ADVANCES IN ATMOSPHERIC SCIENCES, VOL. 26, NO. 4, 2009, 763–772

A Daily Temperature Dataset over China and Its Application in Validating a RCM Simulation

XU Ying[1] (徐 影), GAO Xuejie*[1] (高学杰), SHEN Yan[2] (沈 艳), XU Chonghai[1] (许崇海), SHI Ying[1] (石 英), and F. GIORGI[3]

[1] *National Climate Center, China Meteorological Administration, Beijing* 100081

[2] *National Meteorological Information Center, China Meteorological Administration, Beijing* 100081

[3] *The Abdus Salam International Centre for Theoretical Physics, Trieste, Italy*

(Received 30 January 2009; revised 28 February 2009)

ABSTRACT

This paper describes the construction of a $0.5° \times 0.5°$ daily temperature dataset for the period of 1961–2005 over mainland China for the purpose of climate model validation. The dataset is based on the interpolation from 751 observing stations in China and comprises 3 variables: daily mean, minimum, and maximum temperature. The "anomaly approach" is applied in the interpolation. The gridded climatology of 1971–2000 is first calculated and then a gridded daily anomaly for 1961–2005 is added to the climatology to obtain the final dataset. Comparison of the dataset with CRU (Climatic Research Unit) observations at the monthly scale shows general agreement between the two datasets. The differences found can be largely attributed to the introduction of observations at new stations. The dataset shows similar interannual variability as does CRU data over North China and eastern part of the Tibetan Plateau, but with a slightly larger linear trend. The dataset is employed to validate the simulation of three extreme indices based on daily mean, minimum, and maximum temperature by a high-resolution regional climate model. Results show that the model reproduces these indices well. The data are available at the National Climate Center of China Meteorological Administration, and a coarser resolution ($1° \times 1°$) version can be accessed via the World Wide Web.

Key words: interpolation, temperature, regional climate model, China

Citation: Xu, Y., X. J. Gao, Y. Shen, C. H. Xu, Y. Shi, and F. Giorgi, 2009: A daily temperature dataset over China and its application in validating a RCM simulation. *Adv. Atmos. Sci.*, **26**(4), 763–772, doi: 10.1007/s00376-009-9029-z.

1. Introduction

Climate change caused by anthropogenic activities is a central topic in the scientific community and of great public concern. The primary tools available today to study climate change, in particular the detection and projection of changes, are global and regional climate models (GCMs and RCMs) (IPCC, 2007).

The reliability of climate experiment results, including climate change simulations, is largely based on the performance of the models in reproducing the observed state of present day climate. In this regard, of highest concern are surface temperature and precipitation. While the model calculations are performed on regular numerical grids, the spatial distribution of the surface observations used for model validation is irregular, which results in a critical issue for interpolation.

Increasing research effort has been devoted to interpolating irregularly distributed station observations onto regular grids, and substantial progress has been made in recent decades. For example the widely used dataset by the Climatic Research Unit (CRU) of the University of East Anglia includes monthly mean temperature, precipitation, and other variables with land surface global $0.5° \times 0.5°$ resolution for the period 1901–2002 (New et al., 1999, 2000). For global precipitation, Xie and Arkin (1997) developed a monthly mean dataset of CMAP (Climate Prediction Center

*Corresponding author: GAO Xuejie, gaoxj@cma.gov.cn

Merged Analysis of Precipitation) data at 2.5° × 2.5° resolution. Xie et al. (2003) then extended this dataset to pentad mean values [dataset known as the Global Precipitation Climatology Project (GPCP)].

The rapid development of climate models has given a strong impetus for the further upgrading of gridded observational datasets for the purpose of validating model simulations at a range of spatial and temporal scales. The massive increases in computer power over time have allowed a substantial increase in the horizontal resolution of climate models, which is extremely important for better simulation of both global and regional climate, and in particular over the East Asian monsoon region (Giorgi and Mearns, 1991; Gao et al., 2006a). While the resolution of most global models is still in the range of 100–300 km (Meehl et al., 2007), some of them have even been run at resolutions as fine as 20 km for selected time slices (e.g., Mizuta et al., 2006; Kitoh and Kusunoki, 2008). Many GCMs are conducting near-term climate change simulations at horizontal resolutions of 0.5°–1° in support of the IPCC AR5 (the 5th Assessment Report of the International Panel on Climate Change) (Hibbard et al., 2007). In the mean time, RCM simulations have been performed by using grid spacing down to 10–20 km or even less (e.g., Leung et al., 2003; Christensen and Christensen, 2004; Gao et al., 2006b, 2008; Christensen et al., 2007). Validation of such simulations requires high spatial resolution observed gridded datasets. In addition, increasing attention is being paid to changes in atmospheric and climatic extremes (Christensen et al., 2007), and evaluation of the simulation of extremes requires high temporal resolution data at daily, or even sub-daily, scales.

To date, there are few observational datasets for the validation of high-resolution model simulations over China. The monthly 0.5° × 0.5° CRU data over China are mainly based on less than 200 stations which are part of the Global Telecommunication System (GTS) (New et al., 1999). The density of stations is thus low, considering the size of the country, especially in western China. This may lead to large uncertainties when utilizing the data for model validations. Similarly, gridded datasets at the daily scale for the evaluation of extremes over China are even less available.

In previous studies, several methods have been employed to validate RCM simulations. For example, Gao et al. (2002, 2006a) compared model results against a widely used 160-station dataset over China by first interpolating model results onto the station locations. CRU data were also used to validate mean temperature and precipitation (e.g., Gao et al., 2009). Some authors have collected and interpolated relatively sparse station data to continuous fields using simple approaches (e.g., by using the Cressman function in Grads, http://www.iges.org/grads/) to validate climate model simulations (Feng and Fu., 2006).

A high-resolution (0.5° × 0.5°) daily precipitation dataset has been recently developed by Xie et al. (2007) over East Asia, based on gauge observations. The number of stations used in China is about 700 meteorological stations before 2003, plus over 1000 hydrological stations in the Yellow River basin before 1997. Application of this dataset to RCM validation has begun (e.g., Gao et al., 2008). Concerning daily temperature, a coarse resolution of 3.75 (lon)° × 2.5° (lat) global dataset (HadGHCND, http://hadobs.metoffice.com/hadghcnd/, Caesar et al., 2006) and some indices of climate extreme (HadEX, http://www.hadobs.org/, Alexander et al., 2006) are available and have been used in the evaluation of GCM simulations (e.g., Xu et al., 2009).

Efforts have been made to produce gridded temperature data over China, mainly by authors working in the fields of ecology and geography, to fit their specific needs (e.g., Chen et al., 2001; Pan et al., 2004; Yan et al., 2005; Li et al., 2006). These interpolation procedures usually employ professional software such as GIS (Geographic Information System) and fine resolution DEM (Digital Elevation Model) systems to obtain multi-annual mean monthly temperature. Thus, these datasets do not include interannual variability. Further, few high-resolution gridded datasets at the daily scale are available which are suitable for model validation over China.

In this paper, we develop a 0.5° × 0.5° daily temperature dataset over China (hereafter referred to as CN05) to meet the urgent demand for validation of high-resolution climate models at a range of spatial and temporal scales. The dataset is based on 751 station observations over China. It extends from 1961 to 2005, including three variables: daily mean (Tm), maximum (Tmax), and minimum (Tmin) temperature. In section 2, the data and interpolation method are described. Section 3 presents the results and a brief comparison with the CRU data at the monthly and annual mean scale, while section 4 shows the application of CN05 to validation of a high-resolution RCM simulation. Finally, a summary and concluding discussion is given in section 5.

2. Data and methodology

The observational data are derived from the "Daily Surface Climate Variables of China" catalog (SURF_CLI_CHN_MUL_DAY ver4.0, date 20060426) issued by the National Meteorological Information

Center of the China Meteorological Administration (NMIC/CMA). The dataset starts on 1 January 1951, and ends on 31 December 2005, with a total of 753 stations throughout mainland China. It consists of over 70 climate variables, although we focus on daily Tm, Tmax, and Tmin in the present study. The data was previously screened for primary quality control by removing data with excessive departures from climatology, historical records, or the surrounding stations, and those with a mismatch among variables. The number of stations left ranges from 624 to 693 depending on the dates.

Here, we analyze the time period 1961–2005, which is often used for validation of climate models (New et al., 2000). Data for leap days (29 February) are not included in the interpolation for simplicity. This does not cause a substantial problem for model validation, especially when considering that many climate model calendars do not include leap years. Moreover, two of the total 753 stations are located in the islands of the South China Sea, and are not included in the analysis. It is also noted that stations in Taiwan are not included, and thus the results are basically limited to mainland China.

The distribution of the 751 stations, including the GTS stations, and the topography of China is shown in Fig. 1. As expected, the much higher density of stations used here compared to the GTS ones is evident from the figure. The distance between stations is generally within tens of kilometers over eastern China. The station density is not as high over western China, where the density of population and urban establishments is much lower. In particular no stations are found over the northwestern part of the Tibetan Plateau, a region largely uninhabited. Results will thus necessarily be very uncertain over this region.

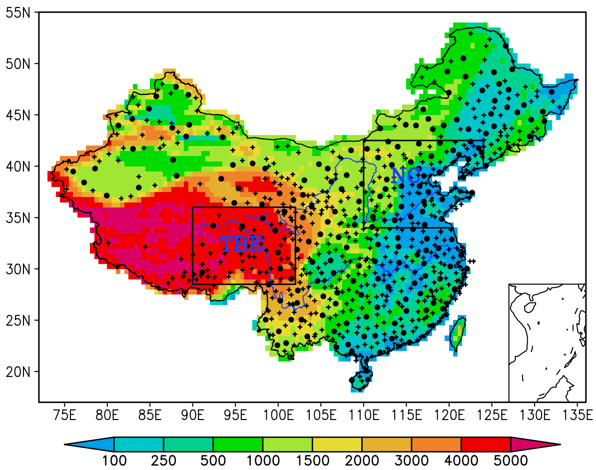

Fig. 1. Distribution of the 751 stations employed in this study. The GTS stations are included in the 751 stations and marked by dots, the rest are by crosses. The squares are the sub-regions used in the analysis.

The methodology of our interpolation basically follows the method by which the CRU dataset was created. A detailed description of the process can be found in New et al. (1999, 2000, 2002). More specifically, a widely used anomaly approach (e.g., HadGHCND; Xie et al., 2007; Sun et al., 2006) is employed in the gridding. This consists of two steps.

Firstly, a 30-year mean daily temperature for 1971–2000 is calculated for each of the 365 calendar days at each station. We use the period of 1971–2000 instead of 1961–1990 used in CRU to maintain a higher density of the stations. Further extension of the dataset in the future can be conducted directly based on this climatology without having to recalculate it every time.

Stations with more than 1/3 (10 years) missing data are excluded from the analysis. The total number of stations included in the final calculations is slightly different from day to day, but is in the range of 654–662. Then, the mean is interpolated onto a regular $0.5° \times 0.5°$ grid. This gridded dataset represents the climatology. Thin-plate smoothing splines (ANUSPLIN) (Hutchinson, 1995, 1999) are used for the interpolation. The spline surfaces are fitted as functions of latitude, longitude, and elevation. The same elevation data as in the CRU dataset are used (http://www.cru.uea.ac.uk/timm/grid/CRU_TS_2_1.html, see Fig. 1). This $0.5° \times 0.5°$ elevation data is derived from the mean of thirty-six $5'$ pixels present in each $0.5°$ cell. It is noted that the elevation is a co-predictor, and thus a topographic correction for the gridded data is calculated during the interpolation.

In the second step, a daily deviation for 1961–2005 is created relative to the 1971–2000 reference period for each contributing station. The deviations are then gridded as anomalies. Angular distance weighting (ADW) interpolation is applied in this step. The ADW basically employs a distance weighting function so that stations closest to the grid point of interest carry a larger weight. The eight nearest stations in our study are used in estimating values at each grid point.

Finally, the CN05 dataset is derived by merging the climatology and the anomalies for the full 1961–2005 period.

3. Results

3.1 *Monthly mean temperature*

Figures 2a and 2b show the multi-annual monthly mean Tm calculated from CN05 in January and July, respectively. The period of 1961–2002 is selected in

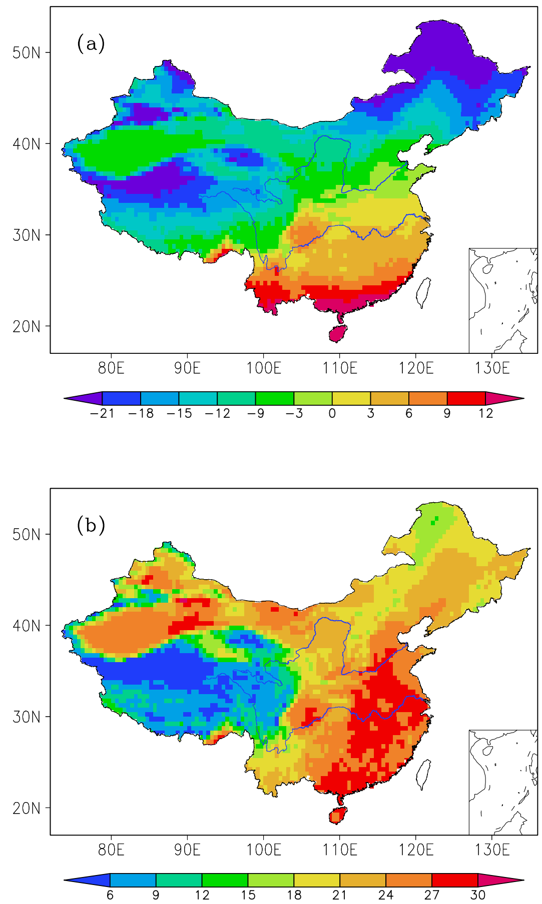

Fig. 2. Monthly mean (1961–2002) temperature from CN05 (°C) in (a) January and (b) July.

order to facilitate comparison with CRU observations (CRU data are only available until 2002).

In January over eastern China, a distinct latitudinal distribution is found. The temperature drops from over 12°C in southern China to less than −30°C in northeast China (Fig. 2a). In western China, temperature shows a strong dependence on topography (Fig. 1), with temperatures higher than −10°C in basins and as low as −20°C over high peaks. A seasonal evolution is found when comparing Figs. 2a and 2b, with the latitudinal distribution in July being much weaker than in January over eastern China. The lowest temperatures are found over the Tibetan Plateau.

Differences between CN05 and CRU for multiannual monthly mean Tm in January and July, Tmin in January, and Tmax in July are shown in Figs. 3a–d, respectively. Tm in the CN05 dataset is generally colder than in the CRU dataset, particularly in January (Figs. 3a and 3b). Differences between the two datasets are usually in the range of 0.5°C–1°C in eastern China and up to 3°C in areas of western China, where there are steep topographic gradients and tightly packed isotherms (Fig. 2a). This is evident, for example, over the transition zone from the eastern edge of the Tibetan Plateau to the Sichuan Basin and from the northwestern part of the Tibetan Plateau (Kunlun Mountains) to the Tarim Basin. Warmer temperatures in CN05 compared to CRU can also be found over several other portions of the domain.

Differences in January Tmin between CN05 and CRU values (Fig. 3c) show warmer temperatures in CN05 by up to 3°C over portions of North, Northeast, and Southwest China. Tmax in July shows greater difference between the two datasets over western China than in the east (Fig. 3d). In general, similar patterns of differences can be found for Tmax, Tmin (Fig. 3c), and, to some extent, Tm (Figs. 3a and 3b).

Both the spatial and temporal correlation coefficients of Tm, Tmin, and Tmax between the two datasets are high, in the range of 0.95–0.99 (not shown here for brevity). Differences between the two datasets of the regionally averaged Tm, Tmax, and Tmin over China for each month are presented in Fig. 4. These show that the CN05 temperatures are generally lower than the CRU ones. The differences in Tm vary from month to month, being maximum in the cold months (∼ −1°C) and minimum in May–June (∼ −0.3°C). Tmax differences show less variation across months, with values ∼ −0.2°C. For Tmin, the differences show some dependence on the month, but to a lesser extent compared to Tm. Regionally averaged Tmin values in CN05 are quite close to those of CRU from April to November, with departures of less than 0.1°C.

The differences between the two datasets can be largely attributed to the use of new and additional stations in CN05. For example, the positive CN05-CRU temperature difference centered at (30°N, 96°E) over the Tibetan Plateau (Figs. 3a–3d) is due to the presence of many more stations in CN05 (Fig. 1). It is also possible that the differences are related to the different periods used in construction the climatology (1971–2000 for CN05 and 1961–1990 for CRU) and/or to the selection of different interpolation domains. For example, the application of this methodology over Australia has shown that gridding over several sub-regions can lead to different and better results compared to gridding over a domain as large as Australia (X. D. Wang, personnel communication). Future studies and tests are needed to test these various hypotheses.

3.2 *Interannual variability and trend*

The regional mean annual anomalies of Tm over North China (NC, 34°–43°N, 110°–124°E) for CN05 in the period 1961–2005 and CRU for 1961–2002 relative to the 1971–2000 mean, as well as the linear trend

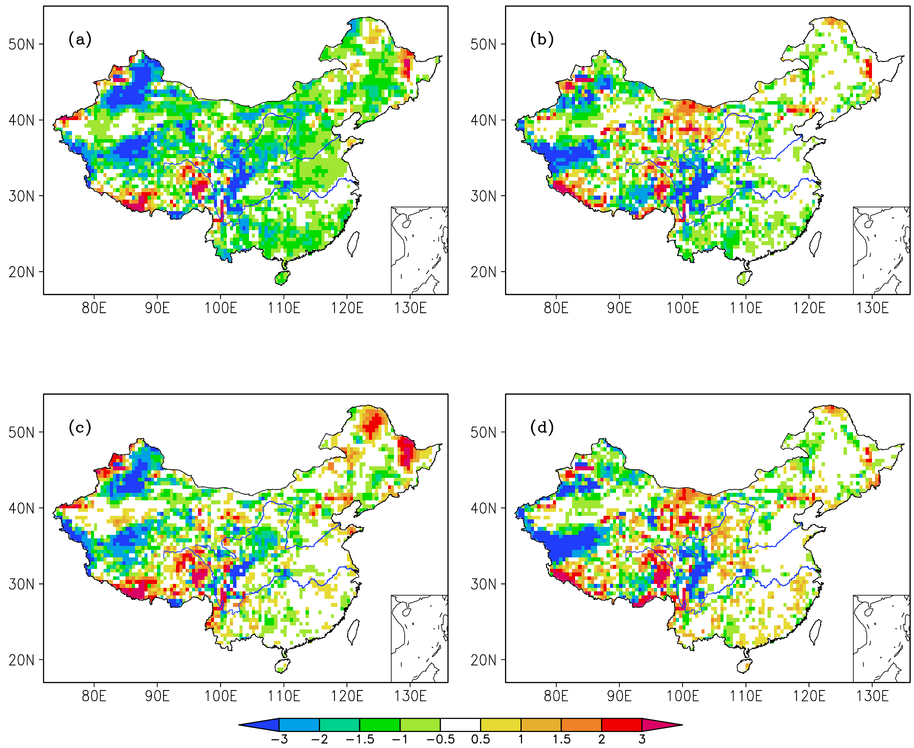

Fig. 3. Differences between CN05 and CRU (°C) for (a) Tm in January, (b) Tm in July, (c) Tmin in January, and (d) Tmax in July.

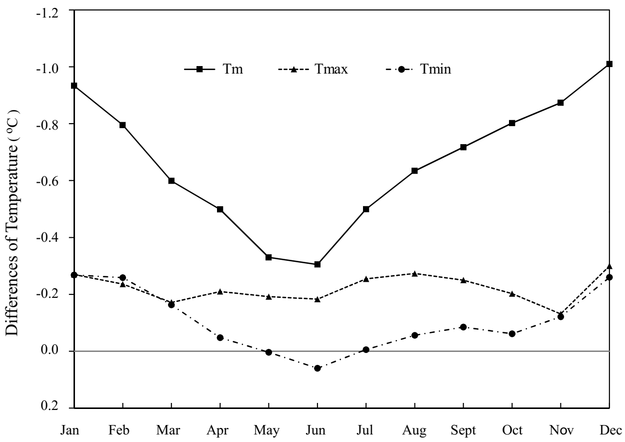

Fig. 4. Differences between the regionally averaged Tm, Tmax, and Tmin in CN05 and CRU over China for each month of the year.

for 1961–2002 from both datasets, are presented in Fig. 5a. It is evident that the anomaly and the trend lines derived from CN05 and CRU match quite closely over NC, with a slightly greater warming trend in CN05, especially after 1980. The linear trend of CN05 is 0.32°C (10 yr)$^{-1}$ decade versus 0.26°C (10 yr)$^{-1}$ in CRU.

Time series of Tmin and Tmax anomalies from the two datasets show similar properties as seen for Tm (figures not shown). The linear trends for both Tmin and Tmax are also larger in CN05 than CRU. Values of the trend for CN05 and CRU are 0.36°C (10 yr)$^{-1}$ and 0.32°C (10 yr)$^{-1}$ for Tmin and 0.25°C (10 yr)$^{-1}$ and 0.17°C (10 yr)$^{-1}$ for Tmax, respectively. The greatest warming is found for Tmin (compared to Tmax and Tm), indicating a greater increase of warm nights in this region in recent decades.

The eastern part of the Tibetan Plateau (TBE) is a region where more stations have been introduced in our dataset (Fig. 1). The regional mean annual anomalies and linear trend of Tm over the TBE (28.5°–36°N, 90°–102°E) are presented in Fig. 5b. It can be noted that the anomalies in the two datasets are not so close to each other as in NC, especially in the 1960s and 1990s. CRU temperatures are 0.1°C–0.3°C higher in the 1960s and about 0.3°C lower in the 1990s, leading to a warming trend of 0.17°C (10 yr)$^{-1}$ compared to 0.24°C (10 yr)$^{-1}$ in CN05. The linear trends for CN05 and CRU are 0.36°C (10 yr)$^{-1}$ and 0.26°C (10 yr)$^{-1}$ for Tmin and 0.14°C (10 yr)$^{-1}$ and 0.08°C (10 yr)$^{-1}$ for Tmax, respectively. Again a greater warming is found during the nighttime compared to the daytime.

3.3 *Lapse rate*

Elevation is a covariate in the thin-plate spline interpolation conducted by the ANUSPLIN software. A

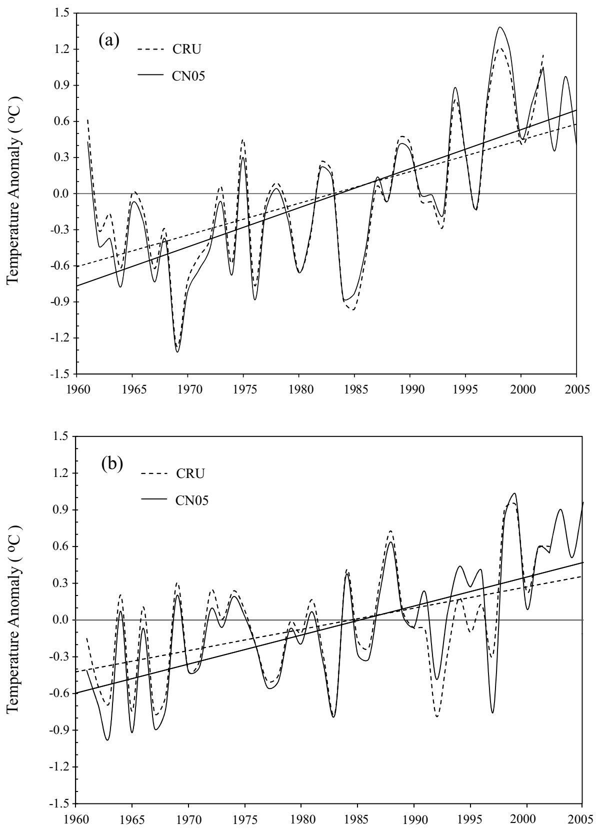

Fig. 5. Interannual variability (°C) and linear trend [°C (10 yr)$^{-1}$] of Tm over (a) North China (34°–43°N, 110°–124°E) and (b) eastern Tibetan Plateau (28.5°–36°N, 90°–102°E) in the CN05 and CRU datasets.

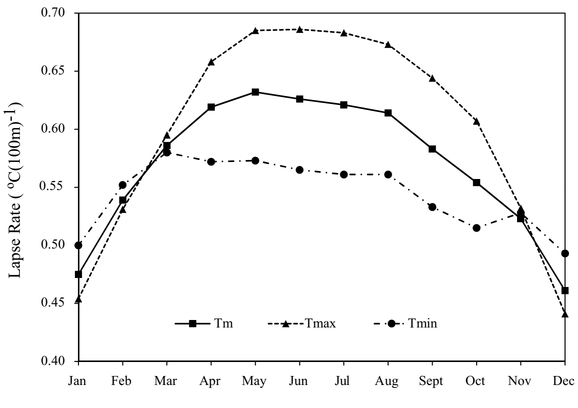

Fig. 6. Monthly mean lapse rate for daily mean (Tm), maximum (Tmax), and minimum (Tmin) temperature.

lapse rate (LR) is estimated through the regression of the elevation and temperature at the stations and is used to calculate an elevation correction for the interpolation. The LR varies from day to day but not from location to location in the same day.

The calculated monthly mean LRs for 1971–2000 are presented in Fig. 6. The LRs for Tm, Tmin, and Tmax are close to each other in the cold months, with values of 0.45°–0.50°C (100 m)$^{-1}$. They become larger and more different from each other in the warm months, indicating that temperature drops more rapidly with elevation at that time. The LR for Tmax is the largest, followed by Tm and Tmin. The above phenomena are consistent with the findings from observational studies over mountain slopes (e.g., Zheng and Fang, 2004).

It is noted that traditionally, a uniform and empirical LR is assumed to be 0.65°C (100 m)$^{-1}$, while in reality this varies with season and space. Only in the warm half of the year are the lapse rates for Tmax and Tm close to this standard value.

4. Applications

A multi-decadal high-resolution climate change simulation over East Asia has been constructed with the International Center for Theoretical Physics (ICTP) RegCM nested within the NASA/NCAR global model FvGCM (Finite-volume GCM) (Gao et al., 2008, 2009). Two sets of simulations were conducted at 20-km grid spacing, one for present day (1961–1990, denoted as RF) and one for future climate conditions (2071–2100, the IPCC A2 scenario). Validation of the mean precipitation and temperature in RF has been reported by Gao et al. (2008, 2009), which show a generally good performance of the model in reproducing present climate. More details about the simulation can be found in the two references cited above.

The new daily dataset CN05 makes it possible to evaluate the model performance at the daily scale over the gridded domain. Here we use three simple indices for extremes, called GD4, FD, and SU25, in order to compare the RF simulation with the CN05 observations. The indices are from Frich et al. (2002) and ETCCDI (Expert Team on Climate Change Detection and Indices, http://cccma.seos.uvic.ca/ ETCCDMI/; Peterson et al., 2001) GD4 is the number of growing degree days, defined as the sum of the days with a daily mean temperature greater than 4°C throughout the year. FD is the number of frost days, defined as the days with Tmin< 0°C, and SU25 is the number of summer days (days with Tmax> 25°C).

The observed (CN05) and simulated GD4 are presented in Fig. 7a and 7b, respectively. Over eastern China, the observed GD4 shows a significant latitudinal gradient (Fig. 7a). It exceeds 360 days in the southern portions of China, and drops to less than 160 days in northeast China. Over western China, GD4 is

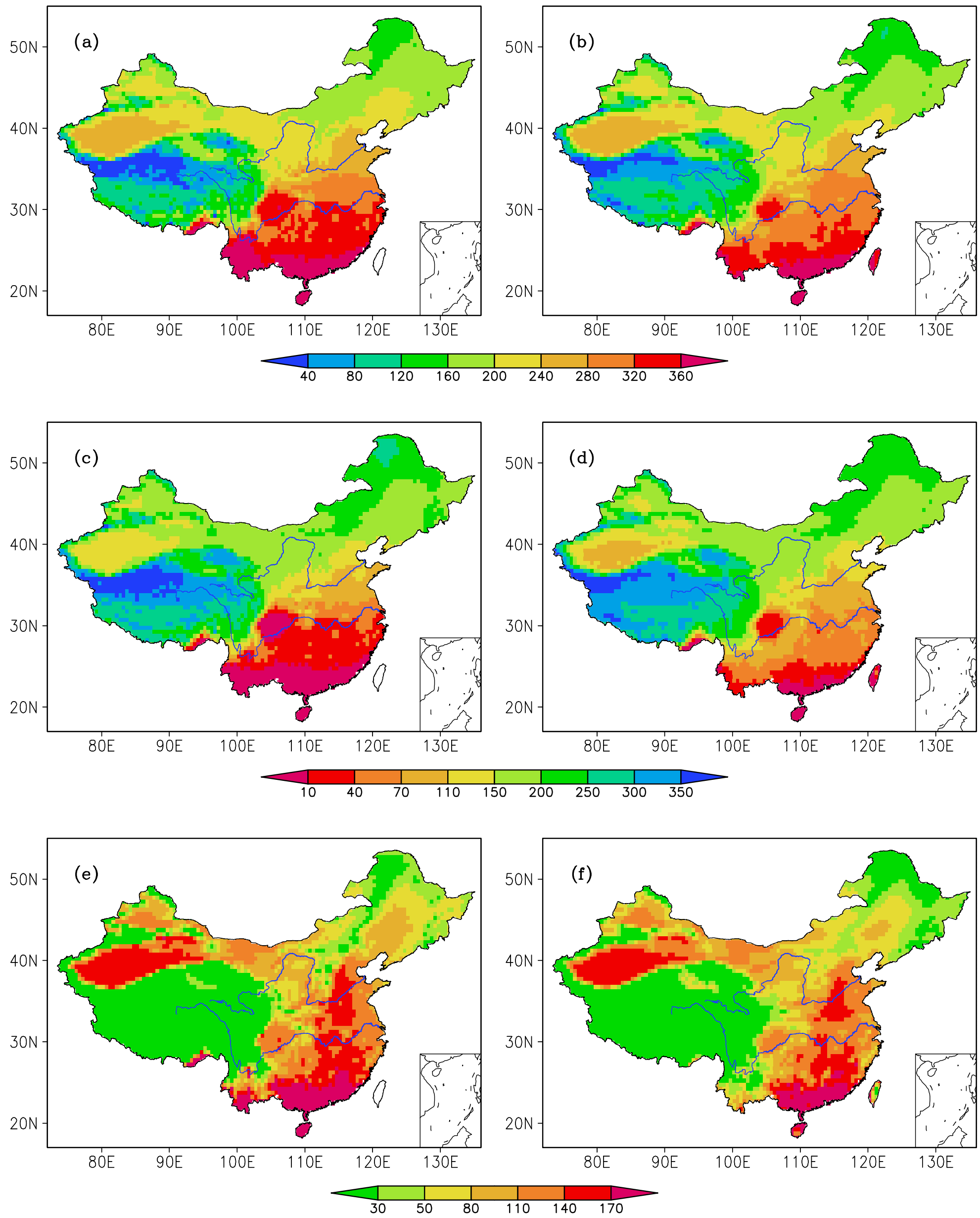

Fig. 7. Indices of extremes: GD4 (growing degree days), FD (frost days), and SU25 (summer days) from CN05 and a regional climate model (ICTP RegCM) simulation, 1961–1990. (a) GD4, CN05; (b) GD4, RegCM; (c) FD, CN05; (d) FD, RegCM; (e) SU25, CN05; (f) SU25, RegCM (units: d yr^{-1})

more dependent on the topography. Higher values are found in the lower basins (up to 240 days) and lower values of less than 40 days are found over the higher elevation mountain areas. In general, the model reproduces both the distribution and magnitude of this pattern, although it underestimates GD4 over eastern China by about 10–20 days, corresponding to a cold bias in these areas (Gao et al., 2009). The largest underestimation, of up to 30 days, is found over the eastern edge of the Tibetan Plateau, and is related to an overestimation of precipitation and the consequent cold bias there (Gao et al., 2009). The model overestimates the SD4 over the Tibetan Plateau and Tarim Basin by about 10–30 days.

The observed FD shows a similar latitudinal distribution over eastern China, as well as topographic dependence over western China. In eastern China the values of FD are less than 10 days in the south and greater than 240 days in the north (Fig. 7c). A maximum FD of nearly the whole year's length (>350) is found over the Tibetan Plateau. The model captures well the basic pattern, but simulates greater FD (by ∼30 days) in South and Southwest China, which also corresponds to a cold bias over these areas (Fig. 7d). Similarly to SD4 and FD, the model also reproduces generally well the overall pattern and magnitude of SU25 (see Figs. 7e and 7f).

5. Conclusion and discussions

A dataset consisting of daily mean, maximum, and minimum temperature on a 0.5° × 0.5° grid has been constructed over mainland China for the 45-yr period of 1961–2005. The dataset (called CN05) is derived from interpolating observations from 751 stations distributed throughout the entire Chinese territory except Taiwan. The interpolation follows basically the same approach used in generating the CRU dataset, whereby a gridded climatology is calculated first, and then a gridded anomaly is added to obtain the final data.

Comparison of the CN05 dataset with CRU at the monthly scale shows basic similarities between the two. However, differences can be found, especially in the areas where new and denser station data have been introduced in CN05. The two datasets show similar interannual variability over North China. But the linear trend of warming from CN05 is slightly larger than that from CRU for all three temperature variables.

As an illustrative example, CN05 is applied to the validation of an RCM simulation for three extreme temperature indices: GD4, FD, and SU. Results show that the model generally captures both the distribution and magnitude of the observed indices (CN05), although with some discrepancies in correspondence to the model mean temperature biases.

Different interpolation methods can lead to different gridded fields. New et al. (1999, 2000) describe the advantages of the anomaly approach, the use of thinplate smoothing splines in generating the mean climatology, and of the angular distance weighting method in interpolating the anomaly data. However, this is based on a global scale estimation. Other methods may perform better over China due to its unique climate characteristics (e.g., the monsoon) and/or complex topography (e.g., the Tibetan Plateau). Tests of other methods may provide more accurate gridded fields, and will be analyzed in future work along with a cross-validation analysis for the interpolation. It is also noted that the station data employed in this study has not been processed with homogenization procedures, such as to account for heat island effects, errors caused by station relocation, etc. Upgrades of the original data with improved quality control and treatments for station relocations and/or missing data are needed to improve the quality of the gridded data (Feng et al., 2004; Li and Yan, 2009; D. L. Chen, personnel communication).

As introduced in Section 1, the resolution of present day RCMs is of the order of 15–20 km or even higher. The 0.5° × 0.5° resolution used in our study was selected to match typical inter-station distances. However, this is not fine enough to evaluate the performance of very high-resolution RCMs. There are over 2000 weather stations across China managed by CMA and over 1000 additional stations under other departments (e.g., hydrology, forestry, agriculture, etc.). Collection of these data to create a higher resolution dataset expanded to cover all of East Asia is planned in future work.

The CN05 dataset was primarily developed for the validation of climate models. However, it has also potential applications in studies such as monitoring observed changes and trends in climate, hydrology, and ecology. A coarse resolution version of the data (1° × 1°) is freely available at http://ncc.cma.gov.cn/Website/index.php?ChannelID =112 & WCHID=110. Information about the full dataset should be directed to the corresponding author or the National Climate Center of China Meteorological Administration.

Acknowledgements. This research is jointly supported by the National Basic Research Program of China (2009CB421407, 2006CB403707, and 2007BAC03A01), the R & D Special Fund for Public Welfare Industry (meteorology) (GYHY200806010), and Chinese Academy of Sciences (Grant No. KZCX2-YW-Q1-02). The authors would like to thank Dr. Liqiang Sun from the International Research Institute for Climate and Society in the U. S. and Dr. Xiangdong Wang from the Australian Bureau of Meteorology, as well as two anonymous reviewers, for their valuable discussions and comments on this work.

REFERENCES

Alexander, L. V., and Coauthors, 2006: Global observed changes in daily climate extremes of temperature and precipitation. *J. Geophys. Res.*, **111**, 1–22, doi: 10.1029/2005JD006290.

Caesar, J., L. Alexander, and R. Vose, 2006: Large-scale changes in observed daily maximum and minimum temperatures: Creation and analysis of a new gridded data set. *J. Geophys. Res.*, **111**, D05101, doi: 10.1029/2005JD006280.

Chen, Z. X., Q. B. Zhou, and B. Xu, 2001: The spatial and temporal patterns for temperature in China. *Re-*

search on Agricultural Resource Utilization and Regional Sustainable Development, H. J. Tang, Ed., China Agricultural Science and Technology Press, Beijing, 230–236. (in Chinese with English Abstract)

Christensen, J. H., and Coauthors, 2007: Regional climate projections. *Climate Change 2007: The Physical Science Basis. Contribution of WGI to the IPCC AR4*, Solomon et al., Eds., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 847–940.

Christensen, O. B., and J. H. Christensen, 2004: Intensification of extreme European summer precipitation in a warmer climate. *Global and Planetary Change*, **44**, 107–117, doi: 10.1016/j.gloplacha.2004.06.013.

Feng, J. M., and C. B. Fu, 2006: Inter-comparison of 10-year precipitation simulated by several RCMs for Asia. *Adv. Atmos. Sci.*, **23**, 531–542, doi: 10.1007/s00376-006-0531-2.

Feng, S., Q. Hu, and W. H. Qian, 2004: Quality control of daily meteorological data in China, 1951–2000: A new dataset. *International Journal of Climatology*, **24**, 853–870, doi: 10.1002/joc.1047.

Frich, P., L. V. Alexander, P. Della-Marta, B. Gleason, M. Haylock, A. M. G. Klein Tank, and T. Peterson, 2002: Observed coherent changes in climatic extremes during the second half of the twentieth century. *Climate Research*, **19**, 193–212.

Gao, X. J., Z. C. Zhao, and F. Giorgi, 2002: Changes of extreme events in regional climate simulations over East Asia. *Adv. Atmos. Sci.*, **19**(5), 927–942.

Gao, X. J., Y. Xu, Z. C. Zhao, J. S. Pal, and F. Giorgi, 2006a: On the role of resolution and topography in the simulation of East Asia precipitation. *Theor. Appl. Climatol.*, **86**, 173–185, doi: 10.1007/s00704-005-0214-4.

Gao, X. J., J. S. Pal, and F. Giorgi, 2006b: Projected changes in mean and extreme precipitation over the Mediterranean region from a high resolution double nested RCM simulation. *Geophys. Res. Lett.*, **33**, L03706, doi: 10.1029/2005GL024954.

Gao, X. J, Y. Shi, R. Y. Song, F. Giorgi, Y. G. Wang, and D. F. Zhang, 2008: Reduction of future monsoon precipitation over China: Comparison between a high resolution RCM simulation and the driving GCM. *Meteor. Atmos. Phys.*, **100**, 73–86, doi: 10.1007/s00703-008-0296-5.

Gao, X. J., Y. Shi, and F. Giorgi, 2009: A high resolution simulation about climate change over China. *Science in China*(*D*), in press.

Giorgi, F., and L. O. Mearns, 1991: Approaches to regional climate change simulations: A review. *Rev. Geophys.*, **29**, 191–216.

Hibbard, K. H., G. Meehl, P. Cox, and P. Friedlingstein, 2007: A strategy for climate change stabilization esperiments. *Eos, Transactions American Geophysical Union*, **88**(20), 217, 219–221, doi: 10.1029/2007EO200002.

Hutchinson, M. F., 1995: Interpolating mean rainfall using thin plate smoothing splines. *International Journal of Geographical Information Systems*, **9**, 385–403.

Hutchinson, M. F., 1999: ANUSPLIN version 4.0 user guide. Centre for Resources and Environmental Studies, Australian National Univeristy, Canberra ACT 0200, Australia.

IPCC, 2007: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group 1 to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Solomon et al. Eds., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 996pp.

Kitoh, A., and S. Kusunoki, 2008: East Asian summer monsoon simulation by a 20-km mesh AGCM. *Climate Dyn.*, **31**(4), 389–401, doi: 10.1007/s00382-007-0285-2.

Leung, L. R., L. O. Mearns, F. Giorgi, and R. L. Wilby, 2003: Regional climate research: Needs and opportunities. *Bull. Amer. Meteor. Soc.*, **84**, 89–95, doi: 10.1175/BAMS-84-1-89.

Li, J., S. C. You, and J. F. Huang, 2006: Spatial interpolation method and spatial distribution characteristics of monthly mean temperature in China during 1961–2000. *Ecology and Environment*, **15**, 109–114. (in Chinese)

Li, Z., and Z. W. Yan, 2009: Application of Multiple Analysis of Series for Homogenization (MASH) to Beijing daily temperature records during 1961–2006. *Adv. Atmos. Sci.*, in press.

Meehl, G. A., and Coauthors, 2007: Global climate projections. *Climate Change 2007: The Physical Science Basis. Contribution of WGI to the IPCC AR4*. Solomon et al., Eds., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 747–845.

Mizuta, R., and Coauthors, 2006: 20-km-mesh global climate simulations using JMA-GSM model—Mean climate states. *J. Meteor. Soc. Japan*, **84**, 165–185, doi: 10.2151/jmsj.84.165.

New, M., M. Hulme, and P. Jones, 1999: Representing twentieth-century space-time climate variability. Part 1: Development of a 1961–90 mean monthly terrestrial climatology. *J. Climate*, **12**, 829–856.

New, M., M. Hulme, and P. Jones, 2000: Representing twentieth-century space-time climate variability. Part 2: Development of a 1901–1996 monthly terrestrial climate field. *J. Climate*, **13**, 2217–2238.

New, M., D. Lister, M. Hulme, and I. Makin, 2002: A high-resolution data set of surface climate over global land areas. *Climate Research*, **21**, 1–25.

Pan, Y. Z., D. Y. Gong, L. Deng, J. Li, and J. Gao, 2004: Smart distance searching-based and DEM-informed interpolation of surface air temperature in China. *Acta Geographysica Sinica*, **59**, 366–374. (in Chinese)

Peterson, T. C., C. Folland, G. Gruza, W. Hogg, A. Mokssit, and N. Plummer, 2001: Report on the activities of the working group on climate change detection and related rapporteurs 1998–2001. WMO, Rept. WCDMP-47, WMO-TD 1071, Geneve, Switzerland, 143pp.

Sun, L., D. F. Moncunil, H. Li, A. D. Moura, F. D. A. D. S. Filho, and S. E. Zebiak, 2006: An operational dynamical downscaling prediction system for Nordeste Brazil and the 2002–04 real-time forecast evaluation. *J. Climate*, **19**, 1990–2007, doi: 10.1175/JCLI3715.1.

Xie, P., and P. A. Arkin, 1997: Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs. *Bull. Amer. Meteor. Soc.*, **78**, 2539–2558.

Xie, P., J. E. Janowiak, P. A. Arkin, R. Adler, A. Gruber, R. Ferraro, G. J. Huffman, and S. Curtis, 2003: GPCP pentad precipitation analyses: An experimental dataset based on gauge observations and satellite estimates. *J. Climate*, **16**, 2197–2214, doi: 10.1175/2769.1.

Xie, P., A. Yatagai, M. Y. Chen, T. Hayasaka, Y. Fukushima, Ch. M. Liu, and S. Yang, 2007: A gauge-based analysis of daily precipitation over East Asia. *J. Hydrol.*, **8**(3), 607–626.

Xu, Y., C. H. Xu, X. J. Gao, and Y. Luo, 2009: Projected changes in temperature and precipitation extremes over the Yangtze River Basin of China in the 21st century. *Quaternary International*, doi: 10.1016/j.quaint.2008.12.020.

Yan, H., N. A. Nix, M. F. Hutchinson, and T. H. Booth, 2005: Spatial interpolation of monthly mean climate data for China. *International Journal of Climatology*, **25**, 1369–1379, doi: 10.1002/joc.1187.

Zheng, C. Y., and J. Y. Fang, 2004: Changes in air temperature variables along altitudinal gradient in Mt. Huanggang, China. *Acta Meteorologica Sinica*, **62**(2), 251–255. (in Chinese)