High-resolution hydrometeorological forecast in Southwest China based on a multi-layer nested WRF model

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Abstract. In this study, a high-resolution (5km:1km) regional hydrometeorological simulation (Weather Research and Forecasting, WRF) in Southwest China was evaluated by comparisons with the multiple General Circulation Model (multi-GCM) ensemble mean from Coupled Model Intercomparison Project phase 5 (CMIP5) and in-situ observation data, to prove its advantage to precisely delineate the regional complex topographical and climatic conditions. The temperature and precipitation were selected to evaluate the model performance skills. Simulations of the spatiotemporal rainfall and near-surface air temperature distribution across the entire research area and at four specific sites (Ganzi, Daofu, Jiulong Huili) were analyzed based on observational data from 2007–2010. Overall, both the WRF and multi-GCM demonstrated satisfactory capabilities in representing seasonal variation, but systematic biases remained. The regional average near-surface air temperature of WRF outputs had cold biases of −4.91, −1.96, −3.92 and −8.17°C in spring, summer, autumn and winter, respectively, and wet biases of 40.5–428.5 mm in cumulative precipitation over the four seasons. Overall, the multi-GCM means had consistent bias, but were closer to regional averages derived from in-situ data. At the four validation stations, the WRF outputs consistently performed better for temperature and precipitation according to the correlation coefficient, root-mean-square error, and index of agreement. The simulation capabilities identified herein can serve as a foundation for addressing WRF model biases and improving projection accuracy in the future.

1. Introduction

Current simulation approaches of regional hydrometeorological variables can be categorized as regional climate models (RCMs) [1, 2], traditional statistical models [3, 4], artificial intelligence and deep machine learning methods [5, 6], or other hybrid methods [7, 8]. RCMs from dynamic downscaling have demonstrated that they can simulate climatic conditions well and improve GCM prediction [9, 10]. This is based on a gradually maturing climate dynamics framework, the advancement and support of high-performance computing efforts, and concerted research efforts in related fields.

Weather Research and Forecast (WRF), a mesoscale regional dynamical downscaling model designed for both meteorological research and operational forecast applications, was used to perform our simulations. There have been numerous research achievements applying WRF to the evaluation of hydrometeorological variables. It is acknowledged that the simulation accuracy of WRF is related to the choices of initial and boundary forcing conditions [11], physics parameterization schemes[12, 13],
spatial resolution [14, 15], data assimilation schemes [16, 17], subgrid orographic parameterization scheme [18-20], dynamical cores [21], and post-processing [22, 23].

Moreover, the physical mechanism of interactions between the land surface and overlying atmosphere can also play a critical role in modulating the hydrometeorological elements, and the terrain complexity exerts a clear influence on surface energy partitioning and atmospheric circulation within the climate system [24, 25]. Therefore, the simulation capability was examined by comparing with a multi-model ensemble mean, which was widely used in CMIP5.

2. Location and description of study area
The terrain elevation in Southwest China is generally high in the northwest and low in the southeast, with complex topography and numerous mountains and rivers. It spans 25°12' to 34°9'N and 96°47' to 102°42'E approximately. The altitude of this region is ranging from 1000–6000 m. The four specific point locations selected were Ganzi, Daofu, Huili and Jiulong, which are representative of the upstream (first two), middle-stream (third) and lower-stream (last) reaches of one watershed in Southwest China, respectively, according to the geographic location of the basin. The climatic conditions are diverse with significant differences in horizontal and vertical directions, where the northwestern plateau is characterized by alpine condition and the downstream areas are tropical and temperate climates in South Asia.

3. Materials and methodology

3.1. Data collection
The observational stations variable used were daily precipitation and temperature from 2007 to 2010, specifically at, Ganzi, Daofu, Jiulong, and Huili. The daily dataset was obtained from the data center of the China Meteorological Administration (website: http://data.cma.cn). The CMIP5 data series can be obtained from http://cmip-pcmdi.llnl.gov/. Detailed information about our selected CMIP5 data is given in Table 1. Statistical characteristics including mean, min, max, St Dev, Cv, C5 and r1[26] calculated from the monthly average temperature and precipitation time series of each gauging station are given in Table 2.

| Model name | Selected variable | Spatial resolution (lon x lat) in degree | Ensemble member adopted | Institution (country) |
|------------|-------------------|-----------------------------------------|-------------------------|-----------------------|
| CESM1 (CAM5) | pr, tas | 1.25° × 0.9424° /0.9425° | RCP45-r1i1p1-r2i1p1-r3i1p1; RCP4.5-r1i1p1-r3i1p1-r7i1p1; esgdata.gfdl.noaa.gov; esgf-data1.ceda.ac.uk; esgfz.dkrz.de; | Community Earth System Model Contributors (USA) |
| HadCM3 | pr, tas | 3.75° × 2.5° | RCP4.5-r1i1p1-r3i1p1-r7i1p1; esgf-data1.ceda.ac.uk; esgfz.dkrz.de; | Met Office Hadley Centre (UK) |
| GFDL-ESM2g | pr, tas | 2.5° × 2.0224° /1.5169° /2.0225° | esgf-data1.ceda.ac.uk; esgfz.dkrz.de; | NOAA Geophysical Fluid Dynamics Laboratory (USA) |

Note: the abbreviations pr and tas represent the cumulative precipitation and near-surface air temperature (2 m above the surface)

| Statistical characteristic | Ganzi | Daofu | Jiulong | Huili |
|---------------------------|-------|-------|---------|-------|
| mean (°C) | 6.60 | 47.95 | 8.54 | 477.79 | 9.58 | 75.42 | 15.68 | 87.89 |
3.2. Model setup

The model configuration is described in Table 3. The configuration included a relatively coarse domain (D1) with 5-km resolution grids covering Southwest China and a 1-km resolution grid nested domain (D2) from 99°E–103°E and 26°N–32°N as shown in Figure 1. The model has 46 vertical levels in a new hybrid coordinate, and the first five levels, excluding the surface, are at or below 200-m height, around 40, 80, 120, 160 and 200 m above the surface. The nested D2 was forced by variables produced by the outer domain (D1), with the smoothing option turned on in the WRF configuration file. The flow chart of WRF model simulation and results analysis is shown in Figure 2.

![Figure 1. Abridged general view of model nesting.](image)

| Model version | WRF Model 4.0 |
|---------------|---------------|
| Domain        | 1             | 2             |
| Period        | 2007–2010     | 2007–2010     |
| Land-surface model | Noah MP[27, 28] |               |
| Horizontal resolution | 5 km       | 1 km          |
| Number of grid points | 380 × 322  | 351 × 681     |
| Integration time | 6 seconds  | 2 seconds     |
| Source        | 0.3° full resolution of 6-hourly CFSR reanalysis data [29] |
| Microphysics  | Thompson scheme [30] |
| Longwave physics | RRTMG scheme[31] | RRTMG scheme[31] |
| Shortwave physics | RRTMG scheme[31] |           |
| Planetary boundary layer | YSU [32] |
| Cumulus      | Modified Kain-Fritsch scheme [33] | None |
|    parameterization |            |               |
| Terrain data | 3-second resolution (90 m) of HydroSHEDS from U.S. Geological Survey [34] |
3.3. Statistics for evaluating model accuracy
The statistics of mean absolute error (MAE), index of agreement (d), root-mean-square error (RMSE), and Pearson correlation coefficient (r) are used to evaluate model accuracy in this paper, and they are calculated by Equation (1)-(4) respectively.

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{\text{sim}_i - \text{obs}_i}{\text{obs}_i} \right)
\]

\[
d = 1 - \frac{\sum_{i=1}^{N} \left( \text{obs}_i - \text{sim}_i \right)^2}{\sum_{i=1}^{N} \left( \text{sim}_i - \overline{\text{obs}} \right)^2 + \sum_{i=1}^{N} \left( \text{obs}_i - \overline{\text{obs}} \right)^2}
\]

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( \text{sim}_i - \text{obs}_i \right)^2}
\]

\[
r = \frac{\sum_{i=1}^{N} \left( \text{obs}_i - \overline{\text{obs}} \right) \left( \text{sim}_i - \overline{\text{sim}} \right)}{\sqrt{\sum_{i=1}^{N} \left( \text{obs}_i - \overline{\text{obs}} \right)^2} \sqrt{\sum_{i=1}^{N} \left( \text{sim}_i - \overline{\text{sim}} \right)^2}}
\]

where \text{sim}_i and \text{obs}_i represent simulated and observed values, respectively, and \(N\) is the total number of values.

4. Results and discussion
For comparison, the observations data and multi-CGM outputs were interpolated to match the WRF high temporal and spatial resolution. WRF, Obs, and GCMs refer to WRF outputs, observational data, and the ensemble mean of multi-GCM from CMIP5, respectively. The spatiotemporal distributions of the selected hydrometeorological variables were analyzed. Then, the accuracy of the simulation results at the sites was evaluated by calculating the \(MAE, d, RMSE\) and \(r\) indices between the WRF/GCMs and Obs.
4.1. Near-surface air temperature

Figure 3 displays the spatial distribution of regional mean temperature for the four seasons from 2007–2010. WRF and the GCMs were in general spatiotemporal agreement with the observations, and that the WRF more accurately delineated the region of high temperature identified by the rectangles in the study area (Figure 3). High resolution WRF results in left column illustrate the detail information, such as higher temperature along rivers embedded in mountains. The results are currently more realistic than interpolated observation plots in middle column due to sparse observation. The WRF output is therefore better than the GCMs result in right column. The differences of four seasons are clearer in WRF results than other two results. Overall, high resolution WRF results demonstrate the significant important role of topography of simulation in this complex geography domain.

Monthly and seasonal distributions of the regional mean temperature are illustrated in Figure 4. The results presented were lower values in the northwest for both outputs, especially in winter. It is demonstrated by the monthly mean temperatures in December, January and February, which were \(-4.39\), \(-5.05\) and \(-4.98\) °C, respectively, in WRF, and \(-2.85\), \(-3.56\) and \(-0.96\) °C, respectively, for the GCMs (Figure 4a). The WRF seasonal mean temperature was consistently colder than the Obs (Figure 4b). The best summer temperature was simulated by the GCMs, with a difference of only 0.06°C (13.18 and 13.24°C for the Obs and GCMs, respectively) (Figure 4b).

Figure 5 illustrates the probability density function (PDF) of seasonal mean errors (model simulation result departures from observations). The values within the dotted rectangle are mean error (first row) and standard deviation (second row) of WRF outputs and GCMs biases, respectively. The GCMs for the four seasons showed lower negative biases except in summer compared to WRF. Mean biases from WRF were \(-4.91\), \(-1.96\), \(-3.92\) and \(-8.17\) °C in spring (Figure 4a), summer (Figure 4b), autumn (Figure 4c) and winter (Figure 4d), respectively. The substantially lower temperature in winter points to the likelihood of extremely small values of downwelling shortwave radiation by WRF. However, the fitted curve of GCM biases were all nonparametric, whereas WRF output errors were normally distributed. The standard deviations of GCMs biases were all smaller than those of the WRF output errors, demonstrating that the PDF distributions of those biases were more concentrated.

Figure 6 shows time series of monthly average temperature for the four stations from 2007–2010, with the climate mean states removed. The values are r (before), RMSE (middle) and d (after) between WRF/GCMS and Obs, respectively, and the asterisk indicates that r is statistically significant at 95%
The correlation coefficients between Obs and WRF are 0.524, 0.779, 0.708 and 0.833, respectively, at Ganzi, Daofu, Huili and Jiulong, which all reached the 95% confidence level as marked by asterisks. The Obs-GCMs monthly average temperature are −0.117, 0.047, 0.250 and 0.158, respectively, which are smaller than the former. In addition, the larger d and smaller RMSE between WRF and Obs indicates better performance of WRF in simulating near-surface air temperature at the Ganzi station.

Figure 5. Probability density function distribution (%) of seasonal mean absolute error (departures from Obs) of temperature, with fitted curves of WRF bias (red) and GCMs (blue).

Figure 6. Time series of monthly mean temperature of the sites based on trend-removed values of Obs (black curve), WRF (blue dotted curve) and GCMs (red dotted curve).
4.2. Precipitation

The spatial distribution of mean precipitation during 2007–2010 is displayed in Figure 7. Precipitation was usually concentrated in the southeast of the study area (with high temperatures). The simulations reproduced the spatiotemporal characteristics of the observations but overestimated it. Regarding monthly and seasonal average precipitation, both outputs greatly overestimated the measured values (Figure 8). The WRF outputs were closer to Obs, except in July, August, September and October (Figure 8a). Therefore, WRF present a better performance in spring and winter (Figure 8b).

![Figure 7. Spatial distribution of mean.](image)

![Figure 8. Monthly and seasonal distribution of mean precipitation.](image)

Figure 9 presents the PDF fitted curve of the biases of the GCMs and WRF outputs. The values with the dotted rectangle are mean error (first row) and standard deviation (second row) of WRF and GCM biases, respectively. The WRF simulated seasonal precipitation average showed a largest bias of 428.51 mm. The GCM error was 315.60 mm, slightly smaller than that of spring (319.11 mm). The deviation of PDF offset from zero in spring and winter also demonstrates the superior simulation of WRF outputs, albeit with consistent positive biases. The bias distributions of both outputs were all nonparametric, and the GCM error distributions were always more concentrated because of smaller standard deviations.

Detrended monthly mean precipitation at the four stations during 2007–2010 from the WRF outputs, Obs and GCMs are plotted in Figure 10. The values are r (before), RMSE (middle) and d (after) between WRF/multi-GCM average and Obs, respectively, and the asterisk indicates that r is statistically significant at 95% confidence level. At Ganzi, Huili and Jiulong stations, there were significant correlation coefficients between WRF and Obs, with values 0.482, 0.457 and 0.713, respectively. Although there was no obvious correlation at Daofu station, which was higher than the GCMs one. Regarding the temperature performance, the precipitation index of agreement (d) of precipitation between WRF and Obs have higher values. For RMSE, WRF outputs present a smaller deviation and therefore better performance at all stations except at Huili station, with RMSE values of 65.586 and 52.808 between WRF/GCMs and Obs, respectively.
4.3. Discussion

In summary, WRF and the GCMs presented consistent systematic deviations. Both outputs generally underestimated near-surface air temperature, but overestimated precipitation. In addition, their performances varied considerably between seasons and months and among different climate variables. Cold biases of temperature and overestimation of precipitation were widespread in the WRF model [35, 36]. The YSU scheme has a tendency to overestimate precipitation intensity in the Asian summer monsoon region [37], which is the potential source of precipitation wet bias and a likely cause of the
near-surface air temperature cold bias in the WRF simulations. To investigate these hypotheses, we calculated temporal correlations of the 4-year time series between mean monthly precipitation biases and mean monthly temperature biases. A strong negative correlation between mean monthly precipitation biases and mean monthly temperature ($r < 0, 72.57\%$) was apparent over study area as shown in Figure 11. The results support the hypotheses that precipitation overestimation is linked to the cold biases of temperature. Most of the GCMs underestimated annual air temperature and overestimated mean annual precipitation, and thereby failed to reproduce observed mean annual air temperature and annual precipitation [38]. This is consistent with the results of the multi-ensemble mean (CESM1 (CAM5), HadCM3 and GFDL-ESM2g) in our study. However, the temperature and precipitation interaction mechanism are not as clear as in the WRF model.

![Figure 11. Spatial correlation analysis between mean monthly temperature biases and mean monthly precipitation biases (Left (WRF) & Right (GCMs)).](image)

5. Conclusions
Overall, our results demonstrated satisfactory capability in representing the seasonal variation and showed a spatiotemporal structure and characteristics similar to the observations. There were positive biases of precipitation, and negative biases of near-surface air temperature. Except for precipitation, the average and standard deviation of the multi-GCM ensemble mean biases had smaller values, yielding a more concentrated and desirable error probability density distribution. Both GCMs and WRF outputs had better skill in summer. The WRF model outperformed the multi-GCM mean for temperature and precipitation at all four selected sites.

Owing to the complexity of the regional climate and topography of Southwest China, and to its central geographic location, there is great difficulty in achieving highly accurate hydrometeorological simulations. Future efforts should be directed toward improvements in land-surface model and planetary boundary layer schemes considering the complexity of topography. Finally, suitable choices for the initial and boundary forcing conditions, data assimilation schemes, and the combination of parameterization schemes and spatiotemporal resolution, can also improve the accuracy of the simulation and resource evaluation.

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