Analysis of Precipitation Diurnal Cycle and Variance in Multiple Observations, CMIP6 Models, and a Series of GFDL-AM4.0 Simulations

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ABSTRACT: The diurnal cycle of precipitation and precipitation variances at different time scales are analyzed in this study based on multiple high-resolution 3-h precipitation datasets. The results are used to evaluate nine CMIP6 models and a series of GFDL-AM4.0 model simulations, with the goal of examining the impact of SST diurnal cycle, varying horizontal resolutions, and different microphysics schemes on these two precipitation features. It is found that although diurnal amplitudes are reasonably simulated, models generally generate too early diurnal peaks over land, with a diurnal phase peaking around noon instead of the observed late afternoon (or early evening) peak. As for precipitation variances, irregular subdaily fluctuations dominate the total variance, followed by variance of daily mean precipitation and variance associated with the mean diurnal cycle. While the spatial and zonal distributions of precipitation variances are generally captured by the models, significant biases are present in tropical regions, where large mean precipitation biases are observed. The comparisons based on AM4.0 model simulations demonstrate that the inclusion of ocean coupling, adoption of a new microphysics scheme, and increasing of horizontal resolution have limited impacts on these two simulated features, emphasizing the need for future investigation into these model deficiencies at the process level. Conducting routine examinations of these metrics would be a crucial first step toward better simulation of precipitation intermittence in future model development. Last, distinct differences in these two features are found among observational datasets, highlighting the urgent need for a detailed evaluation of precipitation observations, especially at subdaily time scales, as model evaluation heavily relies on high-quality observations.

SIGNIFICANCE STATEMENT: High-frequency precipitation data, such as 3-hourly or finer resolution, provide detailed and precise information about the intensity, timing, and location of individual precipitation events. This information is essential for evaluating physically based numerical weather and climate models, which are important tools for understanding and predicting precipitation changes. We compared several global high-resolution observation datasets with nine CMIP6 GCMs and a series of GFDL-AM4.0 model simulations to evaluate the precipitation diurnal cycle and variance, with the goal of examining the impact of SST diurnal cycle, varying horizontal resolutions, and different microphysics schemes on these metrics. Despite the impact of these factors on the simulated precipitation diurnal cycle and variance being evident, our results also show that they are not consistently aligned with observed features. This highlights the need for further investigation into model deficiencies at the process level. Therefore, conducting routine examinations of these metrics could be a crucial first step toward improving the simulation of precipitation intermittency in future model development. Additionally, given the large uncertainties, there is an urgent need for a detailed evaluation of observational precipitation products, particularly at subdaily time scales.

KEYWORDS: Atmosphere; Diurnal effects; Precipitation; Climate models

1. Introduction

Precipitation intermittency, also known as precipitation irregularity, describes the occurrence of precipitation events that are discontinuous, sporadic, or unevenly distributed in time and/or space. It can have important effects on Earth’s hydrological and biogeochemical cycles, as well as on ecosystems, agriculture, and human societies (e.g., Qian et al. 2006; Klink et al. 2014; Prein et al. 2017; Kendon et al. 2017; Pendergrass et al. 2017; Shively 2017; Trenberth et al. 2017). Specifically, high-frequency precipitation intermittency can cause severe impacts on regional...
hydrological systems, including flash floods, landslides, and soil erosion, which can have severe consequences for local ecosystems and communities. Examining high-frequency precipitation variance thus facilitates a comprehensive understanding of precipitation variability across various time scales, offering valuable insights into the underlying dynamics and processes influencing weather patterns. This knowledge plays a pivotal role in predicting future precipitation patterns, assessing regional water availability, and formulating adaptive strategies to address changing precipitation regimes. High-frequency observational precipitation data, such as at 3-hourly or finer resolution, thus play a crucial role in comprehending these events by offering detailed and precise information about the intensity, timing, and location of individual precipitation events. This information is also essential for evaluating physically based numerical weather and climate models, which are important tools for understanding and predicting precipitation. However, despite decades of efforts to improve model performances, weather and climate models still have fundamental deficiencies that limit their ability to simulate precipitation realistically (Sun et al. 2014; Simonin et al. 2017). Furthermore, several serious biases, such as the “drizzling bias,” continue to persist in climate models across many generations (Dai 2006; Trenberth et al. 2017; Knutson and Zeng 2018; Chen and Dai 2019; Fiedler et al. 2020; Chen et al. 2021). Moreover, it is crucial to comprehend the variations in precipitation variability in conjunction with changes in mean and extreme precipitation to decipher the hydrological cycle’s reaction to global warming. Despite intensive study of mean and extreme precipitation changes, precipitation variability has received comparatively less attention. Nonetheless, recent research has shown that most climate models indicate an increase in precipitation variability across the majority of global land areas in response to warming, characterized by an increase in heavy precipitation events and a decrease in light to moderate precipitation (Shia et al. 2012; Dai et al. 2020). It is worth noting, however, that these analyses primarily focus on daily and longer time scales (Pendergrass et al. 2017; Wood et al. 2021).

As high-frequency precipitation products become more widely available, there has been an increase in analysis of precipitation diurnal cycles (Covey et al. 2016; Christopoulos and Schneider 2021; Lee and Wang 2021; Tang et al. 2021, 2022; Tao et al. 2022). However, high-frequency precipitation variability remains relatively understudied in precipitation research (Trenberth et al. 2017; Ahn et al. 2022). By analyzing a satellite precipitation dataset at hourly and 3-hourly time frequencies, Covey et al. (2018) decomposed precipitation variance into three orthogonal components: variance of the mean diurnal cycle, variance of daily mean, and variance of irregular subdaily mean. Their findings revealed that the primary component of high-frequency precipitation variance is from the irregular fluctuations within the diurnal cycle. When compared to the CESM1 model, the first component was adequately simulated, but the model underestimated the latter two components. Specifically, the magnitude of the irregular component was underestimated by a factor of 2–3. These deficiencies may indicate potential erroneous processes associated with cloud generation and precipitation formation in a model and could translate to the predicted climate changes and the resultant impacts. Such deficiencies are reflected in a set of CMIP5 and CMIP6 models, where it was found that the simulated high-frequency precipitation variabilities are systematically underestimated (Ahn et al. 2022). This underestimation can be partially attributed to the relatively coarser resolution of the model in comparison to the observational dataset, as highlighted by Chen and Dai (2018) and Chen et al. (2021). Several studies have highlighted that traditional diagnostics at daily and longer time scales may not fully capture the discrepancies between models and observations at shorter time scales (e.g., Trenberth et al. 2017; Covey et al. 2018). Therefore, analyzing high-frequency precipitation variability can provide valuable insights into atmospheric processes, making it a useful diagnostic tool for climate models. Moreover, the diurnal cycle and high-frequency precipitation variabilities can be influenced not only by model physics and parameterizations but also by other factors such as underlying boundary conditions and model resolution (Covey et al. 2016; Tang et al. 2021; Ahn et al. 2022; Tao et al. 2022). However, the use of multiple models with varying resolutions and moist process parameterizations makes it challenging to distinguish the specific effect of each factor. Consequently, analyzing a set of model simulations that utilize the same model code and physical parameterizations has the potential to bridge this gap in understanding (Chen and Dai 2019).

This study presents objective performance metrics that measure the diurnal cycle and high-frequency precipitation variance based on multiple precipitation products. The same analyses are then applied to nine CMIP6 models and a series of model simulations using Geophysical Fluid Dynamics Laboratory (GFDL) Atmospheric Model (AM4.0), which includes five different experiments. The CMIP6 models offer a broader perspective of general model biases, while the series of AM4.0 simulations enable comparisons between a fully coupled ocean–atmosphere simulation and a simulation driven by prescribed SST and sea ice conditions, simulations with varying horizontal resolutions, and simulations with different cloud microphysics schemes. The article will proceed as follows. Section 2 outlines the observational dataset, the GFDL-AM4.0 model experiments, and CMIP6 models analyzed in this study, as well as the metrics used to measure the diurnal cycle and high-frequency intermittency of precipitation. Section 3 provides a detailed evaluation of the simulated precipitation features by comparing them with the observation. Discussion and conclusions are given in section 4.

2. Data and methods

a. Observational data

This study uses the Multi-Source Weighted-Ensemble Precipitation, version 2 (MSWEP V2; Beck et al. 2019), as the main precipitation product because it provides the longest (from 1979 to the present) high spatial (0.1°) and temporal frequency (3 h) fully global precipitation dataset. This product integrates diverse data sources, including gauge, satellite, and reanalysis data, and considers gauge reporting times to mitigate temporal mismatches between satellite-reanalysis estimates and
TABLE 1. Information about the model and experiment names along with their basic features.

<table>
<thead>
<tr>
<th>Model name (resolution)</th>
<th>Experiment name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM4.0 (100 km)</td>
<td>AM4</td>
<td>It features a horizontal resolution of ~100 km, 33 vertical levels with a one-moment Rostayn–Klein bulk cloud microphysics with a diagnostic precipitation (RK) scheme</td>
</tr>
<tr>
<td>CM4.0 (100 km)</td>
<td>CM4</td>
<td>Same as AM4, but with a fully coupled ocean component</td>
</tr>
<tr>
<td>AM4.0 (50 km)</td>
<td>AM4 (50 km)</td>
<td>Same as AM4, but with a horizontal resolution of 50 km</td>
</tr>
<tr>
<td>AM4.0 (25 km)</td>
<td>AM4 (25 km)</td>
<td>Same as AM4, but with a horizontal resolution of 25 km</td>
</tr>
<tr>
<td>AM4.0-MG2 (100 km)</td>
<td>AM4-MG2</td>
<td>Same as AM4, but with the RK scheme replaced by the two-moment Morrison–Gettelman bulk cloud microphysics with a prognostic precipitation (MG2) scheme</td>
</tr>
</tbody>
</table>

It is found that MSWEP outperforms a variety of precipitation products in both densely gauged (e.g., CONUS) and ungauged regions (e.g., oceans) on various time scales (Beck et al. 2017, 2019).

However, the high-frequency precipitation characteristics, like those analyzed in this study, have not been fully evaluated previously. To account for these limitations and to offer a comprehensive comparison, we supplement the analysis with additional datasets. We utilize the 3-h precipitation dataset from the Tropical Rainfall Measuring Mission (TRMM) version 3B42 (Huffman et al. 2007) during 1998–2016, the hourly precipitation dataset from bias-corrected Climate Prediction Center (CPC) morphing technique (CMORPH) satellite precipitation (Xie et al. 2017) during 1998 to the present, and the 30-min Integrated Multi-satellite Retrievals for GPM (IMERG) from NASA Global Precipitation Measurement (GPM/IMERG; Huffman et al. 2019) from 2015 to 2020. Furthermore, for the CONUS region, we incorporate the hourly NCEP radar-based, gauge-adjusted Stage IV precipitation product (Lin and Mitchell 2005) from 1998 to the present to ensure a comprehensive and robust comparison. These datasets, listed in Table S1 in the online supplemental material, provide valuable insights into MSWEP’s performance and also assist in estimating observational uncertainties.

b. GFDL-AM4.0 simulations and CMIP6 model simulations

A series of simulations based on the GFDL-AM4.0 are conducted. GFDL-AM4.0 features a horizontal resolution of ~100 km, 33 vertical levels, a double-plume convective parameterization, simplified chemistry for aerosols simulation, and aerosol indirect effects (Zhao et al. 2018a,b). GFDL-AM4.0 serves as the atmospheric component for the CMIP6-era GFDL coupled climate and Earth system models (Held et al. 2019; Dunne et al. 2020). The AM4 experiment (see more details in Table 1) is selected as the referenced experiment in this study. It is an AMIP-mode simulation, a standard experimental protocol for global atmospheric general circulation models, in which monthly SST and sea ice concentrations are prescribed to match observations. Although this type of simulation does not account for interactions and feedbacks between the different components of the climate system, it allows for a direct comparison with observation as the SSTs do not respond to surface forcing, and the observed major climate modes, such as El Niño–Southern Oscillation (ENSO) and the Atlantic multidecadal oscillation (AMO), are represented (Wang et al. 2011). The performance of GFDL-AM4.0 in simulating the mean precipitation has been assessed in detail, and it outperforms both previous GFDL models and most CMIP5 models (Zhao et al. 2018a,b).

In addition to the AM4 experiment, we also analyze additional four experiments, including the coupled version of AM4.0 (CM4.0; Held et al. 2019), two finer versions of AM4.0 (50 and 25 km), and a new version of AM4.0 with an updated two-moment Morrison–Gettelman bulk cloud microphysics with prognostic precipitation (MG2) (Guo et al. 2021). All these experiments share the exact same atmospheric component without any retuning strategy. CM4.0 consists of the OM4.0 ocean component, where the SST is calculated over the ocean topmost layer (Adcroft et al. 2019). The model utilizes a hybrid (depth-isopycnal) vertical coordinate, which significantly improves the resolution near the ocean’s surface compared to previous GFDL ocean models. This vertical coordinate can transition between depth levels and isopycnal layers, and the exact depth of the topmost layer may vary depending on the region and latitude. However, it typically maintains a nominal resolution of 1–2 m for the topmost layer. This finer vertical resolution notably enhances the model’s ability to capture and represent diurnal SST fluctuations. These experiments have been widely used to assess important weather phenomena associated with precipitation, such as monsoonal low pressure systems (Dong et al. 2020), atmospheric rivers (Zhao 2020), tropical storms (Zhao 2022), and mesoscale convective systems (Dong et al. 2021, 2022, 2023), and have shown reasonable simulation results.

In addition to the series of AM4 experiments, we have included nine CMIP6 models that offer high-frequency precipitation output (Table S1). These models encompass a range of resolutions and moist process parameterizations. This inclusion allows for a comprehensive comparison of the model biases in GFDL-AM4 within the broader context of general model biases observed in other state-of-the-art CMIP6 models.

c. Data preprocessing

All simulations based on AM4 and from CMIP6 are available during 1980–2014, and the observations were processed during the overlapping time period with the exception of
GPM/IMERG, which lacks overlapping data. Therefore, it is analyzed during its available time span during 2015–20. Both observed and simulated 3-h precipitation values are cumulative over time. However, for datasets with higher temporal frequency (hourly for CMORPH and Stage IV and 30 min for GPM/IMERG), we aggregate them over 3-h intervals to ensure consistency for comparison purposes.

When conducting precipitation diurnal analysis, it is crucial to carefully consider the time bounds used for each dataset. Some observational datasets and model simulations have different time representations for their 3-h data. For example, at 0000 UTC, MSWEP represents the subsequent 3-h precipitation averages (0000–0300 UTC), while the TRMM dataset covers estimations for the 1.5 h before and after (2230–0130 UTC). On the other hand, the model simulations align with the MSWEP dataset, representing the subsequent 3-h precipitation averages (0000–0300 UTC). To ensure consistent analysis, these time differences have been considered when converting UTC to LST in the subsequent analysis. All time values are consistently converted to the subsequent 3-h averages, thereby mitigating any discrepancies caused by varying time representations.

Given that long-term (35 years in this study for MSWEP and model simulations) averaging can effectively remove chaotic fluctuations from high-frequency intermittency statistics (Covey et al. 2018), we limit our analysis to a single ensemble member for each experiment. This approach is supported by the results obtained by comparing three members of the AM4 and CM4 experiments that were initialized differently (figures not shown). Moreover, the comparable results obtained from various observational datasets with different time spans further support and justify this approach.

To facilitate fair comparison, observations and finer-resolution model simulations were first averaged to the AM4 model grid using the Earth System Modeling Framework (ESMF) regridding tool with the “conserve” algorithm to preserve the data’s integral between grids. Additionally, we also used a coarse-graining method for interpolation, and results based on the MSWEP dataset demonstrated comparable outcomes between different interpolation methods.

Although the results presented in this paper primarily rely on composite data from July to represent summer, we also provide statistics for three other months (January, April, and October). It is important to note that the results remain consistent even when using 3 months for each season. Our analysis focuses on a global scale, with separate investigations of land and ocean areas. In addition, we include a specific examination of the CONUS region.

d. Diurnal harmonic analysis

We utilize harmonic analysis to determine the peak time and amplitude of the precipitation diurnal cycles at different frequencies. The time series is first averaged into a 24-h daily composite during the respective analyzed period, followed by Fourier analysis. The mean precipitation daily cycle is then described by the following formulation (Dai 2001; Dai et al. 1999; Yang and Slingo 2001):

\[ P(t) = \overline{P} + \sum_{i=1}^{D/2} A_i \cos \left( \frac{2\pi t}{N} - \phi_i \right) + \text{residual}, \quad t = 1, 2, \ldots, 8, \]

where \( P(t) \) and \( \overline{P} \) represent the 24-h averaging time series and the corresponding daily mean, respectively; \( D \) is the number of observations in each day (equal to 8 here); \( A_i \) and \( \phi_i \) are Fourier coefficients representing the mean-to-peak amplitude and phase (i.e., the time of the maximum value) of the \( i \)th harmonic mode, respectively; and \( t \) stands for the time of the day.

In this study, we focus on the first two harmonic components, namely, the diurnal (24 h) and semidiurnal (12 h) periods, as they account for most of the daily cycle of precipitation at the 3-h interval (Covey et al. 2016).

e. Precipitation variance terms

Following previous studies (Covey et al. 2018; Taylor and Covey 2018), we break down the 3-hourly time series into three components to isolate variations associated with monthly, daily, and subdaily time scales. The following provides a brief overview of the decomposition.

Let \( P_{i,n} \) be a time point precipitation value for hour \( i \) of day \( n \), where \( n \) ranges from 1 to \( N \) days and \( i \) ranges from 1 to \( D \) time points in each day (here, \( D = 8 \) since 3-hourly data are used in this study). The overall time mean of this time series is

\[ \overline{P}_{\text{all}} = \frac{1}{ND} \sum_{n=1}^{N} \sum_{i=1}^{D} P_{i,n}. \]  

(1)

So, \( \overline{P}_{\text{all}} \) is a monthly mean if the time series span either 1 month or a composite of the same month over several years as in this study. The time series can be then expressed as the sum of \( \overline{P}_{\text{all}} \) and the corresponding anomaly \( P'_{i,n} \):

\[ P_{i,n} = \overline{P}_{\text{all}} + P'_{i,n}. \]  

(2)

The anomaly can be further resolved into three components, associated, respectively, with the daily mean anomaly \( (\overline{P}_{\text{bn}}) \), the mean diurnal cycle anomaly \( (\overline{P}_{\text{mca}}) \), and the intermittency of subdaily variation \( (\overline{P}_{\text{id}}) \):

\[ P'_{i,n} = \overline{P}_{\text{bn}} + P_{\text{mca}} + P_{\text{id}}, \]  

(3)

where \( \overline{P}_{\text{bn}}^n = (1/D)\sum_{i=1}^{D} P_{i,n}, n = 1, 2, \ldots, N \) and \( \overline{P}_{\text{mca}}^n = (1/N)\sum_{n=1}^{N} P_{i,n}, i = 1, 2, \ldots, D \). Similarly, we can calculate the daily mean \( \overline{P}_{\text{bn}} \) and mean diurnal cycle \( \overline{P}_{\text{mca}} \) of this time series:

\[ \overline{P}_{\text{bn}} = \frac{1}{D} \sum_{i=1}^{D} P_{i,n}, \quad \overline{P}_{\text{bn}}^n = \frac{1}{D} \sum_{i=1}^{D} \left( \overline{P}_{\text{all}} + P'_{i,n} \right) = \overline{P}_{\text{all}} + \overline{P}_{\text{bn}}^n, \]

\[ n = 1, 2, \ldots, N, \]  

(4)

\[ \overline{P}_{\text{mca}} = \frac{1}{N} \sum_{n=1}^{N} P_{i,n} = \frac{1}{N} \sum_{n=1}^{N} \left( \overline{P}_{\text{all}} + P'_{i,n} \right) = \overline{P}_{\text{all}} + \overline{P}_{\text{mca}}^n, \]

\[ i = 1, 2, \ldots, D. \]  

(5)

Therefore, the corresponding variances, representing the average squared deviations from the mean, can be computed as follows:
It can be observed that the terms in Eq.(3) constitute an orthogonal set as the dot product of any two terms is zero. Therefore, we have the following equation:

\[ s^2_{dm} = \frac{1}{N} \sum_{n=1}^{N} (P_{dn} - \bar{P}_{d})^2 = \frac{1}{N} \sum_{n=1}^{N} (P_{dmax}^n)^2, \]  

(6)

\[ s^2_{mdc} = \frac{1}{D} \sum_{i=1}^{D} (P_{mdc}^i - \bar{P}_{d})^2 = \frac{1}{D} \sum_{i=1}^{D} (P_{mdc}^i)^2, \]  

(7)

\[ s^2_{isd} = \frac{1}{N} \sum_{n=1}^{N} (P_{i,n}^d - \bar{P}_{d})^2, \]  

(8)

\[ s^2_{all} = \frac{1}{N} \sum_{n=1}^{N} \sum_{i=1}^{D} (P_{i,n}^d - \bar{P}_{d})^2 = \frac{1}{ND} \sum_{n=1}^{N} \sum_{i=1}^{D} (P_{i,n}^d)^2. \]  

(9)

The respective standard deviation, denoted as \( s_{dm} \), \( s_{mdc} \), \( s_{isd} \), and \( s_{all} \), is then calculated as the square root of the variance. It can be observed that the terms in Eq. (3) constitute an orthogonal set as the dot product of any two terms is zero. Therefore, we have the following equation:

\[ s^2_{all} = s^2_{mdc} + s^2_{dm} + s^2_{isd}, \]  

(10)

where \( s^2_{isd} = s^2_{all} - s^2_{mdc} - s^2_{dm} \) is defined as the variance resulting from irregular subdaily variations, which occur at periods shorter than 24 h and are not harmonics of the diurnal cycle. For further information on the derivation, the reader is referred to Taylor and Covey (2018).

3. Results

a. Mean precipitation features

Although mean precipitation is not the focus of this study, a good simulation of the mean pattern is a prerequisite basis for the subsequent analysis. We evaluate the spatial distribution of the observed and simulated precipitation of composite Julys from 1980 to 2014 (Fig. 1). Composites of the other 3 months yield qualitatively similar comparison results between observation and AM4 model simulations; we have selected July for demonstration purposes as it provides a clearer signal over the Northern Hemisphere. Compared to MSWEP, all AM4 experiments simulate the global mean value reasonably well, with the area-weighted bias (±1 standard deviation among five experiments) of 0.12 ± 0.04 mm day⁻¹ and the root-mean-square error (RMSE) of 1.40 ± 0.05 mm day⁻¹. More specifically, as shown in the portrait plot (Gleckler et al. 2008), mean precipitation is overestimated over land for all four seasons in all experiments, with underestimations seen over ocean in January and April (Fig. 2). The mean biases and RMSE are generally larger over land than over ocean. Spatially, all experiments share some common biases, similar to those of the AM4 experiment, with wet biases in the tropical Pacific and west Indian Ocean and dry biases in the east Indian Ocean. These biases were relatively smaller outside the tropical regions. The tropical biases are likely related to the convection parameterization and the interactions between convection and large-scale stratiform clouds, as described in Zhao et al. (2018a,b). Compared to AM4, CM4 exhibits reduced precipitation biases over several regions such as equatorial Africa, the Indian monsoon region, and the northwestern Pacific, as well as over the Amazon region, where the bias changes sign from positive in AM4 to negative in CM4. The dry bias in CM4 was argued to be attributed to a biased long dry season related to the SST biases in the Atlantic region in the coupled model (Held et al. 2019). More detailed performance evaluations of CM4 can be found in Held et al. (2019). AM4-MG2 produces very similar results to AM4, but with slightly smaller mean bias and RMSE. For both finer versions of AM4, the biases in mean precipitation have increased over land, particularly over monsoon regions, but decreased over ocean, primarily over the western Pacific. Over CONUS, all experiments except for CM4 exhibit a dry bias. This deficit has been identified to be associated with the widespread failure of models to capture strong nocturnal rainfall events over the central United States (Klein et al. 2006; Lin et al. 2017), which will be discussed in more detail in section 3a. Statistics (i.e., mean, bias, and RMSE) for the remaining three seasons averaged over land, ocean, and CONUS are summarized in Fig. 2.

While the MSWEP dataset has been compared with many other precipitation products, it is essential to consider the uncertainties introduced during the integration process of multiple data sources (Beck et al. 2019). To address this concern, we extended our comparison by evaluating the results against four additional precipitation products and nine CMIP6 models. In Fig. 3, the results for January and July reveal considerable uncertainties in different observational datasets, which are comparable to those in the model simulations. Notably, when comparing the series of AM4 simulations with other CMIP6 model simulations, we found that they generally fall within the range of the CMIP6 models. It is worth noting that most models tend to overestimate January precipitation over CONUS, while approximately half of them underestimate it during July. This pattern is also evident in April and October (Fig. S1), despite that the biases between model simulations and observations become less pronounced.

b. Diurnal cycle of precipitation

We then start with analysis of the diurnal cycle of precipitation. Figure 4 shows the diurnal harmonic amplitude and phase of precipitation based on MSWEP and AM4 model experiments for composite Julys during 1980–2014. The intertropical convergence zone (ITCZ) and monsoon regions exhibit larger diurnal amplitudes, which generally align with mean precipitation patterns. The ratio between diurnal amplitude and mean precipitation ranges from 30% to 100% over most land areas and from 10% to 30% over most ocean areas. Exceptions occur in extremely dry regions like northern/southern Africa and central Asia (Fig. S2), where values larger than 100% reflect occasional large precipitation events. In terms of diurnal phase, generally, it peaks in the afternoon to evening hours over land and in the midnight to early morning hours over ocean, indicating phase discontinuities along coastal regions that may be linked to the sea breeze effects (Dai 2001; Pritchard and Somerville 2009). Other distinct features are observed over both land and ocean regions. For instance, over the CONUS (Fig. S3), the most notable feature is...
the nocturnal peak of rainfall over the Great Plains, which is accompanied by an eastward propagation signal dominated by mesoscale convective systems formed to the east of the Rocky Mountains (Dai et al. 1999; Jiang et al. 2006). These findings also emerge from inspection of corresponding maps for the semidiurnal harmonic, but the amplitudes are smaller than that of the diurnal component (Figs. S4–S6).

When comparing the MSWEP dataset with the other observational datasets, the overall patterns, including land–sea contrasts (Fig. S7) and nocturnal peaks over the Great Plains (Fig. S8), remain largely consistent. However, significant differences are observed in both the diurnal amplitude and phase among the observational datasets. The diurnal amplitude in the MSWEP dataset, similar to the CMORPH dataset, is generally smaller compared to the TRMM and GPM/IMERG datasets. Additionally, the diurnal phase in the MSWEP dataset is slightly earlier when compared to the other three datasets (Fig. S7). These differences are evident when zooming in over CONUS (Fig. S8), where the TRMM and GPM/IMERG datasets exhibit much larger amplitudes over the central United States compared to the other three datasets. Furthermore, the diurnal phase based on the MSWEP over the central United States generally precedes the other datasets by 1–2 h. The respective semidiurnal results are shown in Figs. S9 and S10, where substantial differences are evident among the datasets.

Figures 4b–f demonstrate the results of the five AM4 experiments, which shows that diurnal amplitudes are similar in magnitude to observation. However, the corresponding diurnal phases among models differ, particularly in simulations...
with varying model resolution. Over land, all experiments analyzed here show a bias where the diurnal rainfall peaks too early in the morning to noon hours. This issue has been noted in various models for decades (Sato et al. 2009; Dirmeyer et al. 2012). While this bias has been reduced to a large extent over the ocean, some differences remain over the western Pacific and the Arabian Sea. The AM4 and CM4 experiments show a close resemblance, suggesting that the diurnal phase problem is not alleviated when the model is fully coupled to an ocean model. This result raises the possibility of local recycling and land coupling as potential factors contributing to the issue. This finding is consistent with a recent study that utilized reanalysis datasets, demonstrating a robust diurnal cycle in precipitation over the ocean, even in the presence of a weak diurnal cycle in SST (Dai 2023). The same resemblance is observed between AM4 and AM4-MG2 experiments, indicating that the new two-moment bulk cloud microphysics with prognostic precipitation does not significantly improve this deficiency. However, we notice that increasing the model horizontal resolution from 100 to 50 and 25 km (Figs. 4d,e) shows changes in the diurnal phase, particularly over tropical rainbands, monsoon regions, Tibetan Plateau, North America, etc. Taking CONUS as an example (Fig. S3), as the resolution refines, more signals emerge over the Rocky Mountains and the northeastern United States when the resolution refines, the disparities become even much more pronounced in the convective component. Conversely, concerning the diurnal phase, larger differences are observed in the large-scale component compared to the convective component. These findings suggest that the explicitly resolved dynamics may contribute to alleviating simulated errors in the diurnal cycle, but subgrid-scale convective parameterization might play a more substantial role in influencing the results. Similar errors are observed in the simulated semidiurnal harmonic. We further extend our analysis to include the CMIP6 models (Fig. S12). In general, the spatial distribution of diurnal aptitudes aligns with the AM4 experiment, albeit with smaller magnitudes. However, the diurnal phases exhibit wide ranges among the models. Over land, some models show precipitation peaks during the morning to noon hours, while others indicate afternoon to evening peaks. Meanwhile, the phases are more concentrated in the morning hours over ocean regions. Focusing on the CONUS, both the simulated diurnal amplitude and phase diverge largely among the models (Fig. S13). These discrepancies are also evident in the semidiurnal harmonics (Figs. S14 and S15).

While maps provide useful information regarding the spatial distribution of precipitation diurnal cycle, they are limited in their ability to provide quantitative assessments, especially when comparing multiple experiments or models. We therefore use the harmonic dial diagram proposed by Covey et al. (2016) to summarize the main results. As depicted in Fig. 5, each point represents either an observation or a model experiment,
with the distance from the center indicating the amplitude and the angle from due north indicating the phase. The observational datasets generally exhibit close agreement with each other on the dial diagram, with the only noticeable difference being the diurnal phase of the MSWEP dataset precedes the other dataset by 1–3 h. This difference is more pronounced when averaging over land compared to over ocean regions. The simulated diurnal and semidiurnal amplitudes are comparable between observations and model simulations over both land and ocean areas. However, the simulated diurnal phases are found to be about 9 h ahead of the observations over land, while being close to observations over ocean. Similar features are observed for the semidiurnal component, except that the simulations lag behind the observations over ocean. Similar features are observed for the semidiurnal component, except that the simulations lag behind the observations. Besides, land areas exhibit a larger scatter among the five experiments than ocean areas for both diurnal and semidiurnal components. There are several factors that may contribute to the discrepancies between land and ocean, including the influence of complex topography effects, evaporation sources, boundary layer properties, and other factors that are not fully represented or accurately simulated in the models (Rio et al. 2009; Wang and Sobel 2017). Averaging over CONUS yields similar results to those of land areas, although the diurnal amplitude is much larger, and the diurnal phase of the observational dataset is slightly advanced. Our quantitative results differ from those shown in Fig. 5 of Covey et al. (2016) and Fig. 14 of Tang et al. (2021), likely due to variations in the analysis, such as different time bounds, latitude ranges, and seasons analyzed. In contrast, both the diurnal and semidiurnal amplitudes and phases demonstrate considerable variability among the CMIP6 models (Fig. 6). Compared to AM4 experiments, the diurnal amplitudes of these CMIP6 models are generally smaller, while the phases are delayed. This disparity is more evident in land and CONUS regions.

c. Precipitation variance

In this section, we analyze the precipitation variances on different time scales. Figure 7 displays the standard deviations of the mean diurnal cycle ($\sigma_{\text{mdc}}$), daily mean ($\sigma_{\text{dm}}$), and irregular subdaily ($\sigma_{\text{isd}}$) precipitation variance based on both the MSWEP and AM4 experiments for composite Julys from 1980 to 2014. The observed spatial distribution of all three components resembles the pattern of mean distribution, characterized by larger values over the ITCZ and monsoon regions (first row of Figs. 7 and 1a). The spatial distribution

![Figure 3: Distribution of the mean precipitation (mm day$^{-1}$) from multiple observational datasets (denoted by green numbers) and model simulations (denoted by black numbers), including the series of AM4 experiments and various CMIP6 models, during (top) January and (bottom) July averaged over global, global land areas, global ocean areas, and CONUS during the period of 1980–2014.](image-url)
of $\sigma_{\text{dav}}$ and $\sigma_{\text{rad}}$ is highly similar, with a centered pattern correlation higher than 0.90 ($p < 0.001$), and only slight variations are seen over the warm pool region, Southern Ocean, and a few landmasses. Their magnitudes are also similar (global means of 3.8 and 4.0, respectively), but both are much larger than $\sigma_{\text{meuc}}$ (global mean of 0.4). To explore the sensitivity of precipitation variances to the spatial resolution of the data, zonal mean panels in Fig. 5 also include MSWEP data at resolutions of 0.25° and 0.5°. In agreement with Trenberth et al. (2017), the observed variances typically increase with higher resolutions, with a mean global rate of less than 10% when the resolution is doubled from 1° to 0.5° and less than 5% when doubled from 0.5° to 0.25°. These increases are especially pronounced over the deep tropics. Compared to other precipitation datasets such as CMORPH, TRMM, and GPM/IMERG, the absolute values of the three precipitation variance components based on the MSWEP dataset are smaller, especially for $\sigma_{\text{rad}}$ over the tropical ocean (Fig. S16). In addition to the aforementioned data sampling issue, this difference can also be attributed to the diverse data source used in constructing the MSWEP dataset. CMORPH, TRMM, and GPM/IMERG mainly rely on satellite-based instantaneous precipitation estimates. MSWEP, although it incorporates them, also makes use of reanalysis and gauge-based cumulative precipitation estimates.
estimates, particularly over the presatellite era (Beck et al. 2019). This merging process may have the effect of smoothing out short-lived and intense precipitation events compared to instantaneous satellite observations, leading to a smaller precipitation variance at the subdaily time scale.

Similar patterns to those in the MSWEP dataset are evident in the AM4 experiment (second row in Fig. 7), and the model reasonably captures the observed distribution of all three components, with the centered pattern correlations being 0.53, 0.79, and 0.81, respectively. While the global mean values are close to the observations, noticeable differences in the zonal distributions are observed in tropical latitudes. The corresponding differences in spatial distribution between AM4 and MSWEP (third row of Fig. 7) are similar to the mean precipitation biases (Fig. 1b). Specifically, the simulated error in $\sigma_{smd}$ is very small, but for $\sigma_{sdm}$ and $\sigma_{sld}$, large positive biases are seen over tropical Africa, South America, and the warm pool region, while large negative biases are observed over tropical central and eastern Pacific, tropical Atlantic, and large parts of North America. This suggests that significant biases still exist in regions with large mean precipitation biases, despite global mean or zonal mean values being comparable to the observations. The overall underestimation of $\sigma_{sld}$ in the tropics can be attributed to the inadequacy of the model to accurately represent many organized transient disturbances at a resolution of 100 km. The relatively smaller difference between MSWEP and AM4 is different from Covey et al. (2018), where they found that the CESM1 model largely underestimated $\sigma_{sld}$ by a factor of 2–3 and $\sigma_{sdm}$ by a factor of 2 at most latitudes, and $\sigma_{smdc}$ by a factor of 2 in the tropics. They further found that the CESM1’s underestimation of $\sigma_{sdm}$ and $\sigma_{sld}$ was common among most CMIP5 models examined in their study. The overall better agreement between AM4 and MSWEP indicates that the AM4 model generally offers a more accurate simulation of precipitation variances. However, it should be noted that the reduced $\sigma_{sld}$ bias may be partially attributed to the use of distinct observational datasets, as illustrated in Fig. S16.

We then compared the results from AM4 and CM4 experiments to investigate the impact of SST diurnal cycle on the simulated precipitation variances. As shown in Fig. 8, these two simulations yielded very similar global mean and zonal

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**Fig. 5.** Harmonic dial plots of the amplitude and phase of Fourier components, after vector averaging over land, ocean, and CONUS, based on observational datasets (black dots) and the model experiments (green dots). Note the different radial scales for each panel.
mean distributions for all three components, but with larger $\sigma_{dm}$ and $\sigma_{isd}$ values in tropical latitudes in CM4 compared to AM4. The differences in the spatial pattern are not uniformly distributed, with positive values mainly distributed over tropical rainbands and North America, while negative values were found over the northwestern Pacific, tropical Indian Ocean, and Amazon regions. These patterns basically follow their differences in the mean precipitation (Fig. 1c), indicating more variance of precipitation with higher average precipitation, and vice versa. The comparison of mean precipitation simulated by CM4 and AM4 has been discussed in Held et al. (2019), where it was found that differences could be traced back to the different SST patterns developed and the effects of coupling on convection and transient disturbances. For example, SST biases in CM4 over the Atlantic are one possible cause of the dry bias seen over the Amazon region. Overall, the diurnal cycle of SST has little impact on the global and zonal mean values of simulated precipitation variances, but regional differences were identified, which presents a challenge for improving the simulated precipitation variance. Future research could explore the impact of different SST patterns to further understand the underlying mechanisms contributing to these differences.

To investigate the impact of horizontal resolution, we compared simulations based on AM4 at three resolutions (100, 50, and 25 km). Although their spatial patterns look similar, simulations with higher resolution generally exhibit larger precipitation variances nearly globally, with larger values over the ITCZ and warm pool region (Fig. 9). Consistent with observations, the precipitation variances are moderately sensitive to the horizontal resolutions, with a global mean increase of 10%–20% between AM4 (50 km) and AM4, and of 5%–10% between AM4 (25 km) and AM4 (50 km). The increasing rates are larger for $\sigma_{isd}$, followed by $\sigma_{dm}$ and $\sigma_{mdc}$. Unlike the CM4 experiment, although global mean precipitation slightly increased by 0.04 and 0.06 mm day$^{-1}$ (Figs. 1d,e and 2), respectively, in these finer-resolution simulations compared to the AM4 experiment, the spatial distribution of their differences in precipitation variances is not consistent with their mean patterns (Figs. 1d,e), which suggests the increased variances in these finer resolution simulations may be associated with a larger fraction of resolved precipitation. This is supported by

Fig. 6. Harmonic dial plots of the amplitude and phase of Fourier components, after vector averaging over land, ocean, and CONUS, based on the CMIP6 model simulations. Note the different radial scales for each panel.
our separate examination of simulated convective and large-scale precipitation (Figs. S17 and 18).

Finally, we analyzed the simulation based on the AM4-MG2 experiment (Fig. 10). The MG2 microphysics scheme can impact the timing, intensity, and spatial distribution of precipitation through various mechanisms, including, but not limited to, alterations in the number and size distribution of cloud and precipitation particles, the rate of conversion of cloud droplets into rain droplets, and the speed of precipitation particle evaporation during their descent through the atmosphere (Gettelman and Morrison 2015). In comparison to the AM4 experiment, the AM4-MG2 simulation produces nearly identical global and zonal precipitation variance patterns for $\sigma_{\text{mdc}}$. However, there are some noteworthy negative differences in $\sigma_{\text{dm}}$ and $\sigma_{\text{isd}}$, the pattern of which generally follows the mean precipitation difference pattern (Fig. 11). This comparison suggests that the adoption of the MG2 microphysics scheme could lead to a reduction in precipitation variance.

All the above analyses are based on composite Julys averaged globally. Figure 11 summarizes spatial averages of all three components, separately taken over all land areas, all ocean areas, and CONUS, for four seasons. The conclusions drawn from July can be extrapolated to the remaining three seasons. Moreover, we find that, for all three components, the averages for land areas are smaller than those for ocean areas. And the differences are notably more significant for $\sigma_{\text{mdc}}$, as it is twice as large over land than over ocean. This finding is consistent with the spatially averaged Fourier amplitudes shown in Fig. 5. Similar features are found over CONUS as over land, albeit with larger values for all three components.

Additionally, it is important to acknowledge the significant discrepancies among different precipitation products. Particularly, the precipitation variances calculated from TRMM and GPM/IMERG datasets appear to be much larger compared to the other three precipitation products. This notable disparity might partially account for the differences observed between our findings and those reported in Covey et al. (2018).

When averaged over the contiguous United States (CONUS), the results from the Stage IV dataset align more closely with the MSWEP and CMORPH datasets than with TRMM and GPM/IMERG. The Stage IV precipitation dataset has long
been regarded as one of the most reliable and widely used datasets for precipitation estimation over CONUS. Consequently, the outcomes from TRMM and GPM/IMERG raise questions regarding their accuracy. It is worth emphasizing that while the similarity between MSWEP and Stage IV over CONUS may not directly apply to the global scale, it remains essential to consider the estimation uncertainties in observational data. These uncertainties can significantly impact research findings and should be carefully evaluated when interpreting and comparing results obtained from different datasets.

Furthermore, we conducted the same analysis in the CMIP6 models. As depicted in Figs. S19 and 20, these models generally show reasonably simulated spatial and zonal distributions of precipitation variances. However, large spreads are observed among the different models. The CM4 experiment stands out as one of the top-performing models in terms of simulating precipitation variances. This finding highlights the relative accuracy and reliability of the AM4 model in capturing precipitation variance patterns compared to other models in the CMIP6 ensemble.

4. Discussion and conclusions

In this study, we investigate the global diurnal cycle of precipitation and precipitation variances at different time scales using multiple 3-hourly precipitation datasets, a series of GFDL-AM4 model experiments, and multiple CMIP6 models. In contrast to CMIP6 models, the AM4 experiments, based on the same GFDL-AM4.0 model, encompass simulations with prescribed SST, fully coupled ocean, varying horizontal resolutions, and different microphysics schemes. This diversity of simulations enables us to assess the impact of diurnal cycle of SST, horizontal resolutions, and novel microphysics scheme on precipitation diurnal cycle and high-frequency variances. We acknowledge that our current analysis may not provide in-depth process-level insights into different atmospheric phenomena, primarily due to the absence of high-frequency related variables. However, this analysis represents a significant initial step toward understanding high-frequency precipitation variability. Despite its limitations, our research sheds valuable light on the challenges faced by the model simulations, laying the foundation for future investigations into high-frequency precipitation variability.

The results demonstrate that, while all AM4 model experiments simulate similar amplitudes, they exhibit systematic phase errors when compared to observations, particularly over land areas. As has been consistently reported in previous studies (e.g., Dai 2006; Tang et al. 2021), model simulations show diurnal phases peaking around noon or morning hours instead of in the late afternoon (or nocturnal peak over CONUS) as observed. This deficiency is more pronounced over land than over ocean, and it is rooted in the misrepresented complex topography effects and land–atmosphere
interactions in the models. The simulated precipitation, especially the convective precipitation, is found to respond too strongly to solar insolation. Consequently, convection in the model is triggered too often and too early over land (Lee et al. 2007; Xie et al. 2002; Xie and Zhang 2000; Xie et al. 2019). More specifically, the diurnal component reveals a 6–12-h difference between MSWEP and AM4 model simulations over land, with the model proceeding observations. In contrast, the simulated phases for the weaker semidiurnal component indicate the model lags MSWEP by 6 h. Over the ocean, simulated phase errors are smaller for both diurnal and semidiurnal components and, compared to land averages, the simulated diurnal phase over the ocean shows a much smaller model spread. These simulated biases are consistently observed in CMIP6 models as well, even though the mean diurnal amplitudes in the CMIP6 models are generally smaller when compared to AM4 experiments (Fig. 6). This indicates that the diurnal and semidiurnal phase errors are a common feature among both AM4 experiments and CMIP6 models, particularly over land areas, and the ocean region tends to exhibit more accurate simulations in terms of phase errors with reduced model spread.

Moreover, the similarity among the five AM4 experiments suggests that neither the inclusion of SST diurnal cycle nor

![Spatial distribution of standard deviation of the mean diurnal cycle](image_url)
the newly introduced microphysics scheme improves the simulation of precipitation diurnal cycle. The former is consistent with Tao et al. (2022), who found that the impact of interactive ocean on the simulation of diurnal cycle of precipitation over a wide area is generally insignificant, as indicated by the comparison between CMIP6 AMIP and CMIP6 historical simulations. It is important to note that most CMIP6 models employ daily atmosphere–ocean coupling intervals, but CM4 uses a much higher frequency of 30 min. Therefore, the expectation that incorporating higher frequencies of coupling intervals between the atmosphere and ocean will lead to significant improvements in the diurnal cycle of precipitation may be unrealistic. While AM4 experiments with increasing horizontal resolution demonstrate variations over mountainous and coastal regions, these changes are not consistently aligned with observations. Specifically, variations in the diurnal phase are mainly from the resolved precipitation processes (Fig. S11). This suggests that these differences may mainly be due to better representation of the topography and coastlines. Hence, for future model development, increasing model resolution alone may not be sufficient. More emphasis should be placed on improving the convective parameterization, enhancing the interactions between convection and boundary layer processes [as discussed in Hourdin et al. (2020) and Park (2014a,b)], and utilizing more sophisticated convective triggering and closure functions (as suggested by Bechtold et al. 2014). A valuable reference for gaining insight into the impact of various processes on the simulated diurnal cycle of precipitation can be found in recent studies (Xie et al. 2019; Tang et al. 2022). These investigations have unveiled the existence of distinct regimes that contribute to biases in GCMs, specifically, the afternoon convective precipitation and nocturnal precipitation regimes. The former has been attributed to the absence of a transition from shallow to deep convection, while the latter is associated with constraints limiting convection within the boundary layer at night. Implementing a unified treatment of shallow and deep convection and enhancing the capacity to represent midlevel convection at night could enhance a model’s ability to simulate the precipitation diurnal cycle.

In terms of standard deviation of precipitation variances, we compare three different components [i.e., the mean diurnal cycle ($\sigma_{mdc}$), daily mean ($\sigma_{dm}$), and irregular subdaily ($\sigma_{isd}$) precipitation variance (mm day$^{-1}$)] for composite Julys of the year 1980–2014 based on (top) the AM4-MG2 experiment and (middle) its difference from AM4 experiment, as well as (bottom) the corresponding zonal mean distributions.
mainly spread over tropical latitudes. Specifically, the comparison between the MSWEP and AM4 experiments reveals negligible bias in $\sigma_{mdc}$, but large biases in $\sigma_{dm}$ and $\sigma_{isd}$. The spatial pattern of the latter two (third row of Fig. 7) shares large similarities with the mean precipitation biases (Fig. 1b), consistent with the findings in Covey et al. (2018) that traditional diagnostic at daily time scales or longer could overlook significant model–observation discrepancies at subdaily time scales. Additionally, when comparing the four remaining experiments with AM4, it is found that the impact of ocean coupling (Fig. 8) and the new microphysics scheme (Fig. 10) on simulated precipitation variances is negligible, with slight variations observed in the tropics. Despite the small effect of simulated SSTs on precipitation variances at most locations, biases in the diurnal cycle of SSTs remain important for some regions, such as the tropical Atlantic, with implications for the Amazon region. In contrast, the precipitation variances in the two finer-resolution simulations increase with resolution (Fig. 9). But the spatial distributions of the differences observed in these simulations are not consistent with their mean patterns (Figs. 1d,e), indicating that the increased variances may be due to a higher fraction of resolved precipitation.

Upon analyzing the CMIP6 models, it is evident that the spatial and zonal distributions of precipitation variances are generally reasonably well simulated, but significant spreads are observed among different models (Figs. S19 and 20), and as a whole, the models tend to underestimate the observed precipitation variances. In this context, the CM4 experiment emerges as one of the top models in simulating precipitation variances. This finding emphasizes the relative accuracy and

FIG. 11. Portrait plot of the observed and simulated standard deviations of the mean diurnal cycle $\sigma_{mdc}$, daily mean $\sigma_{dm}$, and irregular subdaily $\sigma_{isd}$ precipitation variance (mm day$^{-1}$) in four seasons averaged over global, global land areas, global ocean areas, and CONUS during the period of 1980–2014. MSWEPV2 (25 km) and MSWEPV2 (50 km) are results from interpolating the original MSWEPV2 dataset onto grids with 25- and 50-km resolutions, respectively. All other datasets are interpolated onto the same AM4 grids.
reliability of the AM4 model compared to other models within the CMIP6 ensemble in capturing precipitation variance patterns. Routinely evaluating high-frequency precipitation metrics, such as those examined in this study, could benefit model development and provide vital information to better understand long-range prediction and projection, with the potential to have profound effects on a wide range of hydrological systems.

At last, as shown in both diurnal cycle and precipitation variance analyses, it is evident that significant differences exist among different observational precipitation datasets (Figs. S6 and S8). For instance, MSWEP shows a mean diurnal phase over land that is approximately 3 h ahead of the other datasets (Fig. 5). Moreover, the zonal mean of $\sigma_{\text{rad}}$ values from TRMM and GPM/IMERG is nearly twice that of MSWEP over tropical latitudes (Fig. S16). Similar disparities are also found in previous studies (Covey et al. 2018; Tang et al. 2021; Ahn et al. 2022; Tao et al. 2022). These discrepancies may arise due to differences in temporal resolution, as the intermittency of precipitation depends on the sampling intervals. While IMERG and CMORPH have a temporal frequency of 30 min, TRMM and MSWEP are on 3-h temporal frequency. When compared on a 3-h interval, the time bounds could contribute to the disparities. For example, the 3-h MSWEP dataset represents precipitation averages over the past 3 h, whereas the 3-h TRMM dataset provides estimations for the 1.5 h before and after. In the case of a precipitation event within the 3-h window of the MSWEP dataset, it may span two 3-h intervals in the TRMM dataset but with lower intensity. Similar problems could happen when integrating 30-min datasets into 3-h intervals. These disparities may also stem from the calibration processes with ground observation, where the spatial resolution becomes important. CMORPH, GPM/IMERG, and MSWEP have a spatial resolution of 0.1°, while TRMM has a coarser resolution of 0.25°. Comparing individual site measurements with gridded areas poses significant challenges related to averaging and grid size as well as observational density (Herold et al. 2016; Trenberth et al. 2017). Although determining which dataset is more suitable for the precipitation diurnal cycle and variability analysis is a complex task that falls beyond the scope of this study, we must underscore the importance of conducting a thorough evaluation of precipitation observation datasets to establish their appropriateness for such analyses. This evaluation is crucial and urgent as model evaluation and development rely heavily on high-quality observations. Accurately quantifying the uncertainties in observations, especially at subdaily time scales, becomes essential for enhancing the reliability and robustness of model simulations and predictions.

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Data availability statement. The Multi-Source Weighted-Ensemble Precipitation, version 2 (MSWEP V2), precipitation data can be found at https://gloh2o.org/mswep/. The Tropical Rainfall Measuring Mission (TRMM) dataset version 3B42 can be accessed at https://disc.gsfc.nasa.gov/datasets/TRMM_3B42.7/summary. The Integrated Multi-satellite Retrievals for GPM (IMERG) from NASA Global Precipitation Measurement Measurement dataset (GPM/IMERG) can be found at https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGHH_06/summary. The bias-corrected Climate Prediction Center (CPC) morphing technique (CMORPH) can be acquired from https://www.ncei.noaa.gov/data/cmorhigh-resolution-global-precipitation-estimates/access/. The NCEP radar-based, gauge-adjusted Stage IV precipitation data are available at https://data.eol.ucar.edu/cgi-bin/codiac/fgr_form/id=21.093. CMIP6 model outputs are downloaded from https://esgf-node.llnl.gov/projects/cmip6/. The GFDD-AM4.0 model source code can be obtained from https://data1.gfdl.noaa.gov/nomads/forms/am4.0/. The CM4.0 model source code is available online at https://doi.org/10.5281/zenodo.3339397. The original MG2 source code was developed based on the CESM1.3 release, which can be accessed at http://www.cesm.ucar.edu/models/esm21/release_download.html. The AM4.0-MG2 model source codes are available at https://doi.org/10.5281/zenodo.4313356.

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