(y-\mu)/\sigma]^{-1/\xi}\} \qquad (1)$$

  where $\sigma > 0$, $1+\xi(y-\mu)/\xi > 0$. By replacing y with $-y$ and μ with $-\mu$, (1) can also be applied to annual minima.
- (A2) The monthly GCM output can be thought of as the background against which the annual climate extremes might be observed. Here for simplicity, only one predictor is chosen for each annual extreme, i.e., monthly means of daily precipitation, daily maximum and minimum temperatures for P_{max}, T_{max} and T_{min}, respectively.

Model Assumptions

- (A3) Mixed model for downscaling

$$\begin{aligned} \mu_i &= \alpha_{1j}+\alpha_{2j}x_{ij} \\ \log(\sigma_i) &= \beta_{1j}+\beta_{2j}x_{ij} \\ \xi &= \text{const.} \end{aligned} \qquad (2)$$

  where x_{ij} is the monthly mean for the jth month of the ith year in which the annual extreme y_i was observed.
- (A4) Model averaging for projecting future climate change scenarios

$$\begin{aligned} \mu_i &= \Sigma_j p_j(\alpha_{1j}+\alpha_{2j}x_{ij}) \\ \log(\sigma_i) &= \Sigma_j p_j(\beta_{1j}+\beta_{2j}x_{ij}) \end{aligned} \qquad (3)$$

  where p_j is the probability with which an annual extreme was observed in the jth month historically, $\Sigma_j p_j = 1$.

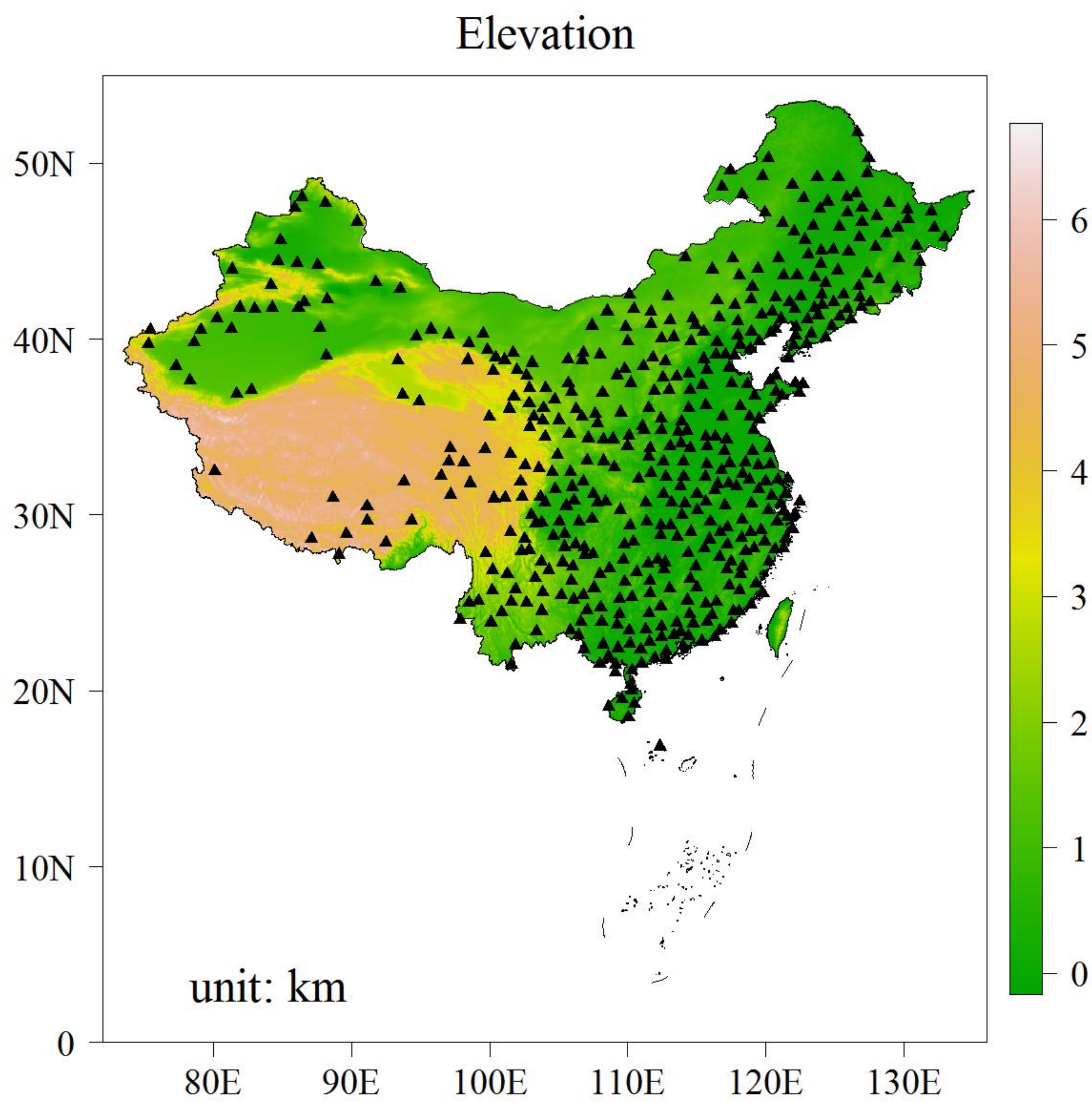
Bayesian Hierarchical Model

- Model specification
  - Data level $y_i \sim GEV(\mu_i, \sigma_i, \xi)$
  - Process level $\mu_i = \alpha_{1j}+\alpha_{2j}x_{ij}$
    $\log(\sigma_i) = \beta_{1j}+\beta_{2j}x_{ij}$
  - Prior level $[\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2], [\boldsymbol{\beta}_1, \boldsymbol{\beta}_2] \sim MVN(\boldsymbol{\gamma}, \boldsymbol{\Sigma})$
    $\xi \sim U(-5, 5)$
    $j \sim Cat(\mathbf{p})$
  - Hyperprior level ……
- Use MCMC algorithm to draw posterior samples for inference. (`R` + `JAGS`)

Applications

- Observation
  - P_{max}, T_{max} and T_{min} series from 489 stations in China
  - Start year (mostly in 1950s) – 2005, all are longer than 50 years.
- Simulation
  - BNU-ESM (Beijing Normal University - Earth System Model) is a fully-coupled earth system model for CMIP5 project.
  - Monthly means of daily precipitation, daily maximum and minimum temperatures from BNU-ESM, interpolated at station locations as predictors.
  - Historical simulation: 1951 – 2005

    RCP2.6, RCP4.5, RCP8.5: 2006 – 2065



Elevation
50N
40N
30N
20N
10N
0
80E
90E
100E
110E
120E
130E
unit: km
6
5
4
3
2
1
0

Fig. 1

Return Level Analysis

- Let $G(y_p) = 1-p$, then the quantile
  $y_p = \mu-\sigma\{1-[-\log(1-p)]^{-\xi}\}/\xi$, for $\xi \neq 0$;
  $\mu-\sigma\{1-[-\log(1-p)]\}$, for $\xi = 0$ (4)
  is the return level (RL) associated with the return period $1/p$. We will focus on
  - $y_{0.5}$: 2-year RL, ‘ordinary state’;
  - $y_{0.02}$: 50-year RL, ‘extreme state’.
- Take (2) into (4), the rate of change of an RL: $r_p \equiv \mathrm{d}y_p/\mathrm{d}x$ can be derived.

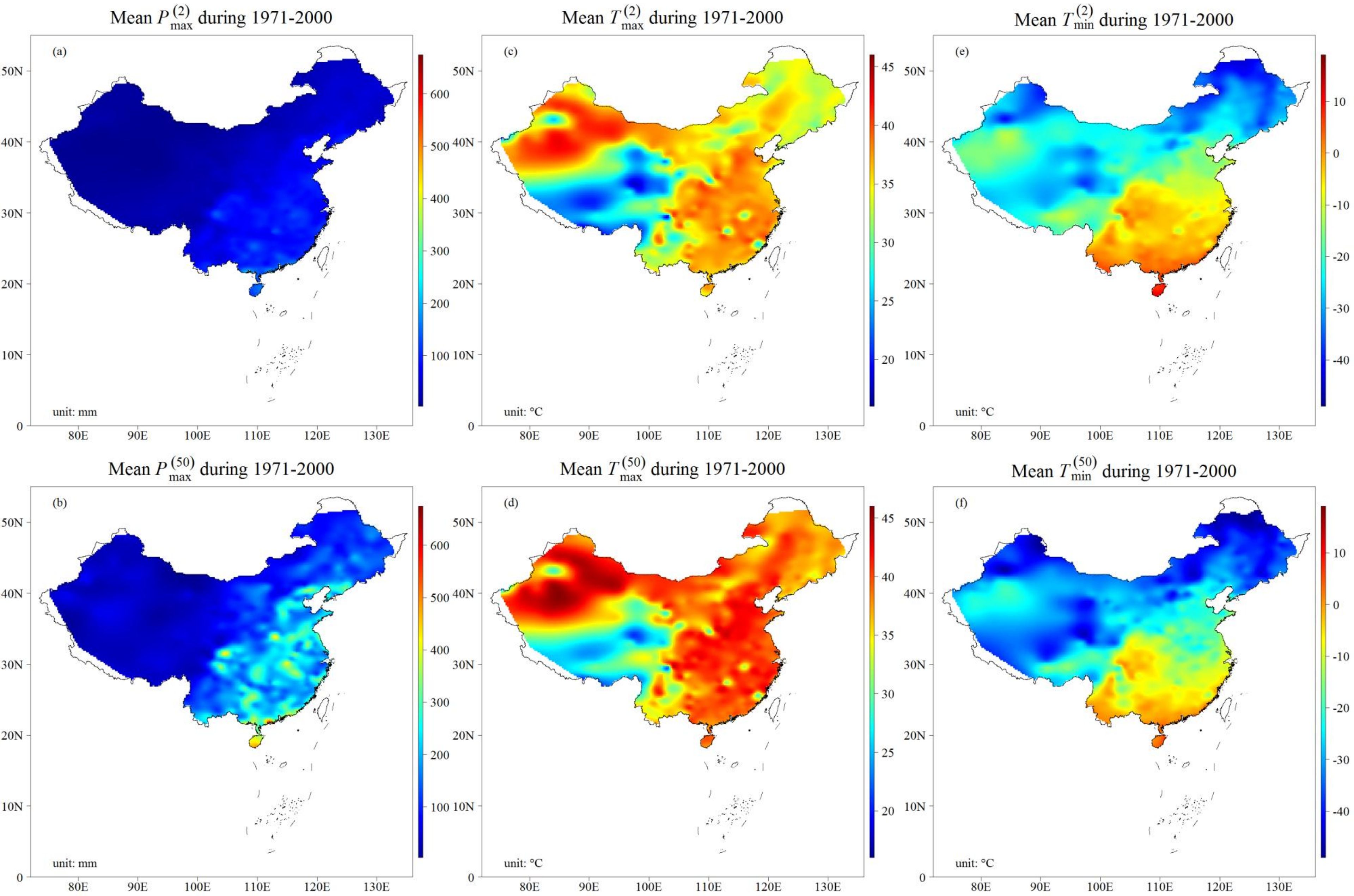


Fig.2 30-year means of 2-year (upper) and 50-year (lower) RLs during 1971-2000

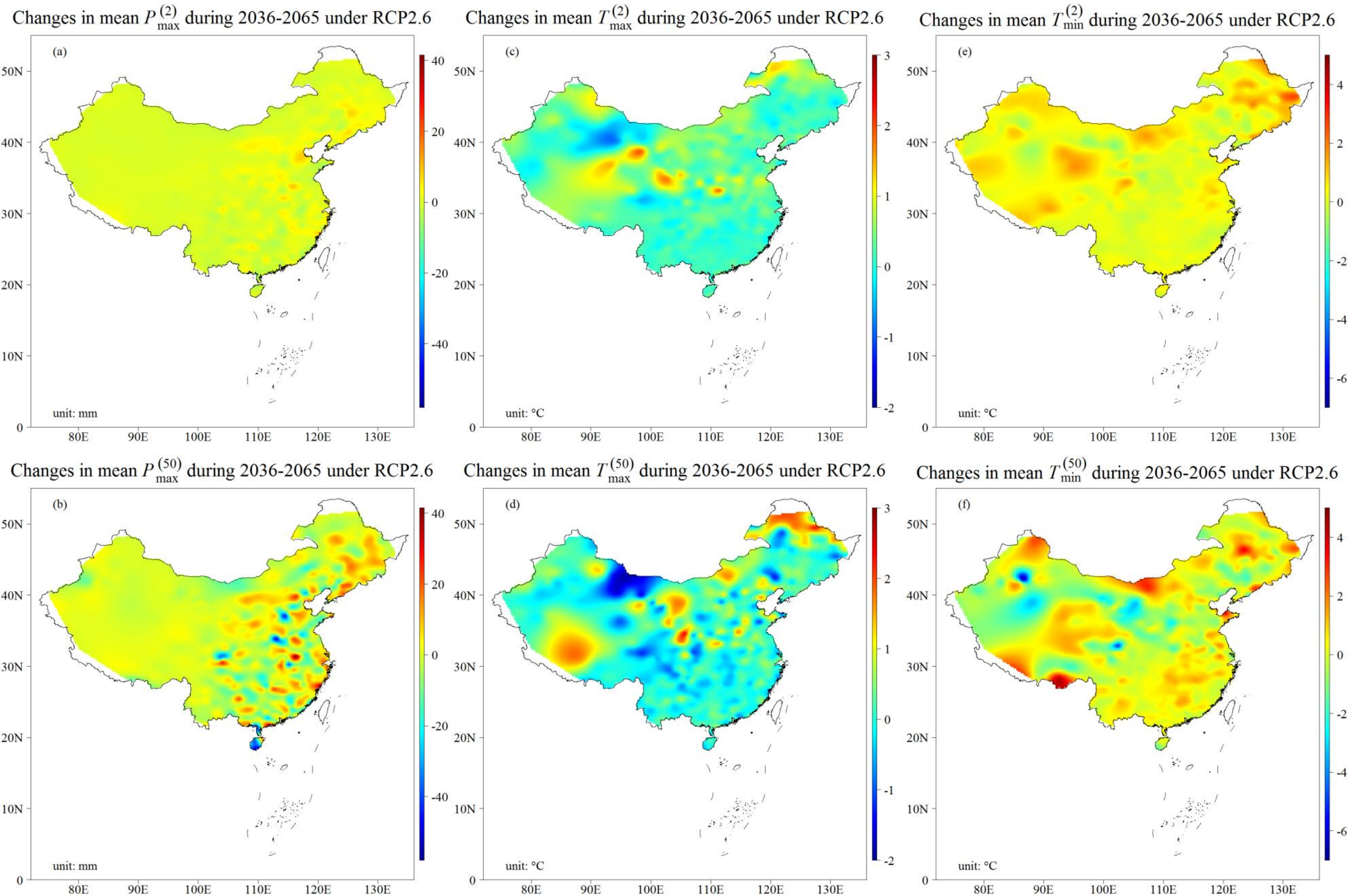


Fig.3 Changes in 30-year means of RLs during 2036-2065 under RCP2.6 relative to 1971-2000

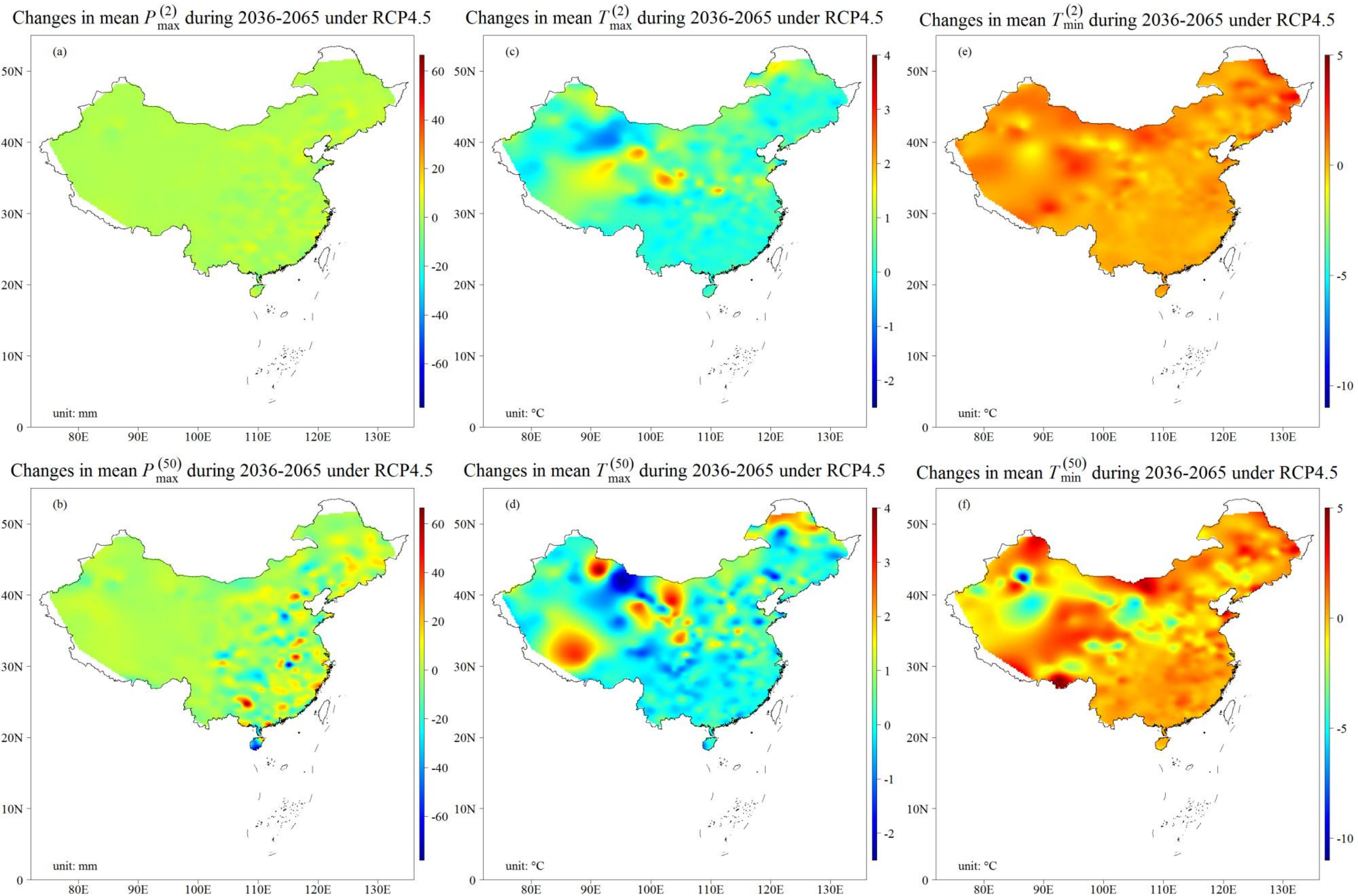


Fig.4 Changes in 30-year means of RLs during 2036-2065 under RCP4.5 relative to 1971-2000

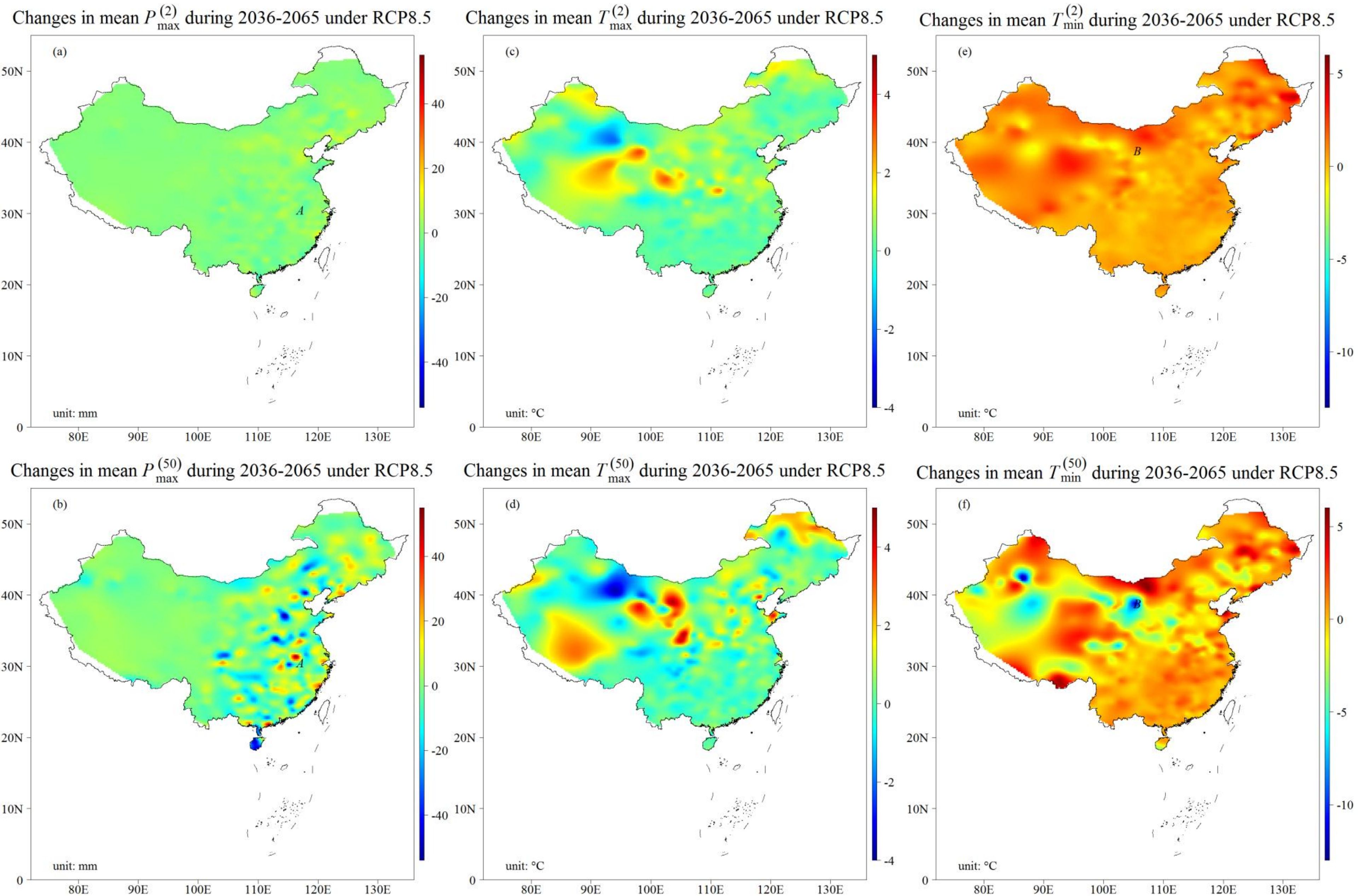


Fig.5 Changes in 30-year means of RLs during 2036-2065 under RCP8.5 relative to 1971-2000

Return Level Analysis

- The results show that
  - Changes in 50-year RLs are always greater than those in 2-year RLs.
  - P_{max} changes most greatly under RCP4.5; T_{max} and T_{min} under RCP8.5.
  - There are many cases in which $r_{0.5}$ and $r_{0.02}$ have opposite signs.

Case Study

- More attentions should be paid to a special change pattern: while the ‘ordinary state’ of an extreme is moderating, its ‘extreme state’ is getting more extreme.
  - Example 1: P_{max} at station *A* under RCP8.5: $r_{0.5} < 0$, $r_{0.02} > 0$, increasing trend in x.
  - Example 2: T_{min} at station *B* under RCP8.5: $r_{0.5} > 0$, $r_{0.02} < 0$, increasing trend in x.
- In both examples, while people feel that climate extremes are moderating, record-breaking extreme events may happen unexpectedly.

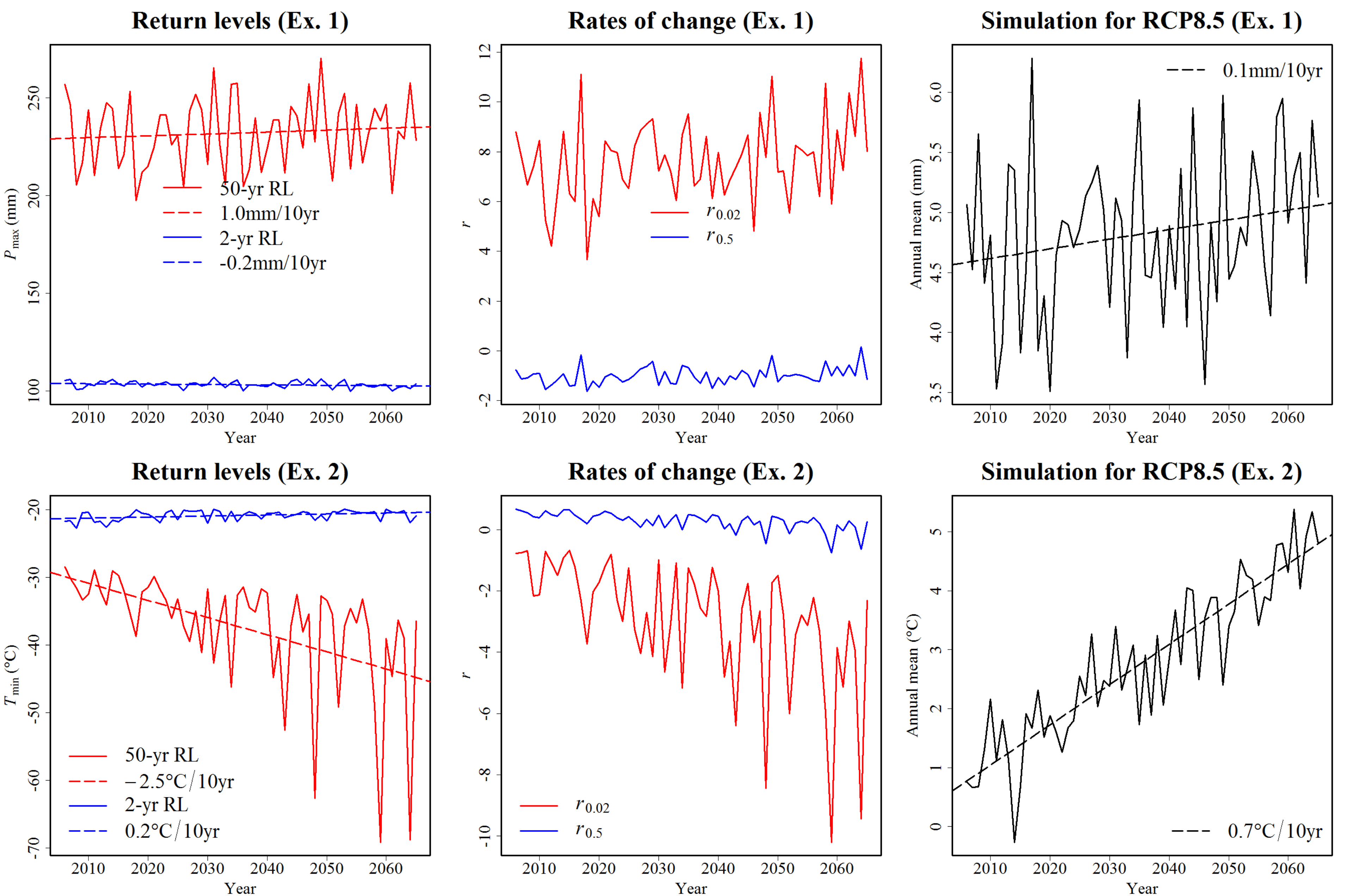


Fig.6 Examples of opposite trends in $y_{0.5}$ and $y_{0.02}$: P_{max} (upper) and T_{min} (lower) under RCP8.5.

Conclusions

- A Bayesian hierarchical model for direct downscaling of annual extremes is developed. Only monthly means from GCMs is required as model predictors.
- The model is applied to project annual extremes in China under future climate change scenarios simulated by BNU-ESM.
- 'Ordinary state' and 'extreme state' of climate extremes may show contrary trends under certain climate change conditions. More attentions should be paid to the potentially enhancing trend in 'extreme state' associated with disasters.

Thank you for your attention!