DTR in Winter Wheat Growing Regions of China: CMIP6 Models Evaluation and Comparation

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Abstract

Winter wheat is widely planted in China. The changes of winter wheat yield and quality are related to the food security of human society. Climate change has an important impact on the yield and quality of winter wheat. Diurnal temperature range (DTR) is an important factor affecting the yield and protein content of winter wheat. Furthermore, climate model is one of the main sources of error in crop model simulations of yields. Therefore, how to improve the accuracy of climate data has become an important concern for scholars. Previous model evaluations for the entire country or region cannot answer which model is suitable for the estimation of future winter wheat yield. Therefore, we evaluated the ability of climate models to simulate DTR within the range of winter wheat growing regions in China to identify the most suitable climate models for winter wheat yield and quality projections. The results show that CMIP6 models can basically reproduce the DTR of winter wheat-growing regions in China, but there are discrepancies in the simulations between nationwide and winter wheat-growing regions. EC-Earth3-Veg has the best simulation of climate DTR for wheat-growing regions (TS=0.848) and nationwide (TS=0.842), and ACCESS-CM2 has the strongest ability to simulate the annual growing season DTR (TS=0.46). In summary, in the estimation of future winter wheat yield, attention should be given to the selection of models suitable for the actual growing regions and the growing seasons of winter wheat.

Highlights

1. Significant differences were found between the ability of CMIP6 models to simulate climate for China and the winter wheat-growing regions in China.

2. Real Chinese winter wheat-growing regions are selected for the CMIP6 models evaluation to obtain more accurate assessment results.

3. Recommendations are made for the most suitable model to simulate diurnal temperature range in winter wheat-growing regions of China.

4. Provide guidance and recommendations for winter wheat yield prediction.

1 Introduction

Winter wheat is widely grown in China (Cao et al., 2011; Song and Dong, 2006) and is one of the major food sources for humans. The changes of winter wheat yield and quality are related to the food security of human society. It is necessary to estimate the future yield of winter wheat. The protein content of wheat is known to be influenced by the environment and other factors (Rao et al., 1993; Baenziger et al., 1985; Vaughan et al., 1990; Smika and Greb, 1973). The yield, quality and growing season of winter wheat vary with geographical location (Wu et al., 2021). Climate change has an important impact on the yield and quality of winter wheat. The diurnal temperature range (DTR) is one of the most important agrometeorological variables in agricultural production. The quality of crops as well as their yields are often largely influenced by DTR. Nutritional quality is an important index to evaluate the quality of food crops...
(Mo et al., 1993), and the amount of protein provided by food crops exceeds 20% of the total consumption of protein (Jin et al., 2018). DTR is an important factor affecting the yield and protein content of winter wheat (Wang et al., 1990). Therefore, DTR is one of the meteorological variables agricultural scientists give great attention to.

To predict the future yield of winter wheat, scholars have developed a variety of crop growth models (Keating et al., 2003; Yu et al., 2014; Zhang et al., 2017; Giltrap et al., 2010). Scholars have successfully predicted wheat yields for several future climate change scenarios based on crop growth models (Lobell and Burke, 2008; Tao and Zhang, 2010; Hatfield et al., 2011). Tao and Zhang (2013) indicate that the yield of winter wheat will decrease in China in future climate scenarios. Future climate data are needed to estimate the yield and quality of winter wheat. The main method to study future climate change is climate model simulation. The latest research points out that the crop growth model has deviation in the prediction results of crop yield, and the climate model is the second main error source (Wang et al., 2020).

The Coupled Model Intercomparison Project Phase 6 (CMIP6) is the latest experiment in simulating global climate through climate models. It brings together the world’s best models and conducts the most colorful experiments with comprehensive coverage of the world and long time series. The latest studies have analyzed and evaluated model simulations for a wide range of climate variables. Kamworapan and Surussavadee (2019) evaluated the ability of 40 CMIP5 models to simulate temperature and precipitation in Southeast Asia during 1960–1999 using observational and reanalysis data, and indicated that 6-GCM-Ensemble and CNRM-CM5-2 were the best models for climate research and prediction in Southeast Asia. Guo et al. (2013) evaluated the annual mean temperature change in China from 1906 to 2005 simulated by the CMIP5 models at a 0.5° × 0.5° resolution combined with two sets of observations from CRU and CN05.1 and compared with the CMIP3 models. The results show that CMIP5 has a better simulation capability compared with CMIP3. Hu et al. (2014) evaluated the ability of 44 global climate models to simulate surface air temperature and precipitation over the Tibetan Plateau from 1986 to 2005 using CMIP5 historical simulations. The CMIP5 model underestimated the annual and seasonal mean surface air temperature in the Qinghai-Tibet Plateau region and can simulate the annual and seasonal mean surface air temperature distribution pattern more effectively than precipitation (Ding et al., 2007). The 44-model ensemble performed better overall than most individual models and the equal-weight ensemble average performed better than the median average.

According to previous studies, climate models have reasonable confidence in the simulation of global surface air temperature (SAT), climate extremes, atmospheric circulation and other elements (Zhou et al., 2006; Lorenz R et al., 2014; Sillmann J et al. 2013a, 2013b; Zhou et al. 2014; Chen and Sun, 2015; Gao et al., 2021), however, there is a large uncertainty in the models’ simulations of DTR. The IPCC Fifth Assessment Report (2013) indicated that the CMIP5 model can well reproduce the large-scale surface temperature patterns, but that in many regions there are large uncertainties in the trends and possible interpretations of DTR (Christy J R, et al., 2006; Fall et al., 2011; Zhou and Ren, 2011). Lewis and Karoly (2013) evaluated the DTR simulated by 27 CMIP5 climate models in four land surface regions (North America, Europe, mid-latitude Asia and Australia) and pointed out that the DTR has decreased in the past
50 years, and the changes simulated by these models are smaller than those observed. The same decreasing DTR trends have been universally observed (Karl et al., 1993; Easterling et al., 1997; You et al., 2017). You et al. (2017) assessed the DTR simulated by 17 CMIP5 models over the Tibetan Plateau (TP) by comparing model simulations with observations over the period 1961–2005. Most CMIP5 models generally underestimated DTR compared with observations, and 15 CMIP5 models reproduced an overall decreasing trend in DTR on the TP, but the rate of the decreasing trend was smaller. It has also been suggested that the pattern differences in the DTR over the TP may be determined by the radiometric variables and total cloudiness in CMIP5 models. Wang and Clow (2020) evaluated the ability of CMIP6 models to simulate the global DTR and showed that CMIP6 models underestimate climatological DTR relative to observations and do not fully reflect the observed spatial and temporal evolution of DTR. The large differences between models appear to be controlled by the daily minimum temperatures. Overall, the CMIP6 models do not improve its ability to simulate temporal changes in DTR from 1901 to 2005 compared with CMIP5 models. The CMIP6 models are generally better than the CMIP5 version in simulating the rapid decline in DTR from 1951 to 1980. Lindvall and Svensson (2015) evaluated the simulation ability of 20 CMIP5 models in simulating the terrestrial DTR of recent and future projections using HadGHCND and CRU and found that the DTR varies considerably between CMIP5 models and that the DTR is often underestimated. However, most models predict a decrease in global mean DTR but an increase over Europe and a decrease over the Sahara Desert. This creates a great deal of confusion in applying the results of climate models to assess the extent to which crops are exposed to climate change.

The retrospective analysis of systematic biases in current climate models as well as their correction is one of the scientific issues that CMIP6 focuses on (Zhou et al., 2019). This suggests that the ability of climate models to simulate climatic variables which are critical in agriculture need to be carefully evaluated to truly provide a more credible understanding and perception of the agricultural impacts of climate change. Moreover, existing assessments of patterns (Lindvall and Svensson, 2015; Zhuang and Zhang, 2020) usually select the entire country or region instead of the real crop-growing regions. However, the previous model evaluations for the entire country or region cannot answer which model is suitable for the estimation of future winter wheat yield, and focus more on the mean temperature and less on the DTR. Therefore, the simulation ability of the DTR was evaluated and analyzed in winter wheat-growing regions in this study to accurately serve the prediction of future yield and quality of winter wheat.

2. Data And Methods

2.1 CMIP6 Model outputs

CMIP6 takes into account the effects of external forcing, including natural factors and human activities, over time in the simulation of historical periods. Global near-surface maximum air temperature and minimum air temperature data simulated by twenty-six CMIP6 models from 1961 to 2014 were retrieved from the CMIP6 website (https://esgf-node.llnl.gov/search/cmip6). The model data used in this study were the simulated results of the near-surface maximum air temperature (Tasmax) and near-surface
minimum air temperature (Tasmin) simulated by 26 CMIP6 models to calculate the DTR. Table 1 shows the information of each model.
### Table 1
Information of CMIP6 models.

| No. | Model name   | Institution (Country)           | Resolution       |
|-----|--------------|---------------------------------|------------------|
| 1   | ACCESS-CM2   | CSIRO-ARCCSS (Australia)        | 1.875°×1.25°     |
| 2   | ACCESS-ESM1-5| CSIRO (Australia)               | 1.875°×1.24°     |
| 3   | AWI-CM-1-1-MR| AWI (Germany)                   | 0.9375°×0.9375°  |
| 4   | AWI-ESM-1-1-LR| AWI (Germany)              | 1.875°×1.875°    |
| 5   | BCC-CSM2-MR  | BCC (China)                     | 1.125°×1.125°    |
| 6   | BCC-ESM1     | BCC (China)                     | 2.8125×2.8125    |
| 7   | CanESM5      | CCCma (Canada)                  | 2.8125×2.8125°   |
| 8   | EC-Earth3    | EC (Sweden)                     | 0.703°×0.703°    |
| 9   | EC-Earth3-Veg| EC (Sweden)                     | 0.703°×0.703°    |
| 10  | EC-Earth3-Veg-LR| EC (Sweden)                 | 1.125°×1.125°    |
| 11  | FGOALS-f3-L  | CAS (China)                     | 1.25°×1.25°      |
| 12  | FGOALS-g3    | CAS (China)                     | 2.0°×2.0°        |
| 13  | GFDL-CM4     | NOAA-GFDL (America)             | 1.25°×1.25°      |
| 14  | GFDL-ESM4    | NOAA-GFDL (America)             | 1.25°×1.0°       |
| 15  | GISS-E2-1-G  | NASA-GISS (America)             | 2.5°×2.0°        |
| 16  | INM-CM4-8    | INM (Russia)                    | 2.0°×1.5°        |
| 17  | INM-CM5-0    | INM (Russia)                    | 2.0°×1.6°        |
| 18  | IPSL-CM6A-LR | IPSL (France)                   | 2.5°×1.25°       |
| 19  | KIOST-ESM    | KIOST (Korea)                   | 1.875°×1.875°    |
| 20  | MIROC6       | MIROC (Japan)                   | 1.40625°×1.40625°|
| 21  | MPI-ESM-1-2-HAM| MIROC (Germany)               | 1.975°×1.975°    |
| 22  | MPI-ESM1-2-HR| MPI-M (Germany)                 | 0.9375°×0.9376°  |
| 23  | MPI-ESM1-2-LR| MPI-M (Germany)                 | 1.875°×1.875°    |
| 24  | MRI-ESM2-0   | MRI (Japan)                     | 1.125°×1.126°    |
| 25  | NorESM2-MM   | NCC (Norway)                    | 1.25°×0.9375°    |
| 26  | NESM3        | NUIST (China)                   | 1.875°×1.875°    |

#### 2.2 Observation data
To evaluate the simulated results of the CMIP6 models, the daily maximum and minimum temperature data of the China high-resolution dataset CN05.1 released by the Open Laboratory for Climate Research of China Meteorological Administration (Wu et al., 2013) were used as observational data in this study. The available starting and ending times of these data are 1961–2018, with a high spatial resolution of 0.5°×0.5°. This dataset has a long time span and high spatial resolution. The generation process of this dataset only used the actual observational data of observation stations for statistical interpolation, covering the entire land area of China (Taiwan province is missing statistical data). Compared with the reanalysis data, the CN05.1 data have greater reliability.

The data of all models were interpolated uniformly to a 0.5°×0.5° grid using the bilinear interpolation method. Due to the different time spans of the model data and observational data, only China's land area was considered in this study, and the study period from 1961 to 2014 was 54 years in total.

2.3 Methods

To facilitate the analysis, a bilinear interpolation method was adopted to interpolate the model data uniformly to the same resolution, corresponding to the grid positions and resolutions of the observed datasets.

According to the Atlas of Fine Agricultural Climatic Resources in China (Mao et al., 2018) and Harvested Area and Yield for 175 Crops (Monferda et al., 2008), the main growing regions of winter wheat in China were selected as the study regions and extracted from the above grid points. All assessments were conducted on these grid points.

According to the research of Wu (2020) and combined with the distribution of winter wheat-growing regions, China was divided into eight subregions in this study. The regional divisions in China are shown in Fig. 1.

2.3.1 Evaluation of climatological DTR

The climate mean from 1995–2014 was selected to evaluate the simulation ability of CMIP6 models to the spatial distribution of the DTR in winter wheat-growing regions in China.

2.3.2 Evaluation of DTR in the winter wheat-growing season

The research results of Wang (2020) indicated that the reviving and maturity periods of winter wheat in northern China mainly occur from March to June. In this study, March to June of the current year was selected as the winter wheat-growing season. 54 years of data from 1961 to 2014 were selected for analysis in this study.

2.3.3 Evaluation of winter wheat-growing season DTR interannual trend
Based on 54 years of data from 1961 to 2014, the interannual variation trend of the DTR in growing season were calculated to evaluate the simulation ability of the CMIP6 models and multimodel data.

### 2.3.4 Multimodel ensemble method

It was revealed in previous studies that the multimodel ensemble mean usually shows a higher reliability to reproduce the present Chinese climate relative to an individual model (Jiang et al., 2005, 2009). Therefore, the following two multipattern ensemble methods were used in this study:

1. Multimodel arithmetic mean ensemble with the same weights (MME);
2. Multimodel median mean ensemble (Median).

### 2.3.5 Performance Metrics

In the evaluation of the CMIP6 models simulation capability to DTR in winter wheat-growing regions in China, quantitative calculations were carried out and are shown in the Taylor diagram. The Taylor diagram compares the consistency between the model results and observations according to the correlation coefficient (R), centralized root mean square error (RMSE'), standard deviation (σ<sub>o</sub> and σ<sub>m</sub>) of the model simulation and observational results (Taylor, 2001).

To further evaluate the overall skills of the CMIP6 model for DTR simulation in China’s winter wheat-growing regions, Taylor skill score (TS) was used. Taylor skill score (TS) is:

\[
TS = 1 - \frac{4(1 + R)^3}{(\sigma_o + \sigma_m)^2 (1 + R_0)^2}
\]

where σ<sub>o</sub> and σ<sub>m</sub> are the standard deviations of the observation and simulation, respectively. R is the spatial correlation coefficient between the simulation and observation, and R<sub>0</sub> is the maximum correlation coefficient attainable. The score is between 0 and 1. When TS is 1, it indicates that the pattern matches the observation perfectly; otherwise, if TS is 0, the pattern does not match at all.

### 3 Results

#### 3.1 Evaluation of climatological DTR

The CMIP6 models can basically reproduce the spatial distribution characteristics of the climate mean DTR (Figure 2), which is consistent with CMIP5 (Lindvall and Svensson, 2015):

1. The DTR increased gradually from low latitudes to high latitudes, and the DTR in winter wheat-growing regions ranged from 8 °C to 12°C.
2. From coastal to inland regions, the DTR gradually increases, and the DTRs of NEC and TP are higher than those of other regions.
Figure 2(e)~(h) shows the simulation results of the multimodel ensembles. When comparing with observations, the multimodel ensemble data are approximately 3°C lower than the observations nationwide and 6°C lower than the observational data in NEC. In addition, the DTR in CY is 2°C higher than the observation.

EC-Earth3-Veg has the best simulation ability among 26 CMIP6 models for simulating the climatological DTR in both the national (TS=0.842) and winter wheat-growing regions (TS=0.848). Regardless of the entire country or in wheat-growing regions, the simulation effect of DTR simulated by the MME and Median is not as good as that simulated by EC-Earth3-Veg. The same conclusions can be drawn across the country. For winter wheat-growing regions, the simulations of EC-Earth3-veg in SWC are relatively small compared with the observed values, while the simulations in other regions are approximately 1°C higher. In the entire country, it also shares the same characteristics, but in NEC, the simulation is approximately 3°C lower, and the biases in some regions are more than 5°C.

The simulated results of each model have great spatial differences (Figure 3). The mean SD within the winter wheat-growing regions is 2.33, and in the country, the standard deviation is 2.72. The consistency within the winter wheat-growing regions is higher than that in the entire country. The SDs of simulations in NEC and TP are slightly higher than those in other regions, at approximately 4°C, and the difference between models is large. This shares the same characteristics with mean temperature (Guo et al., 2013; Zhou and Yu, 2006). The SD of the simulated results in Xinjiang is slightly higher, and the simulated results of the CMIP6 multimodel in this region are greatly different. This indicates that CMIP6 models have good simulation capability in eastern China. In NEC and TP, there are great differences between the simulated results of different models. This indicates that, similar to CMIP5, CMIP6 models are still deficient in their ability to simulate the climate mean surface temperature and DTR in TP, which is also consistent with the previous assessments (Xu and Xu, 2012; Guo et al., 2013; Hu et al., 2014). Improving the model to make the simulation more reliable has become a new challenge for model developers (Meehl et al.,1997; Zhou et al., 2019).

In general, the correlations between simulations and observations are concentrated in the range of 0.5-0.85 in both nationwide and the wheat-growing regions (Figure 4). The SDs of most models are smaller than observations. EC-Earth3-Veg has the highest correlation coefficient with observations in the entire country, which is 0.84. The correlation coefficient for EC-Earth3-Veg with observations is 0.856 in the winter wheat-growing regions, which is higher than that in nationwide. More than 80% of the CMIP6 models have smaller SDs than the observations. The SD of EC-Earth3-Veg-LR (2.38) is the closest to the SD of the observed results (2.46), which can better reflect the true spatial distribution of the DTR. The RMSEs of simulations in winter wheat-growing regions are smaller than the results in the entire nation. Multimodel ensemble collections have good effects on improving the correlation of simulated results. However, it has little effect on improving the SD. Multimodel ensembles effectively decrease the RMSE (Zhi et al., 2010; Wu et al., 2016). In particular, although multimodel ensembles can significantly improve the correlation, there is a large difference between the SDs of the observation results and multimodel ensembles.
We evaluated each region and calculated the TS scores for each model separately, the evaluation results are presented in Figure 5 to show the comprehensive performance of the model more visually.

In general, there are large differences in model performance in different regions: EC-Earth3-Veg scores the highest among the 26 CMIP6 models both nationwide and in the growing regions, with TS scores of 0.84 and 0.85, respectively, for overall better simulation ability. The multimodal ensembles (MME, median) have better simulated results at the national scale than at the growing regions scale. However, the MME (TS=0.72) and Median (TS=0.65) are not as good as the EC-Earth3-Veg. For different regions, EC-Earth3-Veg has the highest TS scores of 0.75, 0.89, and 0.67 in NC, SWC and CY, respectively, which are consistent with the results of nationwide and winter wheat-growing regions assessments. However, the simulation ability of EC-Earth3-Veg is not the best in JH and SWC. This indicates that even the best-performing model among 26 models does not always have the best performance in all regions. The multimodel ensembles (MME, Median) share the same characteristics. Calculating the mean TS scores for each region separately, the results show that the CMIP6 models have better simulation effects in JH (TS=0.57) and NC (TS=0.49); the simulation effects in NWC (TS=0.20) are relatively weak, and there are large differences, which is also related to the complex topography of NWC (Hu et al., 2014).

3.2 Evaluation of DTR in the winter wheat-growing season

According to the observations, the growing season DTR in the wheat-growing regions shows a decreasing trend at a rate of -0.080°C/10a (Figure 6). The same trend is observed at the national scale, with a decreasing rate of -0.185°C/10a. The rate of decrease is greater at the national scale than in the growing regions. The multimodel ensembles can basically simulate these trends with slower rates. CMIP6 models can simulate the corresponding trends better (Figure 7): among 26 CMIP6 models, CanESM5 have the best simulations for the national DTR trend (-0.129°C/10a); BCC-CSM2-MR performs best in winter wheat growing regions (-0.083°C/10a). The decreasing DTR trend has been universally observed since the 1950s (Karl et al., 1993; Easterling et al., 1997; You et al., 2017).

The CMIP6 model can better simulate the spatial distribution of interannual variation in DTR during the growing season with high correlation coefficients (Figure 8):

(1) MRI-ESM2-0 has the highest positive correlation rate at 94.67% in the growing region among all models, it also has the highest positive correlation rate nationwide at 88.03%. The positive correlation rate of MRI-ESM2-0 in the growing region is higher than that nationwide. CMIP6 models have different simulation effects in different regions. For the growing regions, both the observation and simulated results show significant positive correlations in Shandong and SWC.

(2) The positive correlation rate of MME is higher nationwide (positive=92.02%) than that of the single-model simulation but less effective than that of the single-model simulation within the growing regions (positive=94.67%). In contrast, the MME is more effective than the Median. In the entire country, 80.36% of grid points have a positive correlation coefficient, but the distribution of negative correlation grid points
is more extensive. Within the winter wheat-growing regions, the spatial distribution of the Median and MME correlate more consistently with the observations.

There are large differences in the performance of CMIP6 models in different regions (Figure 9): EC-Earth3-Veg has the highest TS score (0.54) nationwide; however, within the growing regions, ACCESS-CM2 simulates better than EC-Earth3-Veg with a TS score of 0.46. The multimodal ensemble data perform better nationwide than those in growing regions. For different regions, ACCESS-CM2 has the highest TS scores of 0.46 and 0.47 in NC and JH, respectively, which are consistent with the assessment results in the growing regions. However, no model always has the best simulation ability in all or most regions: in SWC, GISS-E2-1-G has a TS score of 0.39, which is higher than other models. The multimodel ensemble data (MME, median) have the same characteristics. By calculating the average TS scores for each region separately, we find that the average TS scores of the CMIP6 models are more concentrated in each region, with less variation between regions. Furthermore, the TS scores of the multimodel ensemble data are relatively lower in all regions, and the simulation effects are also not as good as those of the individual models.

The same evaluations were performed to the simulation of annual DTR. The results show that CanESM5 have highest TS scores both in nationwide (0.68) and growing regions (0.58) among 26 models. EC-Earth3-Veg (0.41) and ACCESS-CM2 (0.34) also perform better than most models in nationwide and winter wheat-growing regions, respectively. The CMIP6 models have different simulation effects for DTR of annual and growing seasons, and the models which have best performance for mean DTR of annual and growing seasons are different.

3.3 Evaluation of winter wheat-growing season DTR interannual trend

The CMIP6 models can reproduce the spatial distribution characteristics of growing season DTR trends (Figure 10):

(1) Within the growing regions, according to the observations, the growing season DTR has an increasing trend in CY and southern JH, with a rate smaller than 0.2°C/10a. There is a clear decreasing trend in Shandong, with the rate decreasing between 0.2 and 0.4°C per decade. In SWC, the rate of decline is slow, less than 0.2°C/10a. Nationwide, the increase of DTR mainly occurs in CY, Shaanxi, the southern part of JH and the northern part of SEC. Significant decreasing trends exist in the NWC and TP, as well as in NEC, with some grid points exceeding 0.4°C per decade.

(2) KIOST-ESM (TS=0.46) and MPI-ESM-1-2-HAM (TS=0.37) have the best simulation effects in winter wheat-growing regions and nationwide, respectively. The simulation effects are better in the winter wheat-growing regions overall than nationwide. In addition, the simulated results of the CMIP6 models nationwide have a tendency to increase over a large area in the northern region, which is less consistent with the observation results.
In general, the correlations (Figure 11) between the models and observations are concentrated between 0.1 and 0.55 both nationwide and in growing regions, respectively. The standard deviation varies widely, with most models having smaller standard deviations than observations. For individual models, nationwide, FGOALS-f3-L and INM-CM5-0 have the highest correlations with observations, reaching 0.55 and 0.41, respectively. In the winter wheat-growing regions, the correlation coefficients of EC-NESM3 and MRI-ESM2-0 with observations reach 0.55 and 0.48, respectively, which are higher than the nationwide correlations. The standard deviation of EC-Earth3-Veg-LR (2.38) is closest to that of the observations (2.46), which can better reflect the true spatial distribution of daily temperature differences. The RMSEs of simulations in winter wheat-growing regions are smaller than the results in the entire nation. The multimodal ensembles all perform better in the growing regions than in the entire nation, while the multimodal ensemble data (MME, Median) have better effects on improving the correlations of the simulated results (growing regions: $R_{\text{mme}}=0.67$ and $R_{\text{median}}=0.47$). In particular, the multimodal ensembles, although they significantly improve the correlation, have large differences from the standard deviation of the observed results (Wu et al. 2016).

There are significant differences in the performance of the models in different regions (Figure 12): MPI-ESM-1-2-HAM has the highest TS score, 0.37, in the entire country, while KIOST-ESM has a better TS score, 0.46, in the growing regions. CMIP6 models perform better than both the MME and the Median. In terms of subregions, KIOST-ESM has the highest TS score (0.73) in NC, which is consistent with the evaluation results of the wheat growing regions. EC-Earth3 in JH has the best performance (TS=0.31). No model is capable of providing the best simulation in all or most regions. Multimodel ensembles (MME, median) share the same characteristics. The mean TS scores are calculated separately for each region, and we find that, in general, the mean TS scores of CMIP6 models are more concentrated in each region, and the differences in TS scores between regions are smaller.

## 4 Discussion

Global climate models (GCM) provide high-resolution climate datasets for studies of the impact of climate on crops. Song et al. (2019) corrected the maximum and minimum temperatures in four CMIP5 models and predicted crop water requirements (CWR) for future scenarios in northwest China. It was found that all GCMs showed a significant positive trend in CWRs for all scenarios. Yang et al. (2014) used the APSIM-wheat model combined with 18 GCM ensembles of future scenarios to predict future wheat production changes at six sites in Australia. Ramirez-Villegas et al. (2013) assessed the effectiveness of the CMIP3 and CMIP5 models in simulating climates in tropical climate vulnerable zones and predicted future yield changes for a variety of crops, including wheat. It is worth noting that most GCMs used in the above studies may have a good simulation capability for national or regional climate as a whole, but when applying the output data of GCMs to analyze the impact of climate change on winter wheat or other crops, the simulation capability of these models in the actual wheat-growing regions of the study area was not further evaluated. In this study, we found that most CMIP6 models can simulate the DTR well at the national scale, but these models do not have the best simulation ability in the actual winter wheat-
growing regions. Therefore, the results of climate change effects on winter wheat yield, phenology and quality based on these models may be inaccurate. Climate models are the second largest source of error in predicting wheat yields and the targeted evaluation would reduce this uncertainty.

5 Conclusions

The evaluation of the DTR simulation by CMIP6 models across China and within winter wheat-growing regions from 1961 to 2014 provide an understanding of the model's ability to simulate the spatial distribution and trends of the DTR in China. Our study provides a better definition of the scope of model assessment for winter wheat by using actual winter wheat-growing regions and therefore allows for more targeted assessment results when quantitatively assessing the ability of climate models to simulate critical agrometeorological elements. In this study, the performance of CMIP6 models in reproducing the DTR in winter wheat-growing regions in China was analyzed by comparing model simulations with observations. CMIP6 models can basically reproduce the DTR for winter wheat-growing regions in China, but there are discrepancies in performance between regions. The main conclusions are summarized as follows:

(1) When studying the impact of climate on winter wheat, data from the model with the best simulation effects in the winter wheat-growing regions should be selected. In this study, the following recommendations are made for the CMIP6 models in each region: for the simulation of climatological DTR, EC-Earth3-Veg is recommended in the winter wheat-growing regions, and it is also recommended in NC, SC, and CY. However, EC-Earth3-Veg-LR is recommended in JH and CanESM5 in NWC. For the simulation of DTR in the winter wheat-growing season, ACCESS-CM2 is recommended in winter wheat-growing regions. In each subregion, the model that is recommended differs from each other. ACCESS-CM2 is the recommended model both in NC and JH. In SWC, GISS-E2-1-G is recommended; in CY, AWI-ESM-1-1-LR is the recommended model; and EC-Earth3-Veg is recommended in NWC.

(2) The recommended models have the highest TS scores in their respective regions, which is the main reason for their recommendation. For the simulation of climatological DTR, EC-Earth3-Veg has the highest TS scores (0.84 and 0.85) in both winter wheat-growing regions and the entire country, and the TS scores in NC, SC, and CY are also the highest among the models. EC-Earth3-Veg-LR has the highest TS score (0.84) in JH, higher than EC-Earth3-Veg (0.83). In addition, CanESM5 has a higher TS score in NWC. For the simulation of DTR in the winter wheat-growing season, ACCESS-CM2 has the highest TS score (0.46) in growing regions, EC-Earth3-Veg also has the highest TS score (0.48) in NWC. These models in different subregions also rank highest in their subregions.

(3) In this study, it was found that the assessment of nationwide DTR cannot replace the assessment of DTR in winter wheat growing regions, while the assessment of mean annual DTR cannot replace the assessment of DTR in winter wheat growing seasons. This shows that it is necessary to evaluate specific research areas and research periods. Although the most suitable models for different regions have been recommended, it should be noted that these models represent only the most suitable models for the study
of DTR in winter wheat growing regions. When the study needs the DTR data of the region, it is the most suitable choice for researchers. Similarly, when the entire country or other region is selected as the study area, the model with a relatively best simulation effect in the study area is the most suitable option relative to other models. However, there are differences in the ability of the above models to simulate the climatological DTR and annual DTR in winter wheat growing regions. For example, EC-Earth3-Veg has a good simulation effect on climatic DTR, but ACCESS-CM2 has stronger simulation ability for the simulation of DTR in the winter wheat-growing season. Therefore, attention should be given to selecting the most appropriate data in scientific research.

The CMIP6 models have different simulation effects for DTR in China and winter wheat-growing regions, and the models with best performance in nationwide and growing regions are different. In summary, when studying the relationship between crops and climate, it is important to give attention to selecting the appropriate model for the crop-growing regions for the study, rather than simply choosing the climate model that has good overall simulation effects in the entire country or region.

Declarations

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Author's Contribution

All authors have read and agreed to the published version of the manuscript. Wenqiang Xie analyzed data and wrote original draft. Shuangshuang Wang organized the original data. Xiaodong Yan conceived and designed the study.

Availability of data and material

All data sets used in this study are publicly available.

Code availability

Python code developed for this study is available from the authors upon request.

Ethics approval
The manuscript is conducted within the ethical manner advised by the Theoretical and Applied Climatology. Permissions or licenses were obtained.

**Consent to participate**

Not applicable.

**Consent for publication**

Authors agree to publish this paper.

**Conflicts of interest**

The authors declare no conflict of interest.

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**References**

1. Baenziger, P. S., Clements, R. L., McIntosh, M. S., Yamazaki, W. T., Starling, T. M., Sammons, D. J., & Johnson, J. W. 1985. Effect of Cultivar, Environment, and Their Interaction and Stability Analyses on Milling and Baking Quality of Soft Red Winter Wheat 1. Crop Science, 25(1), 5-8. https://doi.org/10.2135/cropsci1985.0011183X0025000010002x.

2. Cao, Q., Yao, F., Lin, E., Zhang, J., Wang, P., & Qin, P. 2011. Analysis of changing characteristics of agricultural climate resources in the main planted areas of winter wheat in China over last 50 years. Chinese Journal of Agrometeorology, 32(02), 161. https://doi.org/10.3969/j.issn.1000-6362.2011.02.002.

3. Chen, H., & Sun, J. 2015. Changes in climate extreme events in China associated with warming. International Journal of Climatology, 35(10), 2735-2751. https://doi.org/10.1002/joc.4168.

4. Christy, J. R., & Norris, W. B. 2006. Satellite and VIZ-radiosonde intercomparisons for diagnosis of nonclimatic influences. Journal of Atmospheric and Oceanic Technology, 23(9), 1181-1194. https://doi.org/10.1175/JTECH1937.1.
5. Ding, Y., Ren, G., Zhao, Z., Xu, Y., Luo, Y., Li, Q., & Zhang, J. 2007. Detection, causes and projection of climate change over China: an overview of recent progress. Advances in Atmospheric Sciences, 24(6), 954-971. https://doi.org/10.1007/s00376-007-0954-4.

6. Easterling, D. R., Horton, B., Jones, P. D., Peterson, T. C., Karl, T. R., Parker, D. E., ... & Folland, C. K. 1997. Maximum and minimum temperature trends for the globe. Science, 277(5324), 364-367. https://doi.org/10.1126/science.277.5324.364.

7. Fall, S., Watts, A., Nielsen-Gammon, J., Jones, E., Niyogi, D., Christy, J. R., & Pielke Sr, R. A. 2011. Analysis of the impacts of station exposure on the US Historical Climatology Network temperatures and temperature trends. Journal of Geophysical Research: Atmospheres, 116(D14). https://doi.org/10.1029/2010JD015146.

8. Gao, Z., J. Zhu, Y. Guo, N. Luo, Y. Fu, and T. Wang .2021, Impact of Land Surface Processes on a Record-Breaking Rainfall Event on May 06–07, 2017, in Guangzhou, China, Journal of Geophysical Research: Atmospheres, 126(5). https://doi.org/10.1029/2020jd032997.

9. Giltrap, D. L., Li, C., & Saggar, S. 2010. DNDC: A process-based model of greenhouse gas fluxes from agricultural soils. Agriculture, ecosystems & environment, 136(3-4), 292-300. https://doi.org/10.1016/j.agee.2009.06.014.

10. Guo Y.,Dong W.,Ren F.,Zha Z. & Huang J. 2013. Surface air temperature simulations over China with CMIP5 and CMIP3. Advances in climate change research, 4(3), 145-152. https://doi.org/10.3724/SP.J.1248.2013.145.

11. Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurrealde, R. C., Ort, D., ... & Wolfe, D. (2011). Climate impacts on agriculture: implications for crop production. Agronomy journal, 103(2), 351-370. https://doi.org/10.2134/agronj2010.0303.

12. Hu, Q., Jiang, D., & Fan, G. 2014. Evaluation of CMIP5 models over the Qinghai-Tibetan Plateau. Chin. J. Atmos. Sci, 38, 924-938. https://doi.org/10.3878/j.issn.1006-9895.2013.13197.

13. IPCC, 2013: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley(eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.

14. Jiang,D.,Wang, H.,Lang X. 2005. Evaluation of East Asian climatology as simulated by seven coupled models. Advances in Atmospheric Sciences, 22(4), 479-495. https://doi.org/10.1007/BF02918482.

15. Jiang, D., Zhang, Y., & Sun, J. 2009. Ensemble projection of 1–3 C warming in China. Chinese Science Bulletin, 54(18), 3326-3334. https://doi.org/10.1007/s11434-009-0313-1.

16. Jin,J.2018. The changing characteristics of China's food consumption structure and its international comparison.(in Chinese). Proceedings of the 16th China Modernization Research Forum.

17. Kamworapan, S., & Surussavadee, C. 2019. Evaluation of CMIP5 global climate models for simulating climatological temperature and precipitation for Southeast Asia. Advances in Meteorology, 2019. https://doi.org/10.1155/2019/1067365.
18. Karl, T. R., Jones, P. D., Knight, R. W., Kukla, G., Plummer, N., Razuvayev, V., ... & Peterson, T. C. 1993. Asymmetric trends of daily maximum and minimum temperature. Papers in Natural Resources, 185.
19. Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., ... & Smith, C. J. 2003. An overview of APSIM, a model designed for farming systems simulation. European journal of agronomy, 18(3-4), 267-288. https://doi.org/10.1016/S1161-0301(02)00108-9.
20. Lewis, S. C., & Karoly, D. J. 2013. Evaluation of historical diurnal temperature range trends in CMIP5 models. Journal of Climate, 26(22), 9077-9089. https://doi.org/10.1175/JCLI-D-13-0032.1.
21. Lindvall, J., & Svensson, G. 2015. The diurnal temperature range in the CMIP5 models. Climate Dynamics, 44(1-2), 405-421. https://doi.org/10.1007/s00382-014-2144-2.
22. Lobell, D. B., & Burke, M. B. 2008. Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. Environmental Research Letters, 3(3), 034007. http://dx.doi.org/10.1088/1748-9326/3/3/034007.
23. Lorenz, R., Pitman, A. J., Donat, M. G., Hirsch, A. L., Kala, J., Kowalczyk, E. A., ... & Srbinovsky, J. 2014. Representation of climate extreme indices in the ACCESS1. 3b coupled atmosphere–land surface model. Geoscientific Model Development, 7(2), 545-567. https://doi.org/10.5194/gmd-7-545-2014.
24. Mao, L. 2020. Atlas of Refined Agro-climatic Resources in China. Meteorology(02),288.
25. Meehl, G. A., Boer, G. J., Covey, C., Latif, M., & Stouffer, R. J. 1997. Intercomparison makes for a better climate model. Eos, Transactions American Geophysical Union, 78(41), 445-451. https://doi.org/10.1029/97EO00276.
26. Mo, H. D. 1993. Quality improvement of rice grain in China. Sci. Agric. Sin, 26, 8-14.
27. Monfreda, C., N. Ramankutty, and J. A. Foley (2008), Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000, Global Biogeochem. Cycles, 22, GB1022, https://doi.org/10.1029/2007GB002947.
28. Ramirez-Villegas, J., Challinor, A. J., Thornton, P. K., & Jarvis, A. 2013. Implications of regional improvement in global climate models for agricultural impact research. Environmental Research Letters, 8(2), 024018. http://doi.org/10.1088/1748-9326/8/2/024018.
29. Rao, A. C. S., Smith, J. L., Jandhyala, V. K., Papendick, R. I., & Parr, J. F. 1993. Cultivar and climatic effects on the protein content of soft white winter wheat. Agronomy Journal, 85(5), 1023-1028. https://doi.org/10.2134/agronj1993.00021962008500050013x.
30. Sillmann, J., Kharin, V. V., Zhang, X., Zwiers, F. W., & Bronaugh, D. 2013. Climate extremes indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate. Journal of Geophysical Research: Atmospheres, 118(4), 1716-1733. https://doi.org/10.1002/jgrd.50203.
31. Sillmann, J., Kharin, V. V., Zwiers, F. W., Zhang, X., & Bronaugh, D. 2013. Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. Journal of Geophysical Research: Atmospheres, 118(6), 2473-2493. https://doi.org/10.1002/jgrd.50188.
32. Smika, D. E., & Greb, B. W. 1973. Protein Content of Winter Wheat Grain as Related to Soil and Climatic Factors in the Semiarid Central Great Plains 1. Agronomy journal, 65(3), 433-436. https://doi.org/10.2134/agronj1973.00021962006500030023x.
33. Song, X., Song, S., Li, Z., Liu, W., Li, J., Kang, Y., & Sun, W. (2019). Past and future changes in regional crop water requirements in Northwest China. Theoretical and Applied Climatology, 137(3), 2203-2215. https://doi.org/10.1007/s00704-018-2739-3.

34. Song, Y. L., & Dong, W. J. 2006. Influence of drought on winter wheat yield in China during 1961-2000. Journal of Natural Disasters, 15(6), 227-231.

35. Tao, F., & Zhang, Z. 2010. Adaptation of maize production to climate change in North China Plain: quantify the relative contributions of adaptation options. European Journal of Agronomy, 33(2), 103-116. https://doi.org/10.1016/j.eja.2010.04.002.

36. Tao, F., & Zhang, Z. 2013. Climate change, high-temperature stress, rice productivity, and water use in Eastern China: a new superensemble-based probabilistic projection. Journal of Applied Meteorology and Climatology, 52(3), 531-551. https://doi.org/10.1175/JAMC-D-12-0100.1.

37. Taylor, K. E. 2001. Summarizing multiple aspects of model performance in a single diagram. Journal of Geophysical Research: Atmospheres, 106(D7), 7183-7192. https://doi.org/10.1029/2000JD900719.

38. Vaughan, B., Westfall, D. G., & Barbarick, K. A. 1990. Nitrogen rate and timing effects on winter wheat grain yield, grain protein, and economics. Journal of Production Agriculture, 3(3), 324-328. https://doi.org/10.2134/jpa1990.0324.

39. Verón, S. R., De Abelléyra, D., & Lobell, D. B. 2015. Impacts of precipitation and temperature on crop yields in the Pampas. Climatic change, 130(2), 235-245. https://doi.org/10.1007/s10584-015-1350-1.

40. Wang, B., Feng, P., Li Liu, D., O’Leary, G. J., Macadam, I., Waters, C., ... & Yu, Q. 2020. Sources of uncertainty for wheat yield projections under future climate are site-specific. Nature Food, 1(11), 720-728. https://doi.org/10.1038/s43016-020-00181-w.

41. Wang, J., Chen, Y., Tett, S. F., Yan, Z., Zhai, P., Feng, J., & Xia, J. 2020. Anthropogenically-driven increases in the risks of summertime compound hot extremes. Nature communications, 11(1), 1-11. https://doi.org/10.1038/s41467-019-14233-8.

42. Wang, K., & Clow, G. D. 2020. The Diurnal Temperature Range in CMIP6 Models: Climatology, Variability, and Evolution. Journal of Climate, 33(19), 8261-8279. https://doi.org/10.1175/JCLI-D-19-0897.1.

43. Wang,Y.Yang,H. Y. L. R. Y., & Hong, C. 1990. Try to discuss the relationships between the seed qualities of wheat and meteorological conditions. Chinese Journal of Agrometeorology, 11(02), 40550.

44. Wu B., Jiang D., Wang X.2021. Changes in the Growing Season Across China during 1961-2018. Chinese Journal of Atmospheric Sciences (in Chinese), 45(2): 424–434. https://doi.org/10.3878/j.issn.1006-9895.2010.20110.

45. Wu, J, Gao, X. J. 2013. A gridded daily observation dataset over China region and comparison with the other datasets. Diqiu Wuli Xuebao (in Chinese), 56(4), 1102-1111. https://doi.org/10.6038/cjg20130406.
46. Wu, W., & Mu HZ, L. Z. 2016. Projected changes in extreme temperature and precipitation events in Shanghai based on CMIP5 simulations. Climatic and Environmental Research, 21(3), 269-281.

47. Wu, Y., Miao, C., Duan, Q., Shen, C., & Fan, X. 2020. Evaluation and projection of daily maximum and minimum temperatures over China using the high-resolution NEX-GDDP dataset. Climate Dynamics, 55(9), 2615-2629. https://doi.org/10.1007/s00382-020-05404-1.

48. Xu, Y., & Xu, C. 2012. Preliminary assessment of simulations of climate changes over China by CMIP5 multi-models. Atmospheric and Oceanic Science Letters, 5(6), 489-494. https://doi.org/10.1080/16742834.2012.11447041.

49. Yang, Y., Li Liu, D., Anwar, M. R., Zuo, H., & Yang, Y. 2014. Impact of future climate change on wheat production in relation to plant-available water capacity in a semiarid environment. Theoretical and applied climatology, 115(3), 391-410. https://doi.org/10.1007/s00704-013-0895-z.

50. You, Q., Wang, D., Jiang, Z., & Kang, S. 2017. Diurnal temperature range in CMIP5 models and observations on the Tibetan Plateau. Quarterly Journal of the Royal Meteorological Society, 143(705), 1978-1989. https://doi.org/10.1002/qj.3057.

51. Yu, Q., Li, L., Luo, Q., Eamus, D., Xu, S., Chen, C., ... & Nielsen, D. C. 2014. Year patterns of climate impact on wheat yields. International Journal of Climatology, 34(2), 518-528. https://www.doi.org/10.1002/joc.3704.

52. Zhang, H., Li, S., Zhu, Y., Liu, H., Li, S., & Liu, D. 2017. Research progress on wheat crop model. Journal of Agricultural Science and Technology (Beijing), 19(1), 85-93. https://www.doi.org/10.13304/j.nykjdb.2016.130.

53. Zhang, X., & Cai, X. 2013. Climate change impacts on global agricultural water deficit. Geophysical Research Letters, 40(6), 1111-1117. https://doi.org/10.1002/grl.50279.

54. Zhi, X. F., Wu, Q., Bai, Y. Q., & Qi, H. X. 2010. The multimodel superensemble prediction of the surface temperature using the IPCC AR4 scenario runs. Scientia Meteorologica Sinica, 30(5), 708-714. https://doi.org/10.3788/HPLPB20102207.1462.

55. Zhou, B., Wen, Q. H., Xu, Y., Song, L., & Zhang, X. 2014. Projected changes in temperature and precipitation extremes in China by the CMIP5 multimodel ensembles. Journal of Climate, 27(17), 6591-6611. https://doi.org/10.1175/JCLI-D-13-00761.1.

56. Zhou, T., & Yu, R. 2006. Twentieth-century surface air temperature over China and the globe simulated by coupled climate models. Journal of Climate, 19(22), 5843-5858. https://doi.org/10.1175/JCLI3952.1.

57. Zhou T J, Zou L W, Chen X L. 2019. Commentary on the Coupled Model Intercomparison Project Phase 6 (CMIP6). Advances in Climate Change Research, 15(5), 445.

58. Zhou, Y., & Ren, G. 2011. Change in extreme temperature event frequency over mainland China, 1961 – 2008. Climate Research, 50(2-3), 125-139. https://doi.org/10.3354/cr01053.

59. Zhuang, Y., & Zhang, J. 2020. Diurnal asymmetry in future temperature changes over the main Belt and Road regions. Ecosystem Health and Sustainability, 6(1), 1749530. https://doi.org/10.1080/20964129.2020.1749530.
The regional divisions in China (Subregion 1: Northeast China (NEC), Subregion 2: North China (NC), Subregion 3: Jianghuai (JH), Subregion 4: South China (SC), Subregion 5: Southwest China (SWC), Subregion 6: Chuanyu (CY), Subregion 7: Northwest China (NWC), and Subregion 8: Tibetan Plateau (TP)).
Figure 2

Observation and simulated results of the DTR spatial distribution of climatology during 1995-2014 in China (left column displays simulated results of DTR in winter wheat-growing regions; right column shows the national results); (a) and (b) are the models with the highest TS scores. Observation (c) and (d) multimodel ensemble data are shown in (e)~(h).
Figure 3

Standard deviations (SD) between CMIP6 models in winter wheat-growing regions (a) and nationwide (b).

Figure 4

Taylor diagram of simulated results of the spatial distribution of the climate mean DTR from 1995 to 2014 (REF: observation; Distance to REF: centralized root mean square error; Radius: ratio of standard deviation; Azimuth: spatial correlation coefficient; Blue: simulated results of the model across the country; Red: simulated results of the model in the growing regions; and Numbers: the pattern corresponding to the ordinal number in Table 1).
Figure 5

TS scores of climatological DTR simulated by CMIP6 models in each subregion in China. Each column represents a subregion, and each row represents a CMIP6 model.
Figure 6
Growing season DTR (°C) time series simulated by CMIP6 models nationwide (a) and in winter wheat-growing regions (b) in China showing patterns of fluctuations that reflect annually varying correlations of DTR in China. Shading indicates the range of simulated values.
Figure 7

Winter wheat-growing season DTR trends simulated by CMIP6 models and observations. The red lines are the median of model simulated trends, grey dots are the results of CMIP6 models. These red, blue and green dots represent the results of CN05.1, MME and Median, respectively.

Figure 8
Spatial distribution of annual growing season DTR correlations during 1961-2014 in China. (Left column displays simulated results of DTR in winter wheat-growing regions; right column shows the national results); (a) and (b) are the models that have the highest positive rate, and (c) and (d) are the models with the relatively lower positive rate. Multimodel ensemble data are shown in (e)~(h). The black dot represent the correlation of that grid point can pass the significance test.

**Figure 9**

TS scores of annual growing season DTR simulated by CMIP6 models in each subregion in China. Each column represents a subregion, and each row represents a CMIP6 model.
Figure 10

Observed and simulated results of the spatial distribution of DTR trends in China during the growing season 1961-2014 (left column shows simulated results of DTR in winter wheat-growing regions; and the right column shows national results). (a) and (b) are the models with the highest TS scores. (c) and (d) are observed data. The black dot represent the correlation of that grid point can pass the significance test.

Figure 11
Taylor diagram of simulated results of spatial distribution of the DTR variation trend from 1961 to 2014 (REF: observation; Distance to REF: centralized root mean square error; Radius: ratio of standard deviation; Azimuth: spatial correlation coefficient; Blue: simulated results of the model across the country; Red: simulated results of the model in the growing regions; and Numbers: the pattern corresponding to the ordinal number in Table 1).

Figure 12

TS scores of growing season DTR interannual trends simulated by CMIP6 models in each subregion in China. Each column represents a subregion, and each row represents a CMIP6 model.