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Key Points:
- The optimization of the physics schemes over the Tibetan Plateau (TP) is directly relevant to the land-atmosphere coupling study.
- A comprehensive evaluation for the effect of various physics schemes on the precipitation and soil moisture in the central TP is conducted.

Correspondence to:
Z. Xu, xuzhf@tea.ac.cn

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Abstract: The evaluation of the regional climate model is of great importance for model’s developments and applications. We assessed the performance of Weather Research and Forecasting (WRF) cloud resolving simulations with various physics options in terms of precipitation and soil moisture over the central Tibetan Plateau (TP) for a 2-month simulation from July to August in 2015. The simulated precipitation is most sensitive to the microphysics scheme, followed by the land surface model, which plays a vital role in the soil moisture simulation, while the planetary boundary layer and radiation schemes have relatively minor impacts on the precipitation and soil moisture. Specifically, the heavy precipitation event has a close relationship with the land surface model. Among the different WRF schemes, the new Thompson microphysics scheme, the Noah land surface model, the GFDL radiation scheme, and the Mellor–Yamada planetary boundary layer scheme perform relatively better than other options over the central TP. In contrast, the Lin and WRF Single-Moment 6-class microphysics schemes tend to simulate an earlier precipitation peak in the diurnal cycle, excessively higher intensities, and greater frequencies for high precipitation events. The Rapid Update Cycle model performs the worst in the spatiotemporal pattern of precipitation and markedly exaggerates the diurnal variation of soil moisture. These results can provide valuable guidance for further fine-scale simulation studies of land-atmosphere interaction over the TP.

1. Introduction

The Tibetan Plateau (TP) plays a crucial role in the formation of the Asian monsoon climate through its thermal and mechanical forces (An et al., 2001; Liu et al., 2012; Liu & Yin, 2002; Wu et al., 2012; Wu & Zhang, 1998; Xu et al., 2009, 2010; Ye & Wu, 1998; Zhou et al., 2009). The TP climate variabilities are strongly affected by multi-sphere interactions. The soil moisture and precipitation increased in TP in recent decades, the mechanism behind it needs to be further investigated (Bibi et al., 2018; Yao et al., 2019). Given the important role of the TP in Asian weather and climate, the National Science Foundation of China initiated a major research plan in 2013 to systematically investigate the impacts of the changing TP land-atmosphere coupled system on the regional and global climate.

The coupling of soil moisture and precipitation is one of the most important and challenging issues in land-atmosphere interactions studies (e.g., Ma et al., 2009; Seneviratne et al., 2010; Wei & Dirmeyer, 2012). However, we still have limited knowledge on the land-atmosphere interaction process over the TP due to insufficient observational data, complex terrain, and a heterogeneous landscape. A high resolution regional climate model, for example, Weather Research and Forecasting (WRF), is an important tool that enables us to investigate the land-atmosphere interaction at a finer spatial scale. WRF offers a broad spectrum of parameterization options, including multiple schemes for each of the microphysics, land surface, planetary boundary layer (PBL), cumulus, and radiation processes. Studies have indicated that the optimal scheme highly depends on the weather or climate regimes and the application scales, and no scheme universally performs the best (Jankov et al., 2005; Gallus & Bresch, 2006; Cossu & Hocke, 2014; Song & Sohn, 2018). Similar to other regions, the choice of schemes over the TP also depends on the study’s specific purpose (Maussion et al., 2011).

The microphysical scheme is responsible for computing the atmospheric water vapor, cloud liquid water, cloud ice, and precipitation (Eitahan and Magoola, 2018). Previous studies have shown that the choice of...
a microphysical scheme has important impacts on precipitation in regions with complex terrain (Cassola et al., 2015; Chen et al., 2014; Cossu & Hocke, 2014; Liu et al., 2011). For instance, Cossu and Hocke (2014) compared 13 WRF microphysical schemes in a mountain basin of North America during June–August in 2012, and found that results with different microphysical schemes can vary by up to 79% in water vapor, up to 10 times in hydrometeors and up to 64% in accumulated precipitation, by excluding the Kessler scheme that does not consider the ice phase processes. The evaluations with different time scales reached different conclusions over the TP. For example, the comparison of different microphysical schemes suggested that the Thompson scheme performs better than the other schemes in the spatiotemporal variability of precipitation for 1-week to 3-month simulations (Li et al., 2017; Maussion et al., 2011, 2014). He et al. (2012) found that the Lin scheme performs best in a heavy precipitation event simulation over the TP compared with the schemes of Kesser, Ferrier, and the WRF Single-Moment 3, 5, 6-classes. However, Gao et al. (2015) found that the WRF simulations with various microphysics parameterizations do not show significant differences in terms of the spatial pattern and 33-year trend of the annual precipitation over the TP.

Moreover, the role of the land surface model (LSM) in precipitation simulations has been investigated in previous studies (e.g., Smirnova et al., 2016). Jin et al. (2010) and Chen et al. (2014) showed that the spatiotemporal variability of precipitation is less sensitive to the selection of the LSM for 9–12 month simulations over the western United States. Zeng et al. (2012) stated that a heavy precipitation event is strongly linked to the LSMs in the Yangtze–Huai river basin and southern China. Maussion et al. (2011) found that the Rapid Update Cycle (RUC) model is not suitable for the TP region. The impacts of LSM (RUC and Pleim–Xiu) on precipitation are weak for 1-week to 1-month simulations, but they are expected to become more influential for longer simulations (Maussion et al., 2011).

In addition to the physics options, spatial resolution is also an important factor that strongly affects the model simulation. Current studies have indicated that, compared with the relatively coarse resolution (e.g., 14 and 28 km), the fine resolution (e.g., 3.5 and 7 km) presented a more reliable skill in precipitation modeling over the complex terrain (Biskop et al., 2012; Collier et al., 2013; Dimri et al., 2013; Rasmussen et al., 2014; Sato et al., 2008; Tramblay et al., 2013). The coarse resolution simulations generally tend to generate an excessive precipitation amount and rough information of the spatial distribution (Heikkilä et al., 2011; Maussion et al., 2011, 2014; Sato et al., 2008).

The optimization of the physics schemes over the TP is directly relevant to the land–atmosphere coupling study. Specifically, whether or not precipitation and soil moisture are significantly sensitive to the selection of the various physics schemes requires further investigation. A few previous studies evaluated the physics schemes in the TP area at fine spatial scale (e.g., He et al., 2012; Li et al., 2017; Maussion et al., 2011). However, no comprehensive evaluation has been conducted for the effect of various physics schemes on the precipitation and soil moisture in the central TP where the land–atmosphere interaction is potentially strong. We therefore conducted a series of cloud resolving WRF simulations with various physics schemes to examine the applicability of various physical schemes over the central TP. In addition, we also assessed the impacts of the spatial resolution on precipitation and soil moisture by comparing a 15-km WRF simulation with a 3-km simulation.

2. Model and Data

2.1. Model and Experimental Design

The model used is the WRF model with advanced research WRF dynamic core version 3.8.1. The WRF model is a nonhydrostatic model designed for both atmospheric research and operational applications. In this study, the WRF domain is centered at 32°N, 88°E with 311 and 211 horizontal grid points in the west–east and south–north directions, respectively (Figure 1). A horizontal resolution of 3 km is used with 35 vertical levels, and the time step is 18 s. The top of the model is 50 hPa.

According to the previous study results, we performed 10 sensitivity simulations at a horizontal resolution of 3 km with various physics options, including three microphysics process (MP) schemes, three LSMs, three radiation (RA) schemes, and four PBL schemes (Table 1). The employed MP schemes are the new Thompson, Lin scheme, and WRF Single-Moment 6-class (WSM6) scheme. The Thompson scheme is a
well-known double moment bulk scheme (Cassola et al., 2015), while Lin and WSM6 are single moment bulk schemes and mainly predict the mixing ratios of hydrometeors by assuming particle size distribution (Song & Sohn, 2018). The detailed descriptions of MP schemes can be found in Jankov et al. (2011). The assessed LSM schemes are Noah, Noah_MP, and RUC. The Noah LSM has four soil layers with total depth of 2 m and a combined surface layer of vegetation and soil surface. In Noah LSM, there is one vegetation type in one grid cell without dynamic vegetation. Noah_MP has improved the biophysical and hydrological processes based on Noah and introduces a framework for multiple options to parameterize selected processes. In this paper, the dynamic vegetation module in Noah_MP is closed, and the original surface and subsurface runoff scheme (free drainage) is selected, while the other options are the default settings. The RUC model has nine levels and considers one vegetation type in one grid cell without dynamic vegetation. More details on these LSMs and their differences are well documented in previous literature (e.g., Chen et al., 2014; Jin et al., 2010; Zhang et al., 2011). The PBL, RA schemes, and their specific combinations are shown in Table 1. The MP8 can be regarded as a reference experiment because we only change one physics scheme relative to the MP8 experiment at a time to generate other configurations. Thus, the difference between the reference experiment and the other experiments serves

![Figure 1. WRF domain showed by the black line based on topography map.](image)

| Experiment identifier | Resolution | Land surface model | Microphysics | PBL | Radiation |
|-----------------------|------------|--------------------|---------------|-----|-----------|
| LSM2                  | 3 km       | Noah               | New Thompson  | YSU | RRTMG     |
| LSM3                  | 3 km       | RUC                | New Thompson  | YSU | RRTMG     |
| MP2                   | 3 km       | Noah_MP            | Lin scheme    | YSU | RRTMG     |
| MP6                   | 3 km       | Noah_MP            | Single-Moment 6-class | YSU | RRTMG |
| MP8                   | 3 km       | Noah_MP            | New Thompson  | YSU | RRTMG     |
| PBL5                  | 3 km       | Noah_MP            | New Thompson  | Mellor–Yamada | RRTMG |
| PBL9                  | 3 km       | Noah_MP            | New Thompson  | UW scheme | RRTMG |
| PBL11                 | 3 km       | Noah_MP            | New Thompson  | Shin–Hong scheme | RRTMG |
| RA3                   | 3 km       | Noah_MP            | New Thompson  | YSU | CAM scheme |
| RA99                  | 3 km       | Noah_MP            | New Thompson  | YSU | GFDL scheme |
| MP6_15km              | 15 km      | Noah_MP            | Single-Moment 6-class | YSU | RRTMG |

Table 1
WRF Experiments with Various Physics Options
to identify the impact of the changed physics scheme on the meso- and small-scale precipitation and soil moisture. In this study, we turned off the cumulus parameterization scheme in all 3-km simulations, since the 3-km simulation was expected to resolve the convective eddies. A 15-km simulation was also conducted to examine the influences of different horizontal resolutions on precipitation and soil moisture. The initial and lateral boundary conditions of the WRF simulations were provided by the 6-hourly ERA-Interim reanalysis data. Each simulation was integrated over 3 months from 1 June to 31 August 2015. The simulation of the first month was discarded for a spin-up purpose, so only the simulations of the last 2 months were assessed. Our evaluation was limited in the region from 84°E to 92°E and 30°N to 34°N to exclude the spurious precipitation near the boundary zones of the regional climate model.

2.2. Data and Methodology

The hourly precipitation from the meteorological stations within the study domain was obtained from the China Meteorological Administration (CMA). The gauged near-surface soil moisture is from the Naqu network over the central TP. Due to insufficient sites (the sites are mainly located in the southeast part of our domain) and in order to take the observational uncertainties into account in the model evaluation, multiple sources of observational data were used in this study (Table 2), including the Soil Moisture Active Passive Level 4 (SMAP L4) soil moisture product (with a spatial resolution of 9 km and a time interval of 3 hrs), remote sensing precipitation from Global Precipitation Measurement (GPM) mission Level 3 Integrated Multi-satellite Retrievals (IMERG; 0.1°, 0.5 hr) and Tropical Precipitation Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) 3B42V7 version (0.25°, 3 hrs). All the satellite data and model data were regridded to 0.1° × 0.1° resolution, with hourly intervals for precipitation and 3-hr intervals for soil moisture. The data details are as follows.

Hourly CMA precipitation has been widely used and is regarded as the best observed precipitation dataset over the TP (e.g., Ma et al., 2016; Shen et al., 2014; Tong et al., 2014). All the stations are automatic observation systems. Hourly precipitation is observed by siphon or tipping-bucket rain gauges and recorded automatically. Then, hourly precipitation reports from these stations are transferred to CMA. The data all underwent a strict quality control, regarding aspects of the extreme values check, internal consistency check, and spatial consistency check (Ren et al., 2010; Shen et al., 2010).

Among the satellite-based precipitation products, the TRMM–TMPA 3B42V7 (Huffman et al., 2007) and GPM–IMERG (Hou et al., 2014) are generally recognized as the reliable precipitation data evaluated against in situ observations (Koo et al., 2009; Li et al., 2017; Ma et al., 2016; Maussion et al., 2011, 2014; Sato et al., 2008; Tong et al., 2014; Xu, Han, et al., 2017; Zhang et al., 2018). Specifically, the TRMM–TMPA 3B42V7 data merges gauged monthly rainfall and is the best product for the TRMM-era (Ma et al., 2016). As the successor of TRMM, GPM led by the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency provides the next generation of precipitation products. Furthermore, GPM–IMERG has proven to be a substitute for TRMM–TMPA 3B42V7. GPM–IMERG can especially capture the frequency variation for events with different intensities and the diurnal variations (Ma et al., 2016; Xu, Tian, et al., 2017; Zhang et al., 2018).

The Naqu soil moisture observation network is located within an area of 10,000 km² in the central TP (Yang et al., 2013). This area has a fairly smooth landscape with rolling hills. There are 56 stations in three nested networks at different spatial scales (1°, 0.3°, and 0.1°) to match different scales studies. The microscale factors (elevation, slope, aspect, topsoil texture, and soil organic carbon content) have been considered for the representation of soil moisture measurements. Former studies have evaluated mainstream satellite-based soil moisture products, such as Soil Moisture and Ocean Salinity, SMAP, and Advanced Microwave Scanning Radiometer in the TP (e.g., Chen et al., 2013; Zeng et al., 2015; Chen et al., 2017; Jiang et al., 2017; Zhang et al., 2018).
These studies demonstrated that SMAP soil moisture is generally better than the other soil moisture products. The SMAP mission provides soil moisture estimates in the top 5 cm of soil over the global land area. LSMs assimilating SMAP measurements produced a new data, SMAP L4. Specifically, it is generated by assimilating SMAP L-band brightness temperature into the NASA Catchment LSM based on the Goddard Earth Observing System, version 5 (GEOS 5), land data assimilation system. The SMAP L4 product, with complete coverage in space and time, makes it more convenient to compare with the modeled spatial and temporal results.

The WRF performances were validated against the ground observations and satellite data by the statistical metrics of the pattern/temporal correlation coefficient (PCC, TCC), relative bias (RB), and the ratio of standard deviation (RSD). The metrics equations are defined as follows:

$$RB = \frac{\sum_{i=1}^{N} x_i}{\sum_{i=1}^{N} y_i} - 1,$$

$$RSD = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}},$$

$$PCC \text{ or } TCC = \frac{\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N} (x_i - \bar{x})^2 \sum_{i=1}^{N} (y_i - \bar{y})^2}},$$

where $x_i$ and $y_i$ represent the simulated and observational data, respectively. $\bar{x}$ and $\bar{y}$ are the averages of $x_i$ and $y_i$, respectively. $N$ is the number of data points. Meanwhile, the Taylor diagram (Taylor, 2001) was also used to summarize multiple statistics between WRF and observational data.

3. Evaluations of Precipitation

We evaluated the spatial and temporal variation of WRF-simulated precipitation against the gauge data (17 sites) and evaluated the frequency distribution, diurnal cycle, and persistent time using the GPM–IMERG and TRMM–TMPA 3B42V7 data (hereafter referred as GPM and TRMM for short).

3.1. Evaluation Against Ground Observations

3.1.1. Spatial Pattern

The Taylor diagram (Figure 2) shows the PCC, RSD, and RB calculated by the data from 17 stations and model grids where the stations are located. Compared with the gauged precipitation, GPM obviously underestimates the accumulated precipitation, especially in the southeast part of the central TP, by an RB of 77.4%, while TRMM underestimates it by 10.1%. The spatial variability of GPM precipitation is significantly smaller than that of the observation characterized by an RSD of 0.32. Similarly, TRMM also underestimates the spatial variability of precipitation with an RSD of 0.43. The PCC values in Taylor diagram are 0.30 and 0.34 for GPM and TRMM, respectively, indicating that both are unable to capture the spatial pattern of precipitation well (Figures 2 and 3a and 3b).

The PCC between various WRF simulations and observation varies from 0.37 to 0.64 (Figure 2). This indicates that the WRF simulations can generally better reproduce the spatial pattern of precipitation than the TRMM and GPM data. Different from GPM and TRMM, all WRF experiments clearly overestimate the summer precipitation with RBs of 24.6–103.5% relative to the gauged data, which is consistent with previous studies where the WRF precipitation is commonly overestimated (e.g., Chen et al., 2014; Jin et al., 2010; Sato et al., 2008). Meanwhile, WRF also exaggerates the spatial variability, with RSD values from 1.14 to 2.59. What follows are the separate analyses for different types of physical schemes.

i MP8 performs relatively better than the MP2 and MP6 experiments, since the latter two markedly overestimate the summer precipitation amount with RBs of 103.5% and 96.6%, respectively. This indicates...
that, compared with the new Thompson scheme, the Lin and WSM6 schemes severely overestimate the summer precipitation amount.

ii The discrepancies among the LSM2, LSM3, and MP8 experiments are also noticeable, indicating that the land surface process also plays an important role in precipitation simulation. Furthermore, the LSM2 experiment with Noah LSM model relatively outperforms LSM3 with RUC and MP8 with Noah_MP. Although LSM3 shows a smaller RSD of 1.37, it presents much high RB of 71.3% and a low PCC value of 0.45. Furthermore, the LSM3’s PCC barely passes the 90% confidence test, while the correlation coefficients of the rest 3-km experiments all pass the 95% confidence test.

iii The spatial distributions of precipitation generated by the PBL and RA experiments were omitted in Figure 3 because they are very similar to MP8 and LSM2. Our results found that different RA and PBL schemes introduce moderate differences to the spatial pattern of accumulated precipitation, and the GFDL radiation scheme in the RA99 experiment performs better than the other two radiation schemes. As for the PBL effect, the Mellor–Yamada scheme in the PBL5 experiment performs the best in terms of three statistical metrics, then followed by the Shin–Hong scheme in the PBL11 experiment.

iv MP6_15km shows a smaller RB value than MP6, but it generates a worse spatial pattern of precipitation with a PCC of 0.37, which does not reach the significance level of 0.1.

3.1.2. Day-to-day Variations

To assess the temporal variation, we computed the station-averaged daily observational precipitation and the modeled (remote sensing) daily precipitation averaged over the grid cells in which the stations are located. Specifically, to ensure the comparability between the modeled and observational data, we picked out the grid cells of WRF model (or remote sensing data) where the stations are located and took the average of the stations within the same grid cell, then obtained the station-averaged daily precipitation averaged over above grid cells. The time series of the remote sensing and the simulated precipitation were compared with

Figure 2. Taylor diagram showing the model statistics in terms of the spatial accumulated precipitation from July to August in 2015 against the 17 gaused observations.
the station-observed precipitation (Figure 4). GPM markedly underestimates the temporal variability characterized by an RSD of 0.37, while TRMM overestimates it with an RSD of 1.41. GPM and TRMM show dry biases (−79.7% and −17.9%, respectively) relative to the observations, and their TCC values are both 0.63. Compared with GPM and TRMM, the 3-km WRF simulations present positive biases (8.2–77.7% RBs), larger temporal variabilities (1.59–2.04 RSDs), and smaller correlation values (0.36–0.53 TCCs). Moreover, the TCC values in both the satellite data and WRF simulations all reach a significance level of 0.05. Among the WRF experiments, RA99 performs the best in simulating the daily precipitation series, which is followed by LSM2, particularly in terms of the RB and RSD statistics. Similar with the spatial pattern of accumulated precipitation, MP2 and MP6 exhibit the largest biases of 77.7% and 73.0%,
respectively, and the highest temporal variability with RSD values of 2.04 and 2.03, respectively. LSM3 shows the worst temporal variation (TCC of 0.36). The 15-km WRF simulation severely overestimates the temporal variability of precipitation characterized by an RSD of 3.17 against the RSDs of less than 2 in the 3-km WRF simulations.

3.2. Evaluation Against Remote Sensing Data
As the observational precipitation is only available in a few stations, it is hard to represent the variation of precipitation in the central TP area. On the other hand, the TRMM and GPM can generally better capture the temporal variation of precipitation based on the evaluation of section 3.1.2. We evaluated the WRF simulated precipitation against remote sensing precipitation in this section.

3.2.1. Frequency Distribution of Precipitation
Previous studies have suggested that TRMM can well capture light precipitation events, but it overestimates the frequency for heavy precipitation (e.g., Maussion et al., 2014). GPM can generally capture the frequency variation for the events with different intensities, but with lower frequency values than the gauged results (e.g., Ma et al., 2018). Obviously, remote sensing precipitation contains clear uncertainty. We therefore compared the WRF simulations with both remote sensing data to take the observational uncertainty into account. As illustrated in Figure 5, WRF can generally reproduce the frequency distribution of precipitation, especially for precipitation lower than 2 mm hr$^{-1}$. All WRF simulations overestimate the frequency of precipitation ranging from 2 to 8 mm hr$^{-1}$. In terms of precipitation lower than 16 mm hr$^{-1}$, the new Thompson scheme (used in the MP8, LSM, PBL and RA experiments) generally performs better than the Lin and WSM6 schemes (in MP2, MP6 and MP6_15km). However, the new Thompson scheme clearly underestimates the frequency of precipitation higher than 16 mm hr$^{-1}$. Among the different physics options, the microphysics scheme plays the most important role in determining the precipitation frequency, especially for heavy precipitation. After the microphysics scheme, the LSM plays the second most important role in simulating the

![Figure 4. Taylor diagram for station-averaged daily precipitation of GPM, TRMM, and WRF simulations during July and August 2015.](image-url)
precipitation frequency distribution. For example, the frequency distribution shows a relatively larger spread among the MP8, LSM2, and LSM3 experiments than those of the RA and PBL experiments. In addition, the frequencies of the heavy precipitation show large differences between MP6 and MP6_15km. This implies that the horizontal resolution of the WRF model can also significantly affect the frequency distribution of precipitation. Meanwhile, we can see that the overestimated frequency of heavy precipitation accounts for the overestimated accumulation precipitation in the MP2 and MP6 experiments (Figures 2 and 5).

3.2.2. Diurnal Cycle
Zhang et al. (2018) noted that GPM can well capture the diurnal cycle for summer precipitation over the TP, and the maximum precipitation occurred at approximately 19 o’clock. Based on the TRMM data, Singh and Nakamura (2009) found that the hilly area in the central TP usually receives the strongest precipitation in the late afternoon in summer. In our study domain, the precipitation peak appears at 18 o’clock in both GPM and TRMM (Figure 6), while the minimum precipitation occurs at approximately 9 o’clock. The WRF model can correctly reproduce the time of minimum precipitation, but the time of maximum precipitation varies among different experiments. For example, MP2 and MP6 simulate the precipitation peak earlier (16–17 o’clock) than observation, while the peak times in MP6_15km and PBL9 are obviously delayed (21 and 20 o’clock, respectively). The comparison of MP6 with MP6_15km indicates that the coarser resolution simulation tends to produce a delayed peak in the precipitation diurnal cycle, which is consistent with previous studies (e.g., Sato et al., 2008). The possible causes for this have been discussed in early studies from several aspects, such as topography representation, unstable stratification, upward moisture transport, and cloud formation time (Fujinami & Yasunari, 2001; Kurosaki & Kimura, 2002; Kuwagata et al., 2001; Petch et al., 2002; Sato et al., 2008; Shinoda & Uyeda, 2002). MP8 and PBL11 both present two peaks with very close values at 19 and 21 o’clock. LSM3 simulates a reasonable precipitation peak at 18 o’clock, but with obviously overestimated peak precipitation intensity. The remaining experiments (LSM2, RA3, RA99, and PBL5) present a slightly later peak at 19 o’clock. These indicate that the MP scheme and grid resolution have apparent influences on the diurnal cycle, while the LSM, PBL, and RA schemes show moderate effects. Especially, the Lin scheme in MP2, the WSM6 scheme in MP6, and the 15-km resolution are not recommended in the diurnal cycle simulation. Overall, RA99 with the GFDL radiation scheme performs better than the other WRF...
simulations in terms of the precipitation peak intensity and peak time. In addition, relative to GPM and TRMM, all WRF (especially MP2, MP6, MP6_15km) simulations overestimated the precipitation intensity.

### 3.2.3. Consecutive Precipitation Time

The consecutive precipitation time was defined as the time of duration for the event with precipitation greater than 0.01 mm hr$^{-1}$. The spatial patterns of the consecutive precipitation time are generally similar to that of the corresponding accumulated precipitation for both the remote sensing data and WRF simulations (Figures 3 and 7). This suggests that precipitation persists a longer time in regions with more precipitation. The daily averaged persistence time is approximately 1.5–3.5 hr in GPM and 5–9 hr in TRMM, which suggests that the precipitation persistence time derived from different satellite data contains large uncertainties over the central TP. To quantitatively measure the model performance, we calculated the PCC, RSD, and RB for the TRMM and WRF simulations, using GPM precipitation as the reference data. The intercomparison of the WRF simulations with various physics options indicates that the consecutive precipitation time is mainly controlled by the MP scheme. The daily averaged consecutive precipitation times are approximately 2–9, 1.5–6, and 1–5 hr in the MP2, MP6, and MP8 experiments, respectively, which are in a reasonable range according to the GPM and TRMM results (Figure 7). Clearly, the MP experiments with the Lin and WSM6 schemes generate a longer precipitation persistence time than the experiments with the new Thompson scheme (Table 3). According to the above discussion, the overestimations of the heavy precipitation frequency, intensity, and persistence time all account for the overestimated accumulated precipitation over the central TP (Figures 2 and 5–7). Meanwhile, all the WRF simulations fail to reproduce the fine-scale spatial pattern of the consecutive precipitation time because there is no significant correlation between the WRF simulations and GPM data. The excessively large RB value of 227.6% from MP6_15km indicates that the 15-km grid resolution is not suitable for the simulation of the consecutive precipitation process over the central TP.

### 4. Evaluation of Soil Moisture

Previous studies found that both SMAP L3 and L4 products can capture the temporal variation of in situ observations in the upper reach of Heihe River Watershed (Zhang et al., 2017). Reichle et al. (2017)
indicated that the SMAP L4 performs well on the Ngari soil moisture observation site, with an unbiased root mean square error of 0.04, a bias of 0.01, and a correlation coefficient of 0.77. In our study domain, the SMAP L4 product was not yet assessed in previous studies. Thus, we first assessed the SMAP L4 and WRF soil moisture against the observational data over the Naqu network before the WRF evaluation over the entire domain. The grid points with lakes were excluded from our evaluation to avoid the possible mismatch in land cover between model grids and stations. In this study, we only assessed the soil moisture in the top layer soil. The depths of top layer of soil were 0–5 cm for the SMAP L4 and Naqu network, 0–7 cm for Noah and Noah_MP, and 0–4 cm soil moisture for the RUC model.

4.1. Evaluation Against the Naqu Observation Network

Over the Naqu network, the daily series, including the station-averaged and grid-averaged top soil moisture calculated from SMAP/WRF grids in which the stations are located, were processed.
in the same way as those in section 3.1.2. The SMAP L4 daily soil moisture curve is much lower than the observed one, especially for the high soil moisture. In other words, SMAP L4 apparently underestimates the amplitude of fluctuation. As shown in the Taylor diagram (Figure 8b), its RSD is only 0.38, and its RB is −26.5%. However, SMAP L4 displays a high temporal correlation of 0.85 with the observed soil moisture. As for the diurnal cycle in the Naqu network (Figure 8c), the observation presents the lowest soil moisture at 9 o’clock, and the highest appears at 15 o’clock. SMAP L4 reproduces the lowest soil moisture at 9 o’clock, and it fails to reproduce the peak value near 15 o’clock.

Like the SMAP L4 product, the WRF experiments also do not reproduce the peak soil moisture at 15 o’clock. All the WRF experiments present significant TCC with the observational soil moisture, but overestimate the low soil moisture magnitude compared with the observational results. The discrepancy among different LSM experiments is most significant, while the other 3-km experiments show very close statistics. These suggest that the LSM scheme plays a dominant role in simulating the soil moisture, while the soil moisture is less sensitive to the MP, PBL, and RA schemes. Specifically, LSM2 with the Noah model performs best for the soil moisture’s daily series and diurnal cycle. It well models the temporal variation characterized by a

Figure 8. (a) Daily soil moisture and (b) its corresponding Taylor diagram, (c) and diurnal cycle of soil moisture derived from WRF simulation, SMAP L4, and observational data in Naqu network during July to August, 2015.
higher correlation coefficient of 0.77 and shows closer fluctuation amplitude to that of in situ observation with an RSD of 0.84 and a RB of 23.1%. Although LSM3 with the RUC model simulates the acceptable statistics (TCC of 0.81, RSD of 0.64, RB of 17.7%), it obviously exaggerates the diurnal variation (Figure 8c). The other simulations with the Noah_MP model present a similar fluctuation amplitude to that of SMAP L4 in the diurnal cycle. The discrepancy between MP6_15km and MP6 is insignificant in the Naqu network, and MP6_15km even simulates a higher TCC of 0.84 and lower RB of 22.7% than those of MP6 (0.74 and 35.0%, respectively).

Figure 9. Spatial pattern of soil moisture averaged from July to August, 2015. The Unit is m$^3$/m$^3$. The background gridded results are the soil moisture derived from SMAP L4 or WRF, the dots filled with different colors represent the soil moisture in 32 stations in Naqu network.
The spatial pattern of the daily average soil moisture derived from SMAP L4 is essentially consistent with the observation characterized by a PCC of 0.52. SMAP L4 shows close soil moisture values with observations in the southwest part, however, it underestimates them in the rest of the region (Figure 9a). The corresponding RB and RSD values are $-29.2\%$ and 0.62, respectively. As shown in Table 4, the gaps between different WRF experiments are not very large. Generally, the LSM scheme plays a relatively important role in reproducing the soil moisture spatial pattern, followed by the MP scheme, while the other physics schemes have minor effects. Among the WRF experiments, none of them show a significant advantage in simulating the spatial soil moisture in the Naqu network, since all experiments show close statistics, and no experiments perform best in all statistics. To save space, Figure 9 only illustrates the experiments with different LSM and MP schemes and the MP6_15km experiment. The 15.3–34.8% RB implies that the WRF overestimates the soil moisture value moderately. Moreover, the WRF-modeled soil moisture in the east part matches with the observation better than SMAP L4. However, WRF markedly underestimates the spatial heterogeneity, with RSD values less than or equal to 0.13. The PCCs from MP2 (0.28), LSM2 (0.22), LSM3 (-0.04), RA 99 (0.31), and PBL9 (0.38) do not reach a significance level of 0.05. The other experiments show the significant PCC values of 0.41–0.59 at the significance level of 0.05. Similar with the evaluation of the temporal variation of soil moisture, the MP6_15km experiment performs slightly better than the MP6 in simulating the spatial pattern and magnitude of daily average soil moisture in the Naqu network.

4.2. Evaluation Against the SMAP Product Over the Domain

Given that the Naqu network only covers a very small part of our study domain and that SMAP L4 can capture the temporal variation of the soil moisture over the Naqu stations, we mainly used SMAP L4 to validate the WRF soil moisture in terms of the temporal variation, and roughly assessed the spatial pattern over the entire domain. The results, taking SMAP L4 as the reference, showed that the temporal correlations of the daily soil moisture from all WRF experiments are significant at a level of 0.05. Among the 3-km WRF experiments (Figure 10), the smallest TCC is from LSM3 (0.87), and the second smallest is from LSM2 (0.89), while the other values are approximately 0.91. Meanwhile, the above 1.0 RSD values show that the WRF simulates a larger temporal variability relative to SMAP L4. These results suggest that the 3-km WRF simulations for the daily soil moisture over the entire domain are reasonable. The characteristics in the diurnal variation for the entire domain are almost the same as the Naqu network results, in which LSM3 markedly overestimates the diurnal variation. Note that the WRF simulation with a coarse resolution of 15 km shows the worst time variation in the study domain, characterized by a TCC of 0.71.

In the spatial distribution of the soil moisture’s temporal correlation with SMAP L4 (Figure 11), the WRF shows generally worse correlations at the west part with negative TCC values, but it performs better in the middle and east regions with TCC values of 0.60–0.80. Moreover, the relatively low TCC (0.87) of the grid-mean daily soil moisture in LSM3 mentioned above is mainly due to the poor correlation over the southwest corner. In addition, compared with MP6, MP6_15km presents smaller TCCs in most areas. This again indicates that the coarse spatial resolution of 15 km is not suitable for the soil moisture simulation over the domain. In addition, the WRF can generally reproduce the SMAP L4 spatial pattern, which is characterized by dry soil moisture in the north central region and wet soil moisture in the southwest and southeast regions.

5. Overall Model Performance in Simulating the Precipitation and Soil Moisture

Sections 3 and 4 discuss WRF’s ability for simulating the precipitation and soil moisture, respectively. In this section, we evaluated the WRF’s overall performance in the precipitation and soil moisture simulations using a multivariable integrated evaluation (MVIE) method (Xu, Tian, et al., 2017). The MVIE provides a framework that can evaluate the model performance in simulating the individual variables as well as the overall model performance in simulating multiple variables. In addition to the commonly used statistics, for example, the correlation coefficient (CORR), the ratio of the modeled standard deviation to the observed one (RSD), and root mean square deviation (RMSD), the MVIE also computes three statistical quantities, namely, the root mean square length (RMSL) of a vector field, the vector field similarity coefficient (Rv), and the root mean square vector deviation (RMSVD), in order to measure the model performance in simulating multiple variables from various aspects. Rv describes the pattern correlation between the model and
observation in terms of multiple variables. Similarly, the RMSL and RMSVD measure the amplitude and overall difference between the model and observation. The multivariable integrated evaluation index (MIEI) can rank the model’s overall performance in simulating multiple variables. A smaller MIEI implies a better model performance. A detailed introduction on these statistics quantities can be found in Xu et al. (2016, 2017b). Considering that the CMA precipitation stations and Naqu soil moisture network cover different regions, only the performances of the grid-averaged daily series against the ground observations are discussed here. The daily series were derived by the same processing method as in sections 3.1.2 and 4.1. Here we name the precipitation from the GPM and the soil moisture from the SMAP L4 as the satellite data.

Table 5 summarizes the model performance in simulating individual variables and the overall model performance in simulating multiple variables. All WRF simulations overestimate the temporal variability of observation in terms of multiple variables. Similarly, the RMSL and RMSVD measure the amplitude and overall difference between the model and observation. The multivariable integrated evaluation index (MIEI) can rank the model’s overall performance in simulating multiple variables. A smaller MIEI implies a better model performance. A detailed introduction on these statistics quantities can be found in Xu et al. (2016, 2017b). Considering that the CMA precipitation stations and Naqu soil moisture network cover different regions, only the performances of the grid-averaged daily series against the ground observations are discussed here. The daily series were derived by the same processing method as in sections 3.1.2 and 4.1. Here we name the precipitation from the GPM and the soil moisture from the SMAP L4 as the satellite data.

Table 5

| Experiment/SMAP | RSD  | RB(%) | PCC  |
|-----------------|------|-------|------|
| MP2             | 0.05 | 34.8  | 0.28 |
| MP6             | 0.06 | 33.1  | 0.51*|
| MP8             | 0.11 | 27.5  | 0.41*|
| LSM2            | 0.09 | 21.2  | 0.22 |
| LSM3            | 0.12 | 15.3  | −0.04|
| RA3             | 0.09 | 26.2  | 0.59*|
| RA99            | 0.08 | 25.2  | 0.31 |
| PBL5            | 0.13 | 26.2  | 0.53*|
| PBL9            | 0.10 | 32.0  | 0.38 |
| PBL11           | 0.12 | 28.0  | 0.50*|
| MP6_15km        | 0.04 | 21.18 | 0.55*|
| SMAP            | 0.62 | 29.2  | 0.52*|

*PCC reached the significance level of 0.05.

Table 4

The Statistical Indices were Obtained From the Station-located-grid Mean Soil Moisture in Naqu Network Between WRF/SMAP L4 and Observation During July to August, 2015

| Experiment/SMAP | RSD  | RB(%) | PCC  |
|-----------------|------|-------|------|
| MP2             | 0.05 | 34.8  | 0.28 |
| MP6             | 0.06 | 33.1  | 0.51*|
| MP8             | 0.11 | 27.5  | 0.41*|
| LSM2            | 0.09 | 21.2  | 0.22 |
| LSM3            | 0.12 | 15.3  | −0.04|
| RA3             | 0.09 | 26.2  | 0.59*|
| RA99            | 0.08 | 25.2  | 0.31 |
| PBL5            | 0.13 | 26.2  | 0.53*|
| PBL9            | 0.10 | 32.0  | 0.38 |
| PBL11           | 0.12 | 28.0  | 0.50*|
| MP6_15km        | 0.04 | 21.18 | 0.55*|
| SMAP            | 0.62 | 29.2  | 0.52*|

*PCC reached the significance level of 0.05.

Figure 10. (a) Daily soil moisture and (b) its corresponding Taylor diagram, (c) diurnal cycle in the entire study area during July to August, 2015.
precipitation but underestimate the temporal variability of soil moisture. LSM2 and LSM3 perform relatively better in simulating the soil moisture, characterized by RSD values closer to 1 compared to the other WRF experiments. However, they apparently overestimate the RSD values (1.68, 2.02) for precipitation. For the overall temporal variability of the precipitation and soil moisture, RA99 generates the RMSL with the closest proximity to 1 (1.21), and MP6_15km presents the largest RMSL of 1.81. In terms of the correlation coefficient, the WRF model can better reproduce the temporal variation of the soil moisture with correlation coefficient values ranging from 0.7 to 0.84. In contrast, the correlation coefficient of the precipitation varies from 0.36 to 0.53. If we take both the soil moisture and precipitation into account, the LSM2 experiment shows the best variation characterized by the highest Rv of 0.53. Note that the LSM2 experiment exhibits the second highest correlation coefficient for soil moisture (0.77) and the third highest correlation coefficient for precipitation (0.46). The RMSVD and MIEI index take both variables (soil moisture and precipitation) and both statistics (RSD and CORR) into account, which summarizes the overall model performance. The smaller values in the RMSVD and MIEI are from LSM2 (1.16 and 1.09, respectively) and RA99 (1.12 and 1.16, respectively). The MP6_15km performs the worst in RMSVD and MIEI. These results indicate that, in terms of the daily series in the observational stations, LSM2 and RA99 perform best in the overall simulations for precipitation and soil moisture. Relative to the WRF simulations, the satellite product presents a higher Rv (0.74), and a lower

![Figure 11. Spatial distribution of time correlation coefficient between WRF and SMAP L4 daily soil moisture during July to August, 2015.](https://example.com)
6. Discussions

The overestimated WRF precipitation may be related to the excessive water vapor transfer from the lateral boundary, especially in the near-surface level, as the coarse resolution model used to generate ERA-Interim reanalysis may underestimate the effect of topography drag. Thus, an additional experiment with two nested domains was conducted. The Himalayas in the southern TP is the major pathway of water vapor transport from South Asia to the TP (e.g., Lin et al., 2018). Therefore, the outer domain covers the whole TP approximately from 22.35°N to 40.83°N and 71.28°E to 104.72°E with resolution of 9 km, while the inner domain is still 3 km as mentioned in section 2.1. Given that the MP8 experiment was regarded as a reference experiment, this nested experiment used the same physics options as those in MP8 experiment, thus referred to as MP8_nested.

Compared with the spatial pattern of MP8 precipitation, the MP8_nested precipitation does decrease over the southeast region but increases over the northwest part (Figure 12b). Furthermore, its spatial correlation with GPM (0.213) is less than that of MP8 (0.467). Relative to the stations’ precipitation, the bias values are −16.17% and −5.38% for the station-average daily series and the spatial pattern, respectively. Meanwhile, MP8_nested shows poorer performance in the diurnal cycle of precipitation than the MP8 experiment (Figure 12c). Its peak time is postponed to 0 o’clock, while the lowest precipitation is slightly delayed to 10 o’clock. Moreover, the precipitation intensity gets stronger (weaker) than MP8’s before (after) 10 o’clock. We also found that the frequency for heavy precipitation (8–32 mm hr⁻¹) is larger than that in MP8 and very close to MP6’s result as shown in Figure 5. In addition, the consecutive precipitation time (3–6 hrs) from MP8_nested is longer than the time of MP8 (1–5 hrs). These results are probably due to the complex steep terrain over the southern TP. Similar with precipitation spatial pattern, the top soil moisture decreases (increases) over the southeast (northwest) region, with the range of −0.8–0.8 m³/m³, while the other characteristics are similar to the MP8 results.

Table 5

| METRICS | RSD | RMSL | CORR | RMSD | RMSV | MIEI |
|---------|-----|------|------|------|------|------|
|         | Pre SM |      |      | Pre SM |      |      |      |
| MP2     | 2.07 0.48 | 1.50 0.45 | 0.71 | 0.42 | 1.85 0.74 | 1.41 1.37 |
| MP6     | 2.06 0.50 | 1.50 0.53 | 0.74 | 0.49 | 1.75 0.71 | 1.34 1.31 |
| MP8     | 1.75 0.50 | 1.29 0.43 | 0.75 | 0.44 | 1.60 0.71 | 1.24 1.24 |
| LSM2    | 1.68 0.84 | 1.33 0.46 | 0.77 | 0.53 | 1.51 0.64 | 1.16 1.09 |
| LSM3    | 2.02 0.64 | 1.50 0.36 | 0.81 | 0.42 | 1.90 0.61 | 1.41 1.32 |
| RA3     | 1.76 0.53 | 1.30 0.45 | 0.73 | 0.45 | 1.59 0.71 | 1.23 1.22 |
| RA99    | 1.64 0.50 | 1.21 0.51 | 0.74 | 0.50 | 1.42 0.71 | 1.12 1.16 |
| PBL5    | 1.71 0.52 | 1.27 0.44 | 0.74 | 0.45 | 1.55 0.71 | 1.21 1.21 |
| PBL9    | 2.00 0.50 | 1.46 0.39 | 0.70 | 0.39 | 1.85 0.74 | 1.41 1.36 |
| PBL11   | 1.73 0.51 | 1.28 0.44 | 0.75 | 0.45 | 1.57 0.70 | 1.21 1.22 |
| MP6_15km| 2.52 0.45 | 1.81 0.49 | 0.84 | 0.45 | 2.20 0.67 | 1.63 1.55 |
| Satellite data | 0.38 0.38 | 0.38 0.62 | 0.85 | 0.74 | 0.82 0.71 | 0.76 0.95 |

Note. Pre (SM) is the grid-averaged daily precipitation (soil moisture) during July–August in 2015. The RSD is the ratio of modeled to observed root mean square values, describing the time variability for each variable. CORR (RMSD) is the temporal correlation coefficient (root mean square deviation) between WRF/satellite data and observational fields. RMSL, Rv, and RMSVD measure the statistics of two vector fields, which can represent the overall statistics of all fields. RMSL was shown as the ratio of WRF-simulated/satellite-based RMSL to the observed RMSL. MIEI is the multivariable integrated evaluation index. The performance is indicated by the color scale, lighter colors denote better model performance.
7. Conclusions

This study conducted a series of sensitivity experiments with various physics parameterizations and two different spatial resolutions (3 and 15 km) over the central TP during July–August 2015. Overall, the 3-km WRF reasonably simulates the precipitation and soil moisture and generates a better spatial pattern of precipitation against the in situ observation than the GPM and TRMM do.

Based on our assessment, the summer precipitation simulated by the 3-km WRF model in the central TP is most sensitive to the MP scheme, followed by LSM, while PBL and RA have relatively minor impacts. The MP scheme has a significant effect on precipitation in terms of the accumulated precipitation, diurnal cycle, frequency, and persistence time. Overall, the new Thompson scheme outperforms the Lin and WSM6 schemes in the 2-month simulation, which is consistent with other studies for 1-week to 3-month simulations (Li et al., 2017; Maussion et al., 2011). The good performance of the new Thompson scheme can be attributed to its special features, including a double moment for the cloud ice (Cassola et al., 2015), applying the unique mass diameter relationship for snow particles (Song & Sohn, 2018), and adopting the gamma function to represent the graupel category (Jankov et al., 2011). Specifically, the new Thompson microphysics scheme performs well for the events of precipitation less than 16 mm hr$^{-1}$ in the frequency distribution of different precipitation events. However, the Lin scheme (in MP2) and WSM6 scheme (in MP6) tend to overestimate the precipitation amount, which results from an overestimation of the heavy precipitation frequency, intensity, and persistence time. Moreover, the Lin and WSM6 schemes lead to an earlier precipitation peak in the diurnal cycle.

Figure 12. Spatial pattern of accumulated precipitation from July to August in 2015 for the (a) MP8_nested experiment and the (b) difference between the MP8_nest and MP8 experiment. The circles represent the precipitation stations. (c) Diurnal cycle of domain-averaged precipitation derived from MP8_nested, MP8, and satellite data.
Meanwhile, we found the choice of the LSM scheme also has a certain influence on the precipitation’s spatial pattern, frequency, diurnal cycle, and intensity. Furthermore, the effects become stronger with an increase in precipitation. This is similar with Zeng et al.’s (2012) finding that heavy precipitation has a close relationship with the LSM scheme in the Yangtze–Huai river basin and southern China. Moreover, it further validates Maussion et al.’s (2011) assumption that the influence of selecting LSM scheme is weak for 1-week to 1-month simulations, but it is expected to become more influential over a longer period. Among the three LSM schemes we assessed, the RUC LSM used in the LSM3 experiment shows relatively poor performance in terms of the precipitation’s spatial and temporal variations. It is consistent with Maussion et al.’s (2011) result in which the RUC model is found to be less suitable for the TP precipitation simulation. In addition, the WRF with a 15-km resolution generally shows poor performance in the precipitation simulation compared with the 3-km simulations.

The SMAP L4 can well (overall) capture the temporal (spatial) variation of soil moisture in the Naqu observational network, but it underestimates the high soil moisture amount. Hence, SMAP L4 was mainly used to assess the temporal variation of the WRF soil moisture in the study domain. The results showed that WRF can reasonably capture the spatial pattern of soil moisture and generate good temporal variation compared with Naqu observational data and SMAP L4 product. The LSM scheme plays a crucial role in the soil moisture simulation. LSM2 with the Noah LSM generally performs the best, while LSM3 with the RUC model obviously exaggerates the diurnal variation. The 15-km simulation reasonably reproduces the spatial pattern of soil moisture but shows a poor performance in the soil moisture’s temporal variation over the study domain.

To summarize, the microphysics scheme and LSM play an important role in precipitation and soil moisture simulations, while the PBL and radiation schemes have minor impacts on them. Among the different physical schemes, the new Thompson microphysics, Noah model, GFDL radiation, and Mellor–Yamada PBL scheme show better performances than the other schemes in the precipitation and soil moisture simulations over the central TP. The multivariable integrated evaluation indicates that LSM2 with the Noah model and RA99 with the GFDL radiation scheme perform relatively better than the other WRF simulations in terms of the overall simulations of daily precipitation and soil moisture averaged over observational sites.

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