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Key Points:

- Weather Research and Forecasting (WRF) shows added value by reducing the light precipitation frequency
- The much earlier precipitation peak in ERA5, linked to stronger water vapor transport, is corrected in WRF demonstrating added value
- WRF adds value in increasing short-duration events and decreasing long-duration events

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Added Value of Subdaily Precipitation and Its Extremes During a 15-Year Convection-Permitting Simulation Over the Tibetan Plateau

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Abstract In this study, we conduct a 15-year long (2008–2022) convection-permitting simulation over the Tibetan Plateau (TP) using the Weather Research and Forecasting (WRF) model to evaluate its added value compared to ERA5 in characterizing subdaily precipitation and its extremes over the TP. Our findings indicate that the overestimation of precipitation amounts caused by overestimated precipitation frequency in ERA5 is mitigated in WRF mainly through a reduction in light precipitation occurrences. This improvement is likely linked to increased temperatures and decreased relative humidity in the lower troposphere. Moreover, the much earlier precipitation peak in ERA5 is corrected in WRF, a result attributed to differences in related net water vapor transport onto the TP. Additionally, WRF provides a more accurate estimation of the percentage of short- and long-duration precipitation events with only slight underestimations and overestimations, respectively, whereas ERA5 exhibits significantly larger errors. The relatively larger temperature changes in WRF, indicating increased solar heating, are likely responsible for the higher occurrence of short-duration precipitation events. In contrast, the anticyclonic anomalies and northeastern wind anomalies in WRF reduce the persistence of long-duration precipitation. Importantly, WRF also produces more realistic timings of precipitation with different durations compared to ERA5. For extreme precipitation, short-duration extreme events dominate accounting for 50% of extreme precipitation. These events are better reproduced by WRF than by ERA5. Although WRF outperforms ERA5 in estimating the proportion and contribution of extreme events to total precipitation and in capturing their triggering timing, a slight underestimation persists in the simulated proportion and contribution.

Plain Language Summary The Tibetan Plateau (TP) has a significant impact on regional and global weather and climate systems. Precipitation, as a vital component of the climate system, regulates energy flow, water resources, and ecosystems on the TP. Short-duration intense precipitation is particularly important because it can trigger severe disasters like floods, erosion, and debris flows. Predicting these events is challenging due to their small spatial scale, which coarse-resolution models cannot accurately capture. This study uses a high-resolution Weather Research and Forecasting (WRF) model to simulate precipitation over the TP at a 4 km resolution for 15 years (2008–2022). Results show that WRF performs better than the ERA5 data set in capturing subdaily precipitation and its extremes. It reduces overestimations of light precipitation, corrects the timing of precipitation peaks, and more accurately predicts precipitation events of different durations. These improvements are linked to WRF's more detailed representation of atmospheric processes. However, further advancements are needed to improve WRF's ability to simulate extreme short-duration precipitation events, which are essential for reliable disaster prediction and risk reduction.

1. Introduction

Precipitation, widely recognized as an essential component of the climate system, exhibits considerable variability across time and space. Considering its profound significance to economics, agriculture, and the environment, an understanding of the spatial and temporal patterns of precipitation climatology is fundamental for both scientific and practical purposes (Acharya et al., 2020). Intermittency, which includes aspects such as frequency, intensity, duration, and amount, is a key feature of precipitation but is often overlooked (Trenberth et al., 2017). Recent studies increasingly recognize that many physical processes of precipitation occur on very short timescales, which may not be accurately reflected by daily total precipitation amounts (Fowler et al., 2021; Majhi et al., 2022; Trenberth & Zhang, 2018; Westra et al., 2013). For example, individual convective systems

responsible for the most intense precipitation develop over timescales of hours or less, significantly impacting the temporal distribution of precipitation (Wallace & Hobbs, 2006). Precipitation events occurring on short timescales can also result in devastating effects, such as flooding, erosion, and debris flows (Haerter et al., 2010). Therefore, it is increasingly important to study precipitation in terms of its subdaily variation and extremes alongside improving our understanding of daily scale precipitation (Trenberth, 2011).

The Tibetan Plateau (TP), known as the “Water Tower of Asia,” supports several large rivers (e.g., the Yellow River, the Yangtze River, and the Indus) in Asia (Immerzeel et al., 2010; X. Xu et al., 2008) providing water to more than 1 billion people who live downstream (Yao et al., 2022). It therefore plays an essential role in maintaining and renewing water resources in Asia (Qu et al., 2019), and the temporal variability of its precipitation is of paramount importance to the socioeconomic development of both local and downstream areas (Yuan et al., 2021). In this region, short-duration heavy precipitation on subdaily scales represents a severe threat to human lives, property, and ecosystems (G. Zhao et al., 2022). However, most studies of TP precipitation focus primarily on daily and coarser timescales, leading to a limited understanding of precipitation patterns at finer temporal resolutions and insufficient knowledge of high-risk regions for precipitation-triggered natural disasters (Francipane et al., 2021; H.-L. Lu et al., 2024).

Mountains, due to their complex orography, play a critical role in shaping the distribution of precipitation and its extremes (Archer & Fowler, 2018; M. Chen & Yao, 2023; Schiemann et al., 2009). Using precipitation observations from 80 gauge stations spanning 1980–2013, H.-L. Lu et al. (2024) investigated the subdaily precipitation structure over the TP. Their findings revealed a general increase in the frequency of nocturnal precipitation with moderate intensity during these years along with more frequent subdaily precipitation extremes in the southwestern foothills of the TP. Exploiting hourly precipitation data collected from 303 weather stations between 1995 and 2015, Y. Zhao et al. (2023) studied the diurnal cycle of intensity-frequency structures over the southeastern TP and its surrounding areas. They found that the southeastern TP generally exhibits a nighttime peak, whereas adjacent low-terrain regions are characterized by a bimodal structure. Despite the societal and scientific importance of understanding subdaily precipitation, its physical characteristics at finer spatial scales are challenging to determine due to the limited coverage of rain gauge networks (Maussion et al., 2011; Ren et al., 2024).

With advances in satellite observations and modeling techniques, more gridded data sets from satellite remote sensing, atmospheric reanalysis, and high-resolution modeling have become available for studying precipitation across various spatial and temporal scales (Guo et al., 2019; Y. Jiang et al., 2023; Wu et al., 2023). Although global circulation models (GCMs) and regional climate models (RCMs) are able to capture precipitation behavior on longer timescales (e.g., seasonal), their ability to simulate sub-daily precipitation variation remains highly uncertain (Förster & Thiele, 2020) largely due to parameterization uncertainties, such as those in convection schemes (Gu et al., 2020; Prein et al., 2013). With advancements in supercomputing, dynamical downscaling using RCMs has achieved kilometer-scale resolutions, enabling more detailed regional modeling (Kendon et al., 2012; Prein et al., 2015, 2021). These kilometer-scale simulations, particularly at convection-permitting resolutions (grid spacing <4 km in the horizontal direction), not only better represent topography and associated land-atmosphere interactions (Collier & Immerzeel, 2015; Lin et al., 2018; X. Liu et al., 2017; Ma et al., 2023) but also explicitly simulate convective processes such as convection initiation (Ma et al., 2022; Prein et al., 2020; Weisman et al., 1997). Convection-permitting models (CPMs) thus have the potential to be powerful tools for generating high-quality, long-term data sets with high spatiotemporal resolution over the TP.

In recent years, a growing number of studies have investigated the added value of CPMs in simulating subdaily precipitation. For example, Z. Liu et al. (2022) explored a CPM with 4 km resolution and found that it outperformed a coarser-resolution model (~28 km) in simulating summer precipitation at subdaily scales, better capturing a long-lasting peak and a late afternoon maximum. Focusing on nocturnal precipitation, H. Jiang et al. (2024) identified notable underestimations in the southeastern TP and attributed these to fewer clouds and hydrometeors in the CPM. To explain the precipitation diurnal cycle over the TP, W. Lu et al. (2024) conducted a 17-year (1998–2014) WRF simulation at 4 km resolution, finding that TP precipitation frequently occurs in the afternoon or evening, driven by enhanced local convective instability and large-scale water vapor convergence due to solar heating. These studies have significantly advanced our understanding of subdaily precipitation, though many focus on short periods (e.g., a single season) or specific aspects of subdaily precipitation (e.g., the

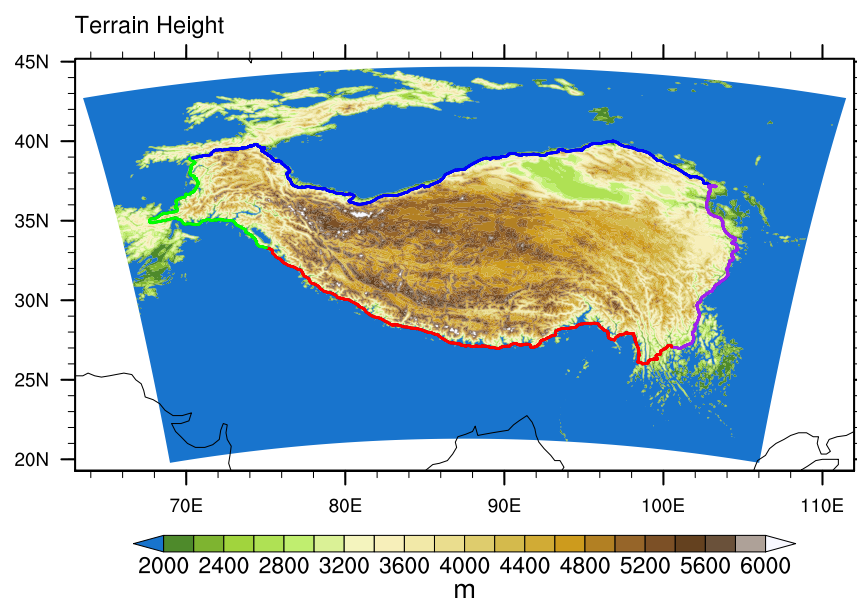


Figure 1. The simulation domain of Weather Research and Forecasting. The southern, western, northern, and eastern boundaries of the Tibetan Plateau are indicated by red, green, blue, and purple lines, respectively.

diurnal cycle). Therefore, more comprehensive research is urgently needed to enhance our understanding of subdaily precipitation variability and inform decision-making.

Based on a 15-year convection-permitting (4 km) simulation along with satellite and reanalysis precipitation products, this study aims to achieve two main goals: (a) to examine the detailed sub-daily characteristics (e.g., frequency, intensity, and duration) of precipitation and its extremes over the TP in observational, reanalysis, and simulation data with an emphasis on identifying the added value of CPMs compared to coarser-resolution reanalysis and (b) to reveal the physical mechanisms underlying the differences between CPMs and their driving reanalysis data sets.

The rest of this paper is structured as follows: Section 2 describes the experimental design, data, and methods used. Section 3 presents the climatological characteristics of subdaily precipitation in terms of frequency, intensity, and duration across data sets. Section 4 analyzes the physical processes affecting subdaily precipitation simulation. Finally, Section 5 provides a summary and discussion.

2. Model, Data, and Methods

2.1. Model Configurations

The WRF model (version 4.3.3) (Skamarock et al., 2019) was continuously integrated over a 15-year period (2008–2022) with a horizontal grid spacing of 4 km and 50 vertical sigma levels. The simulation domain (Figure 1) encompasses the entire TP and surrounding regions, centered at (33°N, 87.5°E), with 651 (South–North) × 981 (west–east) grid points. The model top was set at 25 hPa. Key physics parameterizations included the Thompson microphysics scheme (Thompson et al., 2008), the Rapid Radiative Transfer Model for GCMs for shortwave and longwave radiation (Iacono et al., 2008), the Unified Noah land surface model (F. Chen & Dudhia, 2001), and the Mellor–Yamada–Nakanishi–Niino level-2.5 (MYNN2.5) turbulent kinetic energy scheme for the planetary boundary layer (Nakanishi & Niino, 2009). Since most deep convection processes are explicitly resolved at this resolution, the convection scheme was disabled.

Lateral boundary conditions and sea surface temperatures were updated hourly using the fifth-generation ERA5 reanalysis (grid spacing: 0.25° × 0.25°) (Hersbach et al., 2020) from the European Centre for Medium-Range Weather Forecasts. The simulation spanned 1 December 2007–31 December 2022 with the first month designated as spin-up time. Hourly model outputs for precipitation, temperature, wind, and specific humidity were used for comparative analysis.

2.2. Data Sets

The satellite precipitation product, the Integrated Multi-satellitE Retrievals for the Global Precipitation Measurement mission (IMERG) (Huffman et al., 2020) was employed as the benchmark for model evaluation. IMERG has a spatial resolution of 0.1° and a temporal resolution of 30 min. Previous research indicates that IMERG performs more accurately over the TP across different spatial scales and elevation ranges than the Tropical Rainfall Measuring Mission data set (R. Xu et al., 2017). Consequently, IMERG has been widely applied in studies on precipitation and hydrology over the TP (Gu et al., 2023; D. Li et al., 2022; L. Li et al., 2023).

Hourly outputs from ERA5, which have demonstrated capability in capturing weather systems and diurnal precipitation variations in mountainous regions (Z. Liu et al., 2022), were also utilized. Both ERA5 and WRF outputs were interpolated to the IMERG grid using bilinear interpolation to facilitate quantitative comparisons and evaluate the added value of the convection-permitting WRF model.

2.3. Methods

This study analyzes the intermittency features of precipitation, including the amount, frequency, intensity, and duration. As in previous studies (J. Li, 2018; J. Li & Yu, 2014), precipitation greater than 0.1 mm/hr is defined as measurable rainfall. The precipitation frequency is defined as the percentage of hours with measurable rainfall to total hours. The precipitation intensity is defined as the mean precipitation rates averaged over the hours with measurable rainfall. The precipitation amount is defined as the accumulated precipitation averaged over all hours and is the product of precipitation frequency and intensity. Precipitation events are classified based on their durations with no more than 1 hr of intermittence during a specific precipitation event (Yu et al., 2007). The duration of a precipitation event is defined as the number of hours from the beginning to the end of the specific event. The precipitation events are sorted into short duration (1–3 hr), medium duration (4–6 hr), and long duration (>6 hr) types. If the duration is 1 hr, the peak time of this precipitation event overlaps with its start and end time; otherwise, the peak time of a precipitation event is the hour when the precipitation reaches its maximum within the event.

The 95th percentile (P95) of historical hourly precipitation during 2008–2022 was used as the threshold for extreme events. P95 was calculated for each grid point. If precipitation at any hour of an event exceeded the P95 value, the event was classified as an extreme precipitation event.

In this study, spatial correlation coefficient (SCC), root mean square error, and relative bias () are used to quantitatively evaluate the performance of ERA5 and WRF against IMERG. These statistical metrics can be calculated as follows:

$$\text{SCC} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2}$$

$$\text{RB} = \frac{\sum_{i=1}^n (y_i - x_i)}{\sum_{i=1}^n x_i} \times 100$$

where x_i and y_i denote the observed and simulated value at the i th grid point, and $\bar{x}$ and $\bar{y}$ denote the mean values of observation and models, respectively.

3. Results

3.1. Mean Precipitation Amount, Frequency, and Intensity

3.1.1. Spatial Distribution

Figure 2 depicts the spatial distribution of summer mean precipitation amount, frequency, and intensity during 2008–2022 from IMERG along with the biases in ERA5 and WRF. The observed precipitation amount,

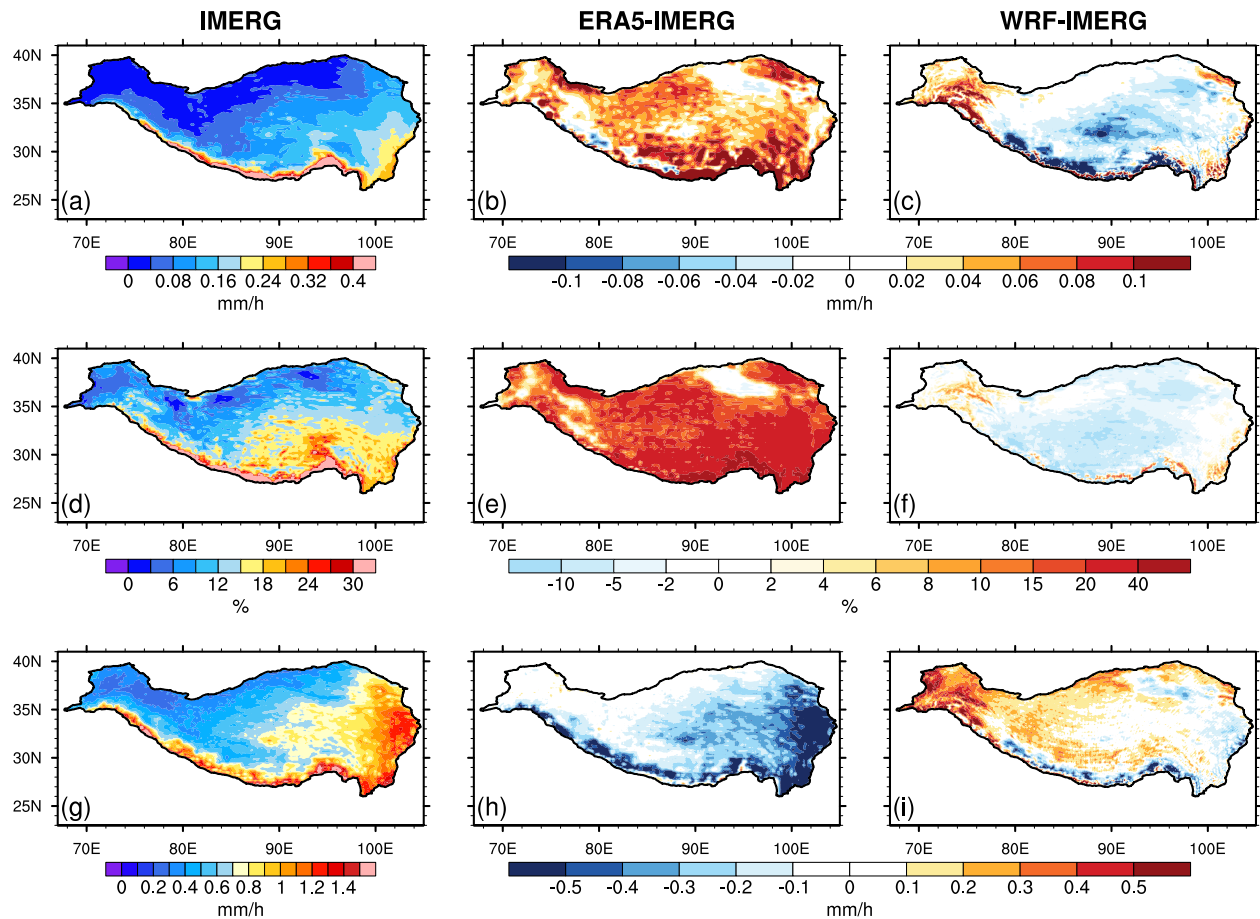


Figure 2. The spatial distribution of summer mean precipitation amount, frequency, and intensity averaged during 2008–2022 from (a, d, and g) IMERG as well as the biases in (b, e, and h) ERA5 and (c, f, and i) Weather Research and Forecasting.

frequency, and intensity all exhibit a clear gradient decreasing from the southeastern TP to the northwestern TP (Figures 2a, 2d, and 2g), a pattern also evident across different seasons (figure not shown). The precipitation frequency exceeds 30% over the southeastern corner of the TP and along its southern border but is below 10% over the northern TP, which has higher elevation. Similarly, the precipitation intensity decreases from 1.5 mm/hr over the eastern TP to 0.2 mm/hr over the northeastern TP. Consequently, these gradients shape the spatial pattern of precipitation amount.

Both ERA5 and WRF successfully reproduce the spatial patterns of precipitation amount, frequency, and intensity with the SCCs exceeding 0.80, 0.75, and 0.70, respectively (Table 1). ERA5 substantially overestimates the precipitation frequency by 20%, particularly over the southern TP (Figure 2e), but underestimates the precipitation intensity by over 0.5 mm/hr primarily over the eastern TP (Figure 2h). The notably overestimated precipitation amount, especially over the southern TP (Figure 2b), is likely due to the overestimation of frequency in this region.

The added value of WRF at the convection-permitting scale is evident in the significantly reduced precipitation frequency. It slightly underestimates the precipitation frequency over the central and southern TP (Figure 2f), which explains its minor underestimation of precipitation amount in these areas (Figure 2c). WRF tends to overestimate precipitation intensity over the western TP (Figure 2i) aligning with the overestimated precipitation amount in this region (Figure 2c). Overall, compared to WRF, ERA5 generates more frequent but less intense precipitation over the TP. The differences in precipitation amount between ERA5 and WRF are primarily attributable to their representation of precipitation frequency consistent with prior results on the daily scale (Z. Liu et al., 2022).

Table 1

The Spatial Correlation Coefficient, Uncentered Root Mean Square Error, and Relative Bias of the Summer Mean Precipitation Amount, Frequency, and Intensity As Well As Short-Duration, Medium-Duration, and Long-Duration Events Over the Tibetan Plateau in ERA5 and Weather Research and Forecasting Compared Against IMERG

	ERA5			WRF		
	SCC	RMSE	RB	SCC	RMSE	RB
Amount	0.90*	0.10 mm/hr	61.57%	0.81*	0.07 mm/hr	−9.21%
Frequency	0.82*	22.96%	152.46%	0.77*	6.06%	−19.51%
Intensity	0.75*	0.32 mm/hr	−33.64%	0.70*	0.23 mm/hr	9.01%
Short duration	0.16*	36.93	−39.72%	0.59*	33.32	−30.40%
Medium duration	0.18*	10.44	3.94%	0.75*	7.93	−19.09%
Long duration	0.58*	31.08	277.07%	0.73*	6.47	−11.76%

Note. The symbol * indicates that the SCC is statistically significant at the 0.01 level.

To further assess the differences in precipitation frequency across data sets, Figure 3 shows the frequency of precipitation in different strength categories based on the IMERG, ERA5, and WRF data sets across seasons. Hourly precipitation is classified into four strength categories following the World Meteorological Organization standards. Light precipitation (0.1–2.5 mm/hr) frequency ranges from below 2% in winter to about 14% in summer (Figure 3a). ERA5 markedly overestimates light precipitation frequency in all seasons, whereas WRF performs better in this regard. The spatial pattern of light precipitation frequency (figure not shown) is similar to that of mean precipitation frequency (Figures 2d–2f) in both data sets, suggesting that biases in mean precipitation frequency are primarily due to light precipitation biases.

Regarding moderate precipitation (2.5–10 mm/hr), ERA5 underrepresents its frequency, whereas WRF overestimates it (Figure 3b). The underrepresentation in ERA5 mainly occurs in the southeastern TP, whereas the

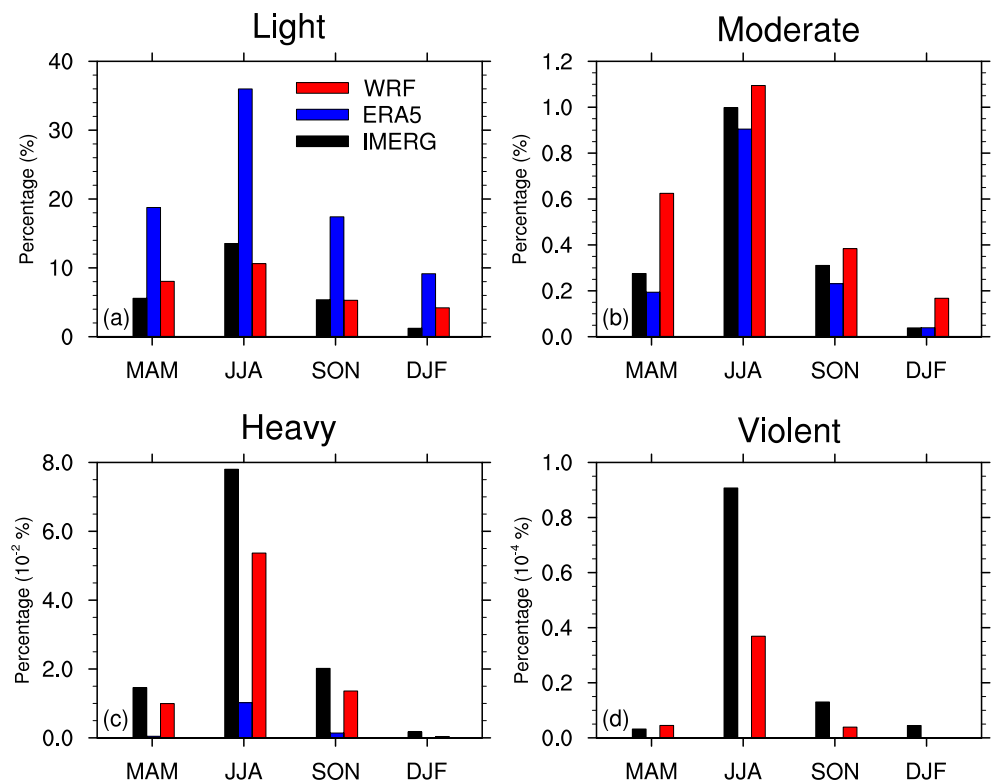


Figure 3. Frequency of precipitation with different grades (light: 0.1–2.5 mm/hr, moderate: 2.5–10 mm/hr, heavy: 10–50 mm/hr, and violent: >50 mm/hr) over the Tibetan Plateau in IMERG, ERA5, and Weather Research and Forecasting.

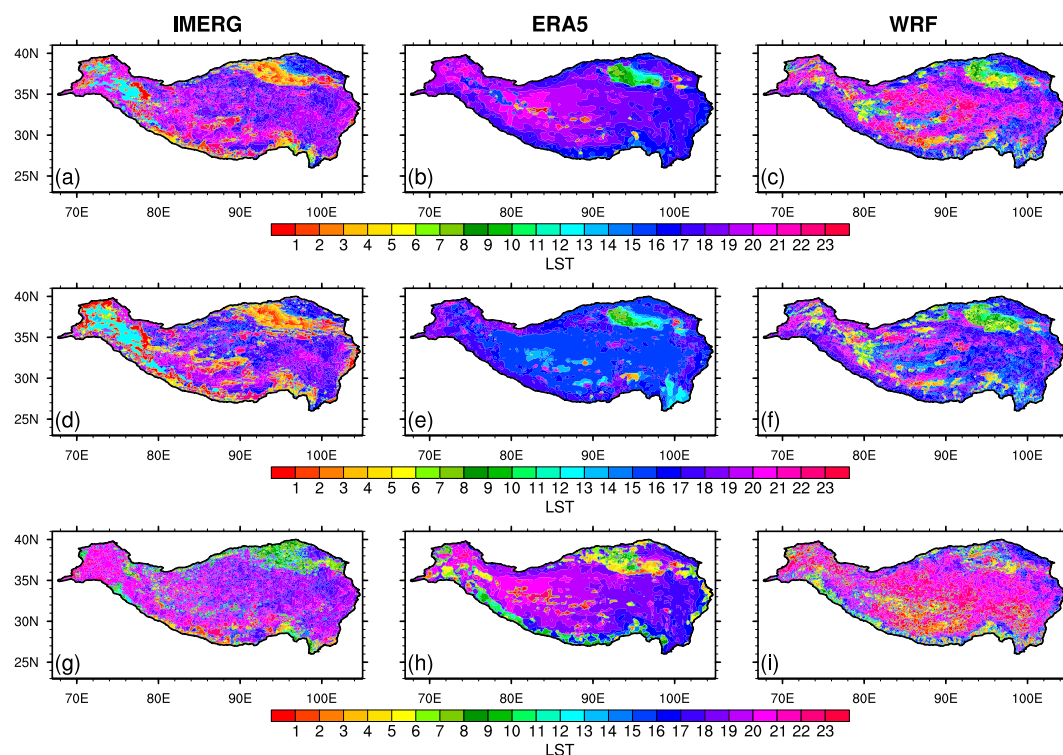


Figure 4. The spatial distribution of diurnal peak timing of summer precipitation amount, frequency, and intensity during 2008–2022 in (a, d and g) IMERG, (b, e and h) ERA5, and (c, f and i) Weather Research and Forecasting.

overestimation in WRF is concentrated along the TP's eastern border and in the western TP (figure not shown) contributing partly to the spatial pattern of mean precipitation frequency. For heavy (10–50 mm/hr) and violent (>50 mm/hr) precipitation, which occur less frequently, ERA5 barely simulates these events, whereas WRF demonstrates notable improvement with a much smaller underestimation (Figures 3c and 3d).

3.1.2. Diurnal Variation

The diurnal variation of precipitation is one of its most important properties influenced by geographic features and local atmospheric dynamics. Figure 4 presents the diurnal peak timing of summer precipitation amount, frequency, and intensity during 2008–2022 as observed in IMERG and ERA5 and WRF.

The observed diurnal peaks for all metrics mostly occur from late afternoon to around midnight except in the Qaidam Basin (Figures 4a, 4d, and 4g). The WRF CPM experiment accurately reproduces the peak timing of precipitation amount, occurring around 16:00–22:00 local solar time (LST), particularly over the eastern TP. However, it simulates a later peak timing compared to IMERG over the central TP (Figure 4c). In contrast, the peak timing of precipitation amount in ERA5 is significantly earlier over the eastern TP and along the southern border of TP (Figure 4b).

For precipitation frequency, ERA5 shows peak timing in the early afternoon (Figure 4e) much earlier than observations. This discrepancy may result from convective precipitation being overly triggered in the afternoon. WRF improves this by showing a slightly advanced but more realistic peak timing of precipitation frequency.

The spatial distribution of the diurnal peak timing for intensity is similar to that of precipitation amount in both ERA5 and WRF (Figures 4h and 4i). Overall, ERA5 simulates earlier peak timings for all metrics, whereas WRF provides the added value by postponing these timings closer to observed values.

To gain a more comprehensive understanding, regionally averaged diurnal cycles of summer precipitation amount, frequency, and intensity were also analyzed across four subregions over the TP. These regions were

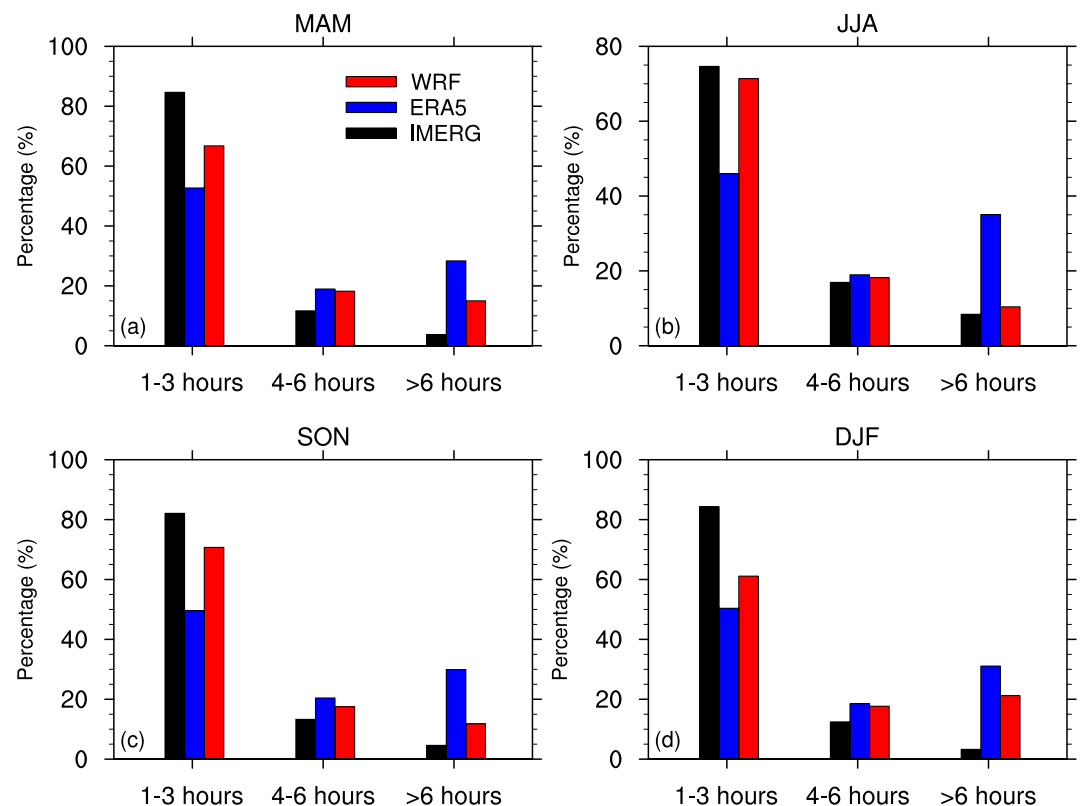


Figure 5. The seasonal ratio of precipitation events with different durations to total precipitation events over the Tibetan Plateau averaged during 2008–2022 in IMERG, ERA5, and Weather Research and Forecasting (a: spring; b: summer; c: autumn; d: winter).

divided using 32.5°N (separating northern and southern TP) and 91°N (separating eastern and western TP) primarily based on terrain and climate differences.

In all subregions, ERA5 overestimates precipitation amount and frequency while underestimating intensity, particularly in the afternoon, whereas WRF provides added value by more accurately representing subdaily precipitation climatology across all subregions.

In summary, WRF demonstrates significant added value in simulating mean precipitation characteristics, particularly by reducing precipitation frequency, especially for light precipitation, and by more accurately capturing the later peak timing of precipitation frequency.

3.2. Precipitation Duration

3.2.1. Spatial Distribution

Duration, a key characteristic of precipitation events that reflects their continuity, is closely associated with their underlying mechanisms and impacts. This makes it an essential metric for assessing the performance of numerical models. Figure 5 presents the ratio of precipitation events with different durations during 2008–2022 in IMERG, ERA5, and WRF.

According to IMERG, most precipitation events over the TP are of short duration accounting for approximately 80% of all events. These short-duration events decrease in frequency from the northern TP to the southern TP (figure not shown). WRF outperforms ERA5 in reproducing the spatial pattern of short-duration events with the SCCs of 0.59 and 0.16, respectively (Table 1). When averaged over the TP, both ERA5 and WRF underestimate the proportion of short-duration precipitation events with ERA5 underestimating by as much as 30% (Figure 5a). However, the WRF provides closer estimates to the observations with its improvement more pronounced in summer.

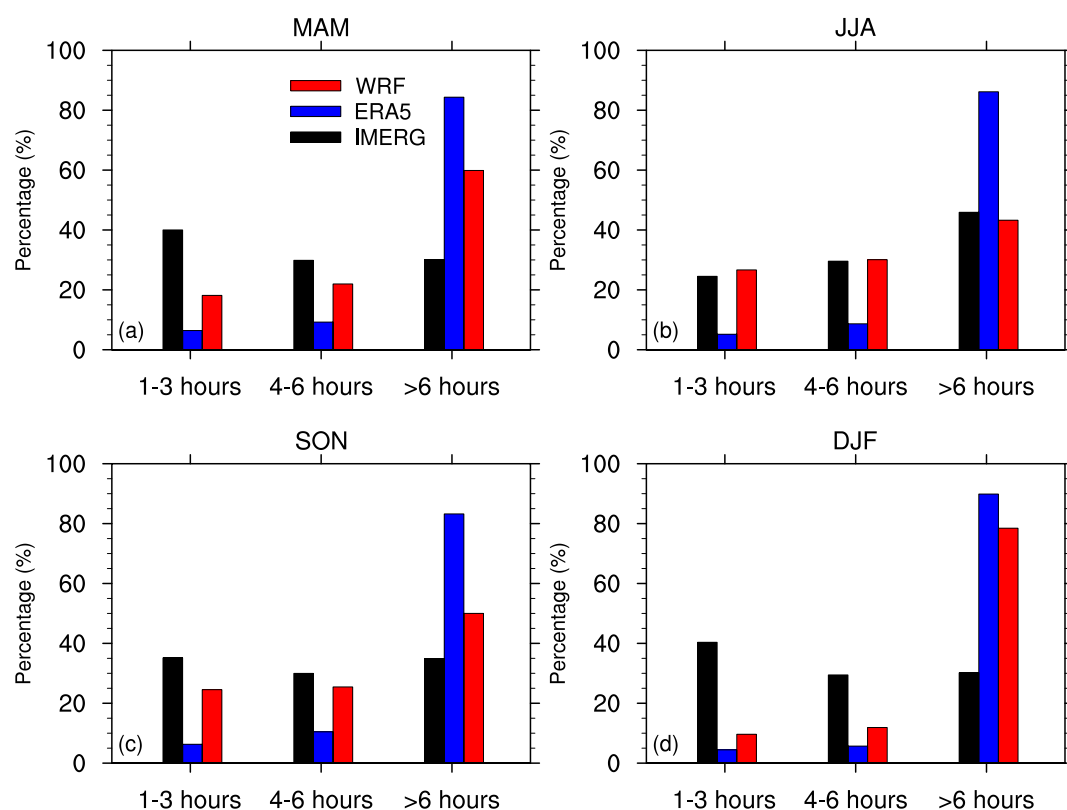


Figure 6. The seasonal contribution of different precipitation events to total precipitation over the Tibetan Plateau averaged during 2008–2022 in IMERG, ERA5, and Weather Research and Forecasting (a: spring; b: summer; c: autumn; d: winter).

In contrast to short-duration events, medium- and long-duration events show a decreasing gradient from the southeastern TP to the northwestern TP (figure not shown). WRF is more skillful in capturing the spatial distribution of medium-duration events with the SCCs of 0.75 and 0.18, respectively (Table 1). Nevertheless, when averaged over the TP, the performance of ERA5 and WRF in estimating the percentage of medium-duration precipitation events exhibits only minor differences with both showing slight overestimations (Figure 5). However, ERA5 significantly overestimates long-duration events, a bias that is notably reduced in WRF especially during summer.

Regarding the contribution of precipitation events of varying durations to total precipitation, IMERG indicates that short-duration events contribute more to total precipitation during cold seasons (Figure 6). In warm seasons, the contribution from long-duration events increases. Both ERA5 and WRF underestimate the contributions of short- and medium-duration events to total precipitation during cold seasons. However, ERA5 attributes more than 80% of total precipitation to long-duration events compared to below 40% in IMERG.

This discrepancy can be explained by ERA5's overproduction of long-duration events and the extended mean duration of these events especially over the southeastern TP, where biases can reach up to 15 hr (figure not shown). These excessive long-duration events likely contribute to ERA5's overestimation of total precipitation. In contrast, WRF significantly mitigates this issue particularly during summer.

3.2.2. Diurnal Variation

Figure 7 illustrates the spatial patterns of the maximum frequency of onset times for short-, medium-, and long-duration events in summer based on different data sets. Short-duration events dominate over the TP, providing a larger sample size for analysis.

According to IMERG, short-duration events most frequently begin in the afternoon typically around 16:00 LST (Figure 7a). This feature is poorly captured by ERA5, where short-duration events predominantly occur at noon

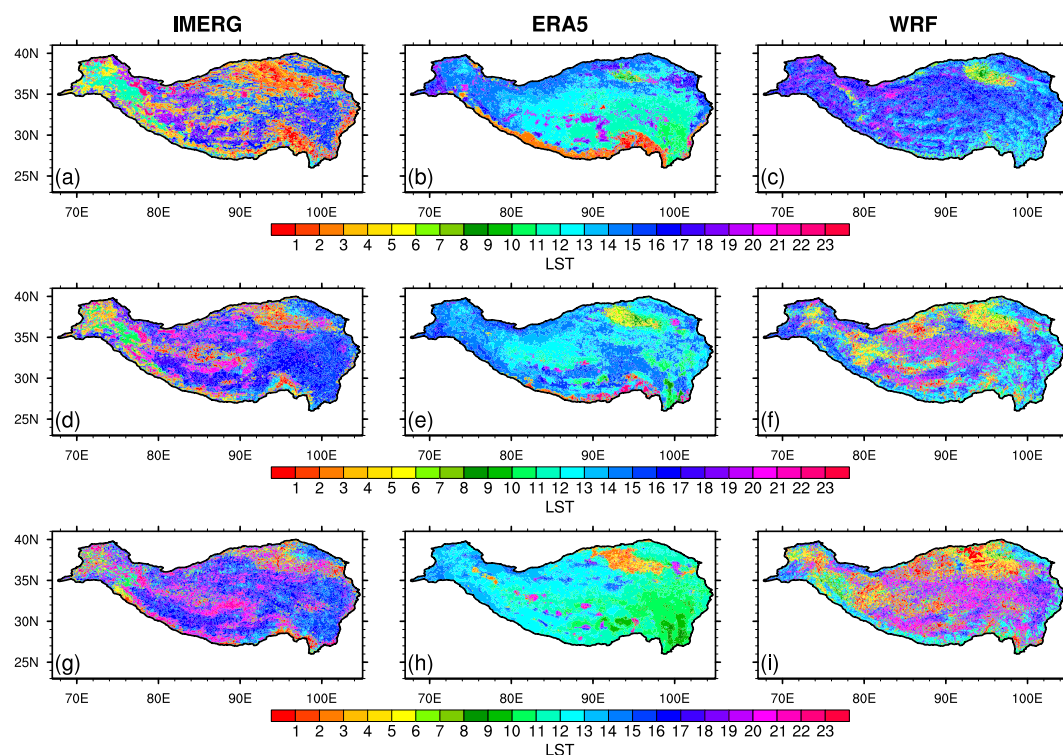


Figure 7. The spatial distribution of the maximum frequency of onset-time for short-, medium-, and long-duration precipitation events during summer in (a, d, and g) IMERG, (b, e, and h) ERA5, and (c, f, and i) Weather Research and Forecasting.

(Figure 7b). In contrast, WRF generally reproduces the afternoon onset times for short-duration events representing a significant improvement over ERA5.

Although ERA5 and WRF perform similarly in simulating the spatial distribution of medium-duration precipitation events, their ability to capture onset times differs. ERA5 produces much earlier onset times, whereas WRF provides more realistic estimates that align better with observations (Figures 7e and 7f). A similar pattern is observed for long-duration precipitation events, where WRF again outperforms ERA5 by simulating onset times closer to the observations (Figures 7h and 7i).

3.3. Extreme Hourly Precipitation

In recent years, increasing attention has been given to subdaily extreme precipitation due to its direct link to flooding and landslides. As extreme precipitation events are more frequent in summer, the following analysis focuses on this season.

Regarding the duration of subdaily extreme precipitation, observations indicate that short-duration extreme events account for approximately 85% of total extreme precipitation events. In contrast, the proportions of medium- and long-duration extreme events are about 10% and less than 5%, respectively (Figure 8a). This suggests that subdaily extreme precipitation is predominantly concentrated within short periods. The WRF simulation provides a better estimate of these proportions with deviations from observations within 10%, whereas ERA5 shows deviations exceeding 30%.

When considering the contribution of extreme precipitation events of different durations to total extreme precipitation, observations reveal that extreme short-duration events contribute approximately 50%, whereas long-duration events contribute only about 20% (Figure 8b). These results emphasize the importance and potential risks associated with extreme short-duration events. WRF underestimates the contribution of short-duration events and overestimates that of long-duration events, indicating a potential underestimation of the occurrence

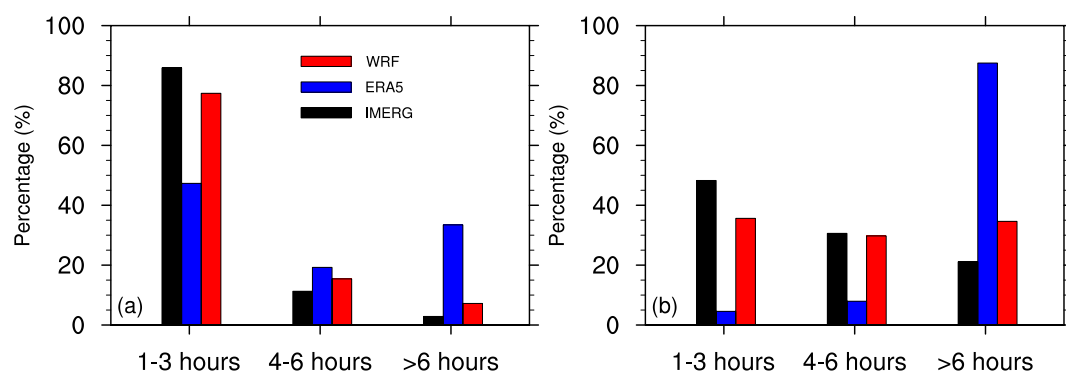


Figure 8. (a) The ratio of different duration of extreme precipitation events to total extreme precipitation events and (b) the contribution of different duration of extreme precipitation events to total extreme precipitation over the Tibetan Plateau averaged during 2008–2022 in IMERG, ERA5, and Weather Research and Forecasting.

and impacts of extreme short-duration events. Despite these biases, WRF still outperforms ERA5, where the contribution of short-duration extreme events is less than 5%, and that of long-duration events exceeds 85%.

A distinct characteristic of subdaily extreme precipitation is the dominance of short-duration events, which significantly contribute to the total extreme precipitation amount. Although ERA5 provides limited realistic insights into this feature, WRF better captures the proportions, contributions, and peak timings of these events demonstrating its added value.

4. Discussion

4.1. Added Value in Peak Timing of Summer Precipitation

In this study, WRF outperforms ERA5 in reproducing the diurnal peak timing of precipitation, a result also reported in previous studies (e.g., Z. Liu et al., 2022; Ma et al., 2022; P. Zhou et al., 2023). These studies suggest that the improvement in WRF may be related to water vapor content and its transport. In this study, SCCs between vertically integrated water vapor and precipitation amount, frequency, and intensity in summer are 0.79, 0.62, and 0.84 (0.67, 0.61, and 0.66) in ERA5 (WRF). This indicates that water vapor plays a crucial role in modulating the occurrence of all three metrics.

Water vapor over the TP originates both from external areas and the TP itself with externally advected water vapor constituting the majority of the TP's total water vapor (Ma et al., 2024). Therefore, to further understand the mechanism underlying the different representations of water vapor peak timing in ERA5 and WRF, this study investigates the net water vapor transport across the TP's boundaries. Compared to WRF, more water vapor flows into and resides within the TP throughout the day in ERA5 particularly from nighttime to early morning (Figure 9). The stronger water vapor flux in ERA5 probably results in more accumulated water vapor, which in turn promotes earlier precipitation development. Further, this pattern can be attributed to the fact that WRF transports less water vapor from the southern boundary (as indicated by red lines in Figure 1) but exports more water vapor from the eastern boundary (as indicated by purple lines in Figure 1). In-depth analysis reveals that the weakened water vapor transport from the southern boundary in WRF is likely attributed to the weakened southerly winds at the lower level (500 hPa), whereas its intensified water vapor transport from the eastern boundary may be associated with the stronger easterly winds at the midlevel (300 hPa).

Previous studies have also explained the earlier diurnal peak in ERA5 from the perspective of convective available potential energy (CAPE), a thermodynamic quantity. Z. Liu et al. (2022) proposed that in ERA5, CAPE grows much faster, peaks earlier, and declines more quickly, which could also account for the later peak timing in WRF.

4.2. Added Value in Light Precipitation Frequency

The reduction in light precipitation frequency has been identified as a contributing factor to WRF's added value. Previous studies have attributed the observed reduction of light precipitation to the effects of temperature at the

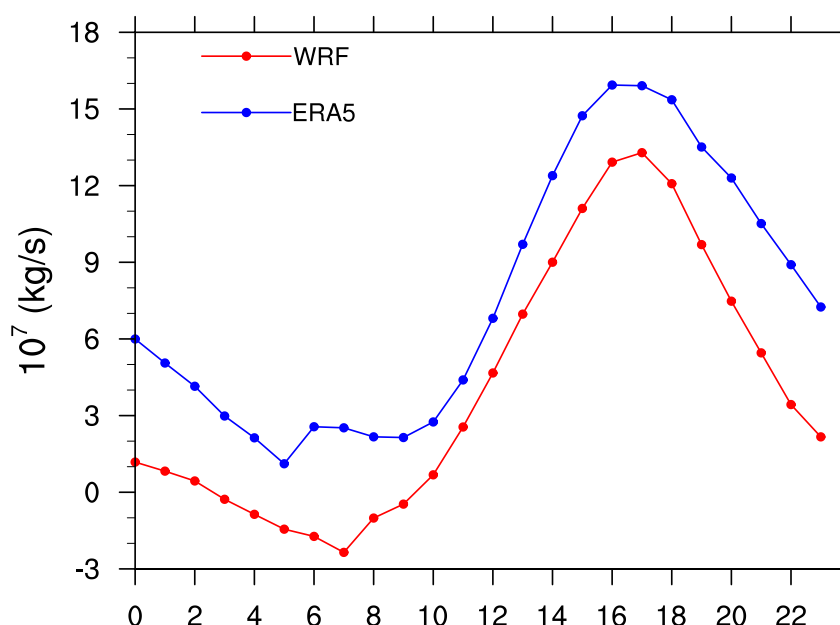


Figure 9. The 15-year averaged summer mean diurnal cycle of net water vapor transport onto the Tibetan Plateau through its boundaries in ERA5 and Weather Research and Forecasting.

daily scale (J. Zhou et al., 2020). Figure 10 illustrates the differences in summer mean light precipitation frequency as well as a composite analysis of temperature and relative humidity at 500 hPa between ERA5 and WRF at the subdaily scale. Compared to ERA5, WRF reduces light precipitation frequency particularly over the central-western TP (Figure 10c). This reduction is accompanied by warm anomalies in low-level temperature (Figure 10f) and negative anomalies in low-level relative humidity (Figure 10i) over the central-western TP. Due to increased temperature in the lower troposphere, the saturation vapor pressure rises, suppressing vapor condensation, which leads to a reduction in relative humidity and a subsequent decrease in light precipitation occurrence.

Additionally, the decrease in light precipitation frequency may be linked to changes in atmospheric stability. As atmospheric stability decreases, upward motion strengthens, precipitation intensity increases, and light precipitation occurrence decreases (Huang & Wen, 2013; Tysa & Ren, 2022). In this study, we compare the differences in upward motion between ERA5 and WRF. The spatial pattern of upward motion in ERA5 and WRF is similar, whereas hourly upward motion is stronger in WRF especially over the western TP (figure not shown). This means that many light precipitation events tend to become heavier, resulting in a decrease in light precipitation occurrences over the western TP.

Thus, the added value of WRF in reducing light precipitation frequency can be attributed to increased temperature and decreased relative humidity in the lower troposphere as well as enhanced upward motion and weakened static stability.

4.3. Added Value in Short- and Long-Duration Events

Compared to ERA5, WRF simulates a larger percentage of short-duration events and a smaller percentage of long-duration events bringing the model closer to the observed distribution. Typically, short-duration events are triggered by strong solar heating, whereas long-duration events are sustained by organized rainfall systems rather than isolated convection (J. Li et al., 2011). Therefore, quantifying the differences in relevant dynamic and thermodynamic fields between ERA5 and WRF can help elucidate the corresponding mechanisms.

Short-duration events tend to peak in the afternoon, so we analyze temperature changes averaged during 14:00–18:00 LST (minus the daily mean). Figure 11 shows the spatial distribution of summer mean short-duration precipitation occurrences and temperature changes in ERA5 and WRF along with the differences between them. More short-duration events occur over the central-western TP (Figures 11a and 11b) consistent with

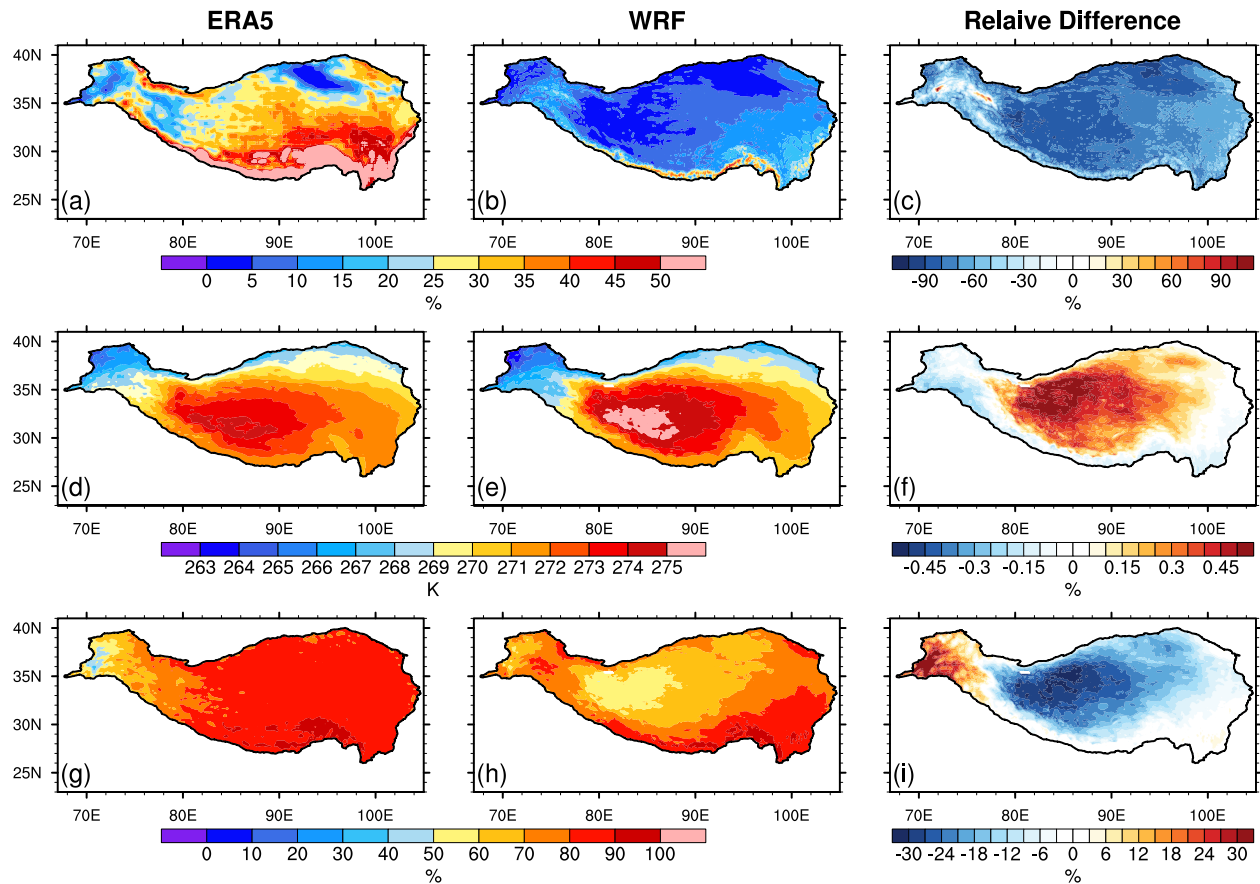


Figure 10. The summer mean light precipitation frequency, composite analysis of temperature and relative humidity at 500 hPa in (a, d, and g) ERA5 and (b, e, and h) Weather Research and Forecasting, (c, f, and i) as well as the relative differences between them.

temperature change patterns (Figures 11d and 11e). The SCC between the number of short-duration events and temperature changes reaches 0.57 in ERA5 and 0.71 in WRF. The areas where WRF simulates more short-duration events (Figure 11c) coincide with more evident temperature changes (Figure 11f) compared to ERA5. These regions are also more abundant in water vapor in WRF than in ERA5 (Figure 11i) similar to the spatial distribution of differences in short-duration events. These factors collectively lead to more short-duration precipitation occurrences in the WRF simulation.

Figure 12 shows the spatial distribution of summer mean long-duration precipitation occurrences, specific humidity at 500 hPa, and horizontal wind fields at 500 hPa in ERA5 and WRF along with the differences between them. Long-duration precipitation occurrences are closely associated with higher specific humidity and strong southwesterly winds at lower troposphere primarily over the southern TP (Figures 12a, 12b, 12d, and 12e). Compared to ERA5, WRF detects less water vapor (Figure 12f). Additionally, two anticyclonic anomalies are observed in WRF (Figure 12f). Along the southern border of the TP, the differences in long-duration precipitation occurrences between ERA5 and WRF are most pronounced coinciding with northeastern wind anomalies in WRF. These joint effects hinder the development and persistence of precipitation in WRF, leading to better representation of long-duration precipitation events.

Although the development and occurrence of short- and long-duration events are governed by different physical processes, WRF better represents these processes—such as local surface solar heating and large-scale circulation—providing added value in increasing short-duration events and decreasing long-duration events.

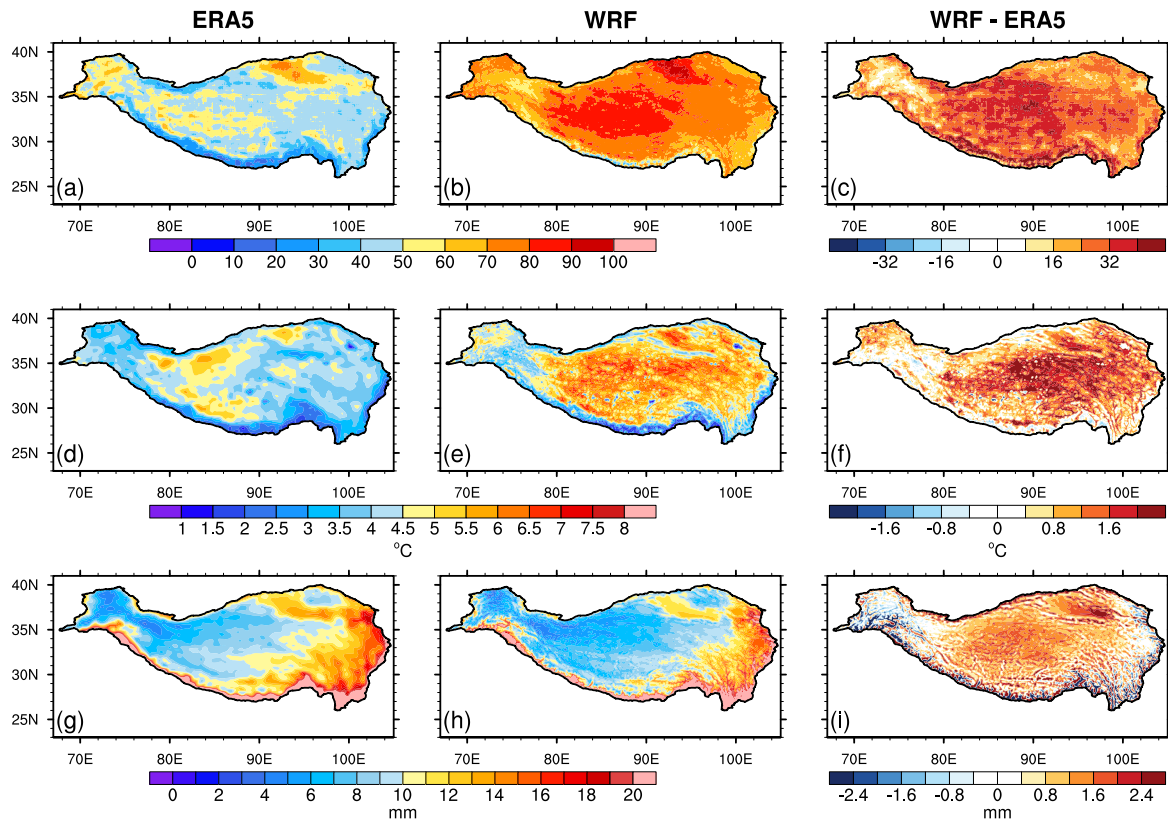


Figure 11. The spatial distribution of summer mean short-duration precipitation occurrences, temperature changes during 14:00–18:00 local solar time (LST) and water vapor availability during 14:00–18:00 LST in (a, d, and g) ERA5 and (b, e, and h) Weather Research and Forecasting as (c, f, and i) well as the differences between them.

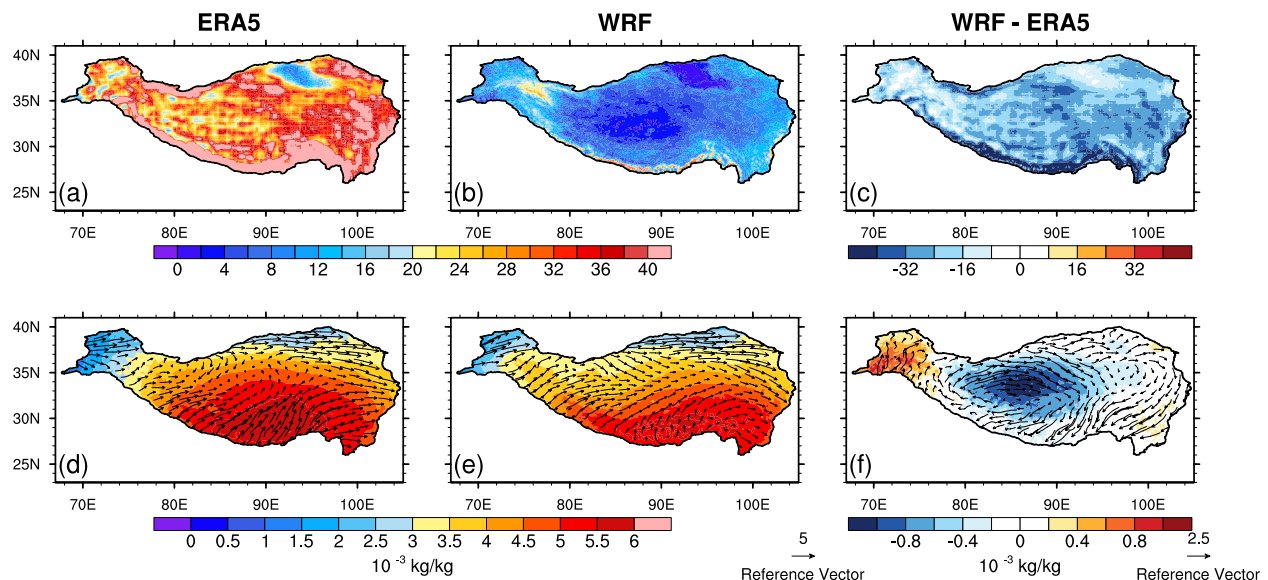


Figure 12. The spatial distribution of summer mean long-duration precipitation occurrences, specific humidity, and horizontal wind field at 500 hPa in (a, b) ERA5 and (d, e) Weather Research and Forecasting (c, f) as well as the differences between them.

5. Conclusions

In this study, a 15-year WRF simulation at a convection-permitting scale (4 km) is conducted over the TP, and its performance in characterizing subdaily precipitation is compared with ERA5 and the satellite-based IMERG data set.

Regarding the climatology of summer precipitation amount, frequency, and intensity, both ERA5 and WRF are capable of capturing their spatial patterns. However, ERA5 significantly overestimates precipitation amount mainly due to the overestimated precipitation frequency especially over the southern TP. This issue is substantially improved in WRF. Additionally, ERA5 tends to overestimate light precipitation occurrences but underestimate moderate precipitation occurrences, which is the opposite of WRF's performance. The diurnal peak timing of summer precipitation metrics occurs much too early in ERA5, but WRF improves this timing. Therefore, the added value of WRF is reflected in its better representation of precipitation frequency, achieved primarily by reducing overestimation (particularly for light precipitation) and delaying the peak timing.

In terms of precipitation duration, both ERA5 and WRF underestimate the ratio of short-duration events, while overestimate the ratio of long-duration events. WRF shows substantial improvement over ERA5 especially in summer. For short-duration events, the deviation is more pronounced in ERA5 (nearly 30%) particularly in summer. For long-duration events, ERA5 not only overestimates the ratio but also overestimates the mean duration of each event, leading to an excessive contribution to total precipitation. Additionally, ERA5 fails to capture the diurnal cycle of precipitation onset times for events of different durations typically starting too early (at noon), whereas WRF more accurately simulates precipitation onset in the afternoon.

Extreme precipitation, defined by the 95th percentile threshold of all historical hourly precipitation, is also evaluated. A distinct feature of subdaily extreme precipitation is that it tends to last for a short period with short-duration events accounting for 50% of extreme precipitation. WRF provides a more accurate estimate of the percentage of extreme short-duration events with deviations within 10%, while ERA5 exceeds 30%. However, WRF tends to underestimate extreme short-duration events and related extreme precipitation, which slightly diminishes its reliability in flood prediction and risk management.

Finally, the added value of WRF is examined from three perspectives. First, its added value in depicting precipitation peak timing is linked to water vapor content and associated water vapor transport particularly during nighttime and early morning. Second, the added value of WRF in reducing light precipitation frequency is likely connected to increased temperature and decreased relative humidity in the lower troposphere. Enhanced upward motion and weakened static stability may also cause many light precipitation events to intensify, reducing the occurrence of light precipitation. Third, the added value of WRF in estimating short- and long-duration events is driven by different physical processes. Larger temperature changes and increased water vapor availability in the afternoon lead to more short-duration precipitation occurrences in WRF. Meanwhile, anticyclonic and north-eastern wind anomalies hinder the persistence of long-duration precipitation.

Several studies have also demonstrated the advantages of CPM over the TP. Although most studies agree on the improved representation of precipitation, they differ in the specific aspects they emphasize. For example, some studies underscore the importance of model physics and parameterizations in improving simulation accuracy, emphasizing that the choice of physical schemes plays a crucial role in precipitation simulation (Lv et al., 2020; P. Zhou et al., 2024). Others broaden their scope to explore various aspects of the atmospheric water cycle, including cloud dynamics and moisture fluxes (P. Li et al., 2021; Zou et al., 2024). Additionally, some research delves into future climate projections using CPMs to assess potential changes in precipitation patterns and its extremes (Zou & Zhou, 2024).

However, one major limitation of existing studies is the relative scarcity of long-term simulations, which restricts the ability to fully assess the robustness and stability of CPMs over the TP. Additionally, the intermittent nature of precipitation has received limited attention, as most research focuses on precipitation intensity, frequency, timing, and extreme events, whereas systematic analyses of precipitation duration and intermittency remain insufficient.

Our study helps bridge this gap to some extent by extending the simulation period to better capture long-term precipitation characteristics. Furthermore, it provides insights into how model physics influence the representation of precipitation intermittency, contributing to a more reliable understanding of convection-permitting

simulations. These results offer a better understanding of the mechanisms behind subdaily precipitation simulation over the TP.

Data Availability Statement

The WRF model, employed to produce the simulation in this study, is available from Skamarock et al. (2019). The ERA5 reanalysis is accessible from Hersbach et al. (2020). The IMERG data set can be accessed from Huffman et al. (2020). The data generated and visualized in this study can be obtained from Ma et al. (2025).

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