Mapping Temperature Changes

Xin Qi, Miaoni Gao, Tao Zhu, Siyu Li, Sicheng He, and Jing Yang

1 Introduction

Under the background of global warming, extreme temperature events have significantly increased and hit various parts of the globe (Alexander et al. 2006; Piao et al. 2010; Fischer and Knutti 2014; Gao et al. 2019; Qi et al. 2019)—for example, extreme high temperature occurred during the summer of 2010 over Central Europe-Russia (Grumm 2011) and the super cold surge swept across China at the end of 2020 (Zheng et al. 2021). As a serious worldwide challenge, extreme temperature events bring severe damages to public health, agricultural production, and socioeconomic systems (Easterling et al. 2000; Sun et al. 2018; Wang et al. 2019). Therefore, assessing future global temperature changes is crucial for tackling climate change and disaster mitigation and prevention.

Several studies have attempted to project future changes in temperature at the global scale or with a focus on certain regions through the coarse global climate models (GCMs) or high-resolution regional climate models (Zobel et al. 2017;

Dosio et al. 2018; Nangombe et al. 2018). However, the global temperature changes including the mean state, variance, and extreme temperature in the future based on fine-resolution multiple GCM outputs are rarely reported in the previous literature. A high-resolution ($0.25^\circ \times 0.25^\circ$) dataset named NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) has been released (Thrasher et al. 2012, 2013), which enables the temperature assessment from a global perspective. NEX-GDDP is a statistical downscaling dataset using the bias correction and spatial disaggregation method based on the simulations of the GCMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) and historical observation (Wood et al. 2004; Maurer et al. 2010). Compared with the original GCM outputs, the historical fidelity of climatology and extreme temperature derived from the downscaled NEX-GDDP has been improved (Bao and Wen 2017; Luo et al. 2020), which provides us a new opportunity to perform a comprehensive assessment of future changes in temperature.

Therefore, this section initiatively investigates the prospective changes in the mean state, variance, and extreme values of global temperature under three greenhouse gas emissions scenarios, including Representative Concentration Pathway (RCP) 2.6, RCP4.5, and RCP8.5, for two target periods (the 2030s and 2050s). The present results provide a fundamental reference for the relevant climate risk identification and assessment.

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2 Data

The global daily maximum and minimum temperature for the period from 1950 to 2100 were retrieved from the NEX-GDDP dataset, including downscaled projections from the 21 models under RCP4.5 and RCP8.5 greenhouse gas emissions scenarios for which daily datasets were produced and distributed under CMIP5. The spatial resolution of the data is 0.25° ($\sim 25 \text{ km} \times 25 \text{ km}$). In addition, the projection with the same resolution for RCP2.6 from the 13 models was assimilated by the Institute of Atmospheric Physics (IAP) and Chinese Academy of Sciences (CAS), which covers the region between 60°S and 90°N (Xu and Wang 2019). The NEX-GDDP dataset can be freely accessed on the following website: <https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp>.

3 Method

Here the temporal range is divided into three periods: the historical period (2000s) defined as 1986–2005, the future period 2030s (2016–2035), and the future period 2050s (2046–2065). Note that summer and winter refer to June–July–August (JJA) and December–January–February (DJF), respectively. Furthermore, the extreme temperature is measured by both an absolute index (TXx) and two percentile indices ($TX90p$ and $TN10p$) according to the definitions of extremes indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Karl and

Easterling 1999; Zhang et al. 2011; Fan et al. 2020). $Tmean$ is defined as the average daily minimum and maximum temperature. $Tstd$ is defined as the standard deviation of the daily mean temperature. TXx refers to the multi-model ensemble of annual maximum near-surface air temperature during the historical period or future time periods based on the NEX-GDDP models. $TX90p$ ($TN10p$) refers to the percentage of the days with the daily maximum (minimum) temperature exceeding (below) the local calendar day 90th (10th) percentile centered on a 5-day window for the base period 1961–1990. In addition, The $Tmean$ change is calculated by subtracting the $Tmean$ during the historical period (2000s) from the $Tmean$ under the RCP scenarios in the future. The model uncertainty of the $Tmean$ is represented by the standard deviation of the $Tmean$ under the RCP scenarios during the different periods based on all selected models. Changes and model uncertainties of $Tstd$, TXx , $TX90p$, and $TN10p$ are calculated in the same way as $Tmean$.

4 Major Findings

Figure 1 shows the daily $Tmean$ over nine regions under different greenhouse gas emissions scenarios, respectively, for the 2030s and 2050s. Compared to the historical period (gray bar), the nine selected regions in all RCP scenarios are expected to experience warming in the future. Under the same RCP scenarios, $Tmean$ in the 2050s is higher than in the 2030s in all regions.

Fig. 1 Area-averaged $Tmean$ in nine regions under different Representative Concentration Pathway (RCP) scenarios. The error bar represents the one standard deviation across all selected models—13 general circulation models (GCMs) (RCP2.6) and 21 GCMs (RCP4.5 and RCP8.5). NAS, MED, NAU, SQF, AMZ, TIB, EAS, SEA, and ENA represent North Asia ($47\text{--}70^\circ\text{N}$, $60.5\text{--}180.5^\circ\text{E}$), Mediterranean

Basin ($30\text{--}47^\circ\text{N}$, $10.5^\circ\text{W}\text{--}37.5^\circ\text{E}$), Northern Australia ($28\text{--}10^\circ\text{S}$, $109.5\text{--}155.5^\circ\text{E}$), South Equatorial Africa ($26\text{--}0^\circ\text{S}$, $0.5\text{--}55.5^\circ\text{E}$), Amazon Basin ($20^\circ\text{S}\text{--}10^\circ\text{N}$, $78.5\text{--}34.5^\circ\text{W}$), Tibet ($30\text{--}47^\circ\text{N}$, $80.5\text{--}104.5^\circ\text{E}$), East Asia ($20\text{--}47^\circ\text{N}$, $104.5\text{--}140.5^\circ\text{E}$), Southeast Asia ($10^\circ\text{S}\text{--}20^\circ\text{N}$, $100.5\text{--}150.5^\circ\text{E}$), and Eastern North America ($25\text{--}50^\circ\text{N}$, $85.5\text{--}60.5^\circ\text{W}$), respectively. The regional division follows Giorgi and Bi (2005)

Fig. 2 Standard deviation of the daily mean temperature (T_{std}) in nine regions under different Representative Concentration Pathway (RCP) scenarios. The error bar represents the one standard deviation across all selected models. Region abbreviations are the same as in Fig. 1

Fig. 3 Annual maximum near-surface air temperature (TX_x) in nine regions under different Representative Concentration Pathway (RCP) scenarios. The error bar represents the one standard deviation across all selected models. Region abbreviations are the same as in Fig. 1

The standard deviations of the daily mean temperature for the nine regions under different greenhouse gas emissions scenarios are shown in Fig. 2. The temperature deviations in most areas are about 0.4 °C in all scenarios. In comparison, the North Asia region exhibits the largest temperature deviation with high uncertainty, while the lowest deviations appear in South Equatorial Africa and Southeast Asia under the RCP2.6 scenarios.

The annual maximum near-surface air temperature for the nine regions under different RCP scenarios is shown for

three epochs in Fig. 3. Similar to the T_{mean} , the rising TX_x occurs in all regions under all scenarios in comparison with the historical period (gray bar). Regions with high TX_x are mainly located in the Mediterranean Basin, Northern Australia, and the Amazon Basin. Additionally, the TX_x difference between the 2050s and the 2030s is larger under the RCP8.5 scenarios.

The percentage of the days with a daily maximum temperature greater than the 90th percentile of the base period for the nine regions under different RCP scenarios is shown

Fig. 4 Percentage of the days with the daily maximum temperature greater than the 90th percentile of the base period ($TX90p$) in nine regions under different Representative Concentration Pathway (RCP) scenarios. The error bar represents the one standard deviation across all selected models. Region abbreviations are the same as in Fig. 1

(RCP) scenarios. The error bar represents the one standard deviation across all selected models. Region abbreviations are the same as in Fig. 1

Fig. 5 Percentage of the days with the daily minimum temperature less than the 10th percentile of the base period ($TN10p$) in nine regions under three Representative Concentration Pathway (RCP) scenarios. The error bar represents the one standard deviation across all selected models. Region abbreviations are the same as in Fig. 1

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in Fig. 4. Invariably, $TX90p$ will increase significantly in all regions in the future, regardless of the scenario. In particular, in the 2050s, $TX90p$ is expected to even exceed the historical period by a factor of four under the RCP8.5 scenario.

The percentage of the days with the daily minimum temperature less than the 10th percentile of the base period is shown for the nine regions under the three RCP scenarios in

three epochs in Fig. 5. Compared to the historical period (gray bar), six of the nine selected regions—North Asia, the Mediterranean Basin, Northern Australia, South Equatorial Africa, Southeast Asia, and Eastern North America—are expected to have a decreased $TN10p$ in the future in all RCP scenarios. In the 2030s, $TN10p$ in the other three regions (the Amazon Basin, Tibet, and East Asia) increases under RCP2.6.

5 Maps

Annual mean temperature (Baseline)

Annual mean temperature (2030s, RCP2.6)

Annual mean temperature (2030s, RCP4.5)

Annual mean temperature (2030s, RCP8.5) **Annual mean temperature (2050s, RCP2.6)**

Annual mean temperature (2050s, RCP4.5)

Annual mean temperature (2050s, RCP8.5)

Annual mean temperature variability (2030s, RCP2.6)

Annual mean temperature variability (2030s, RCP4.5)

Annual mean temperature variability (2030s, RCP8.5) **Annual mean temperature variability (2050s, RCP2.6)**

Annual mean temperature variability (2050s, RCP4.5)

Annual mean temperature variability (2050s, RCP8.5)

Annual maximum air temperature (2030s, RCP2.6)

Annual maximum air temperature (2030s, RCP4.5)

Annual maximum air temperature (2030s, RCP8.5) **Annual maximum air temperature (2050s, RCP2.6)**

Annual maximum air temperature (2050s, RCP4.5)

Annual maximum air temperature (2050s, RCP8.5)

Percentage of days when Tmin < 10th percentile (2030s, RCP2.6)

Percentage of days when Tmin < 10th percentile (2030s, RCP4.5)

Percentage of days when $T_{min} < 10$ th percentile (2030s, RCP8.5)

Percentage of days when $T_{min} < 10$ th percentile (2050s, RCP2.6)

Percentage of days when $T_{min} < 10$ th percentile (2050s, RCP4.5)

Percentage of days when $T_{min} < 10$ th percentile (2050s, RCP8.5)

Percentage of days when Tmax > 90th percentile (2030s, RCP2.6)

Percentage of days when Tmax > 90th percentile (2030s, RCP4.5)

Percentage of days when Tmax > 90th percentile (2030s, RCP8.5) **Percentage of days when Tmax > 90th percentile (2050s, RCP2.6)**

Percentage of days when Tmax > 90th percentile (2050s, RCP4.5) **Percentage of days when Tmax > 90th percentile (2050s, RCP8.5)**

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