Characteristics of Precipitation and Mesoscale Convective Systems over the Peruvian Central Andes in Multi 5-Year Convection-Permitting Simulations

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Abstract

Using the Weather Research and Forecasting (WRF) model with two planetary boundary layer schemes, ACM2 and MYNN, convection-permitting model (CPM) regional climate simulations were conducted for a 6-year period at a 15-km grid spacing covering entire South America and a nested convection-permitting 3-km grid spacing covering the Peruvian central Andes region. These two CPM simulations along with a 4-km simulation covering South America produced by National Center for Atmospheric Research, three gridded global precipitation datasets, and rain gauge data in Peru and Brazil, are used to document the characteristics of precipitation and MCSs in the Peruvian central Andes region. Results show that all km-scale simulations generally capture the spatiotemporal patterns of precipitation and MCSs at both seasonal and diurnal scales, although biases exist in aspects such as precipitation intensity and MCS frequency, size, propagation speed, and associated precipitation intensity. The 3-km simulation using MYNN scheme generally outperforms the other simulations in capturing seasonal and diurnal precipitation over the mountain, while both it and the 4-km simulation demonstrate superior performance in the western Amazon Basin, based on the comparison to the gridded precipitation and MCS genesis along the east slope of the Andes, while thermodynamic factors control the precipitation and MCS activity in the western Amazon Basin and over elevated mountainous regions. The study suggests aspects of the model needing improvement and the choice of better model configurations for future regional climate projections.

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15 Key Points:

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16	•	Characteristics of precipitation and MCSs in the Peruvian Central Andes are inves-
17		tigated based on convection-permitting simulations.
18	•	WRF3km_MYNN outperforms in simulating mountain precipitation; both it and
19		WRF4km_SAAG show superior performance in western Amazon.
20	•	Dynamic factors dominate precipitation and MCSs on the Andean east slope, while

Dynamic factors dominate precipitation and MCSs on the Andean east slope, while
 thermodynamic factors are dominant in western Amazon Basin.

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22 Abstract

Using the Weather Research and Forecasting (WRF) model with two planetary boundary 23 layer schemes, ACM2 and MYNN, convection-permitting model (CPM) regional climate 24 simulations were conducted for a 6-year period at a 15-km grid spacing covering entire 25 South America and a nested convection-permitting 3-km grid spacing covering the Peruvian 26 central Andes region. These two CPM simulations along with a 4-km simulation covering 27 South America produced by National Center for Atmospheric Research, three gridded global 28 precipitation datasets, and rain gauge data in Peru and Brazil, are used to document the 29 characteristics of precipitation and MCSs in the Peruvian central Andes region. Results 30 show that all km-scale simulations generally capture the spatiotemporal patterns of pre-31 cipitation and MCSs at both seasonal and diurnal scales, although biases exist in aspects 32 such as precipitation intensity and MCS frequency, size, propagation speed, and associated 33 precipitation intensity. The 3-km simulation using MYNN scheme generally outperforms 34 the other simulations in capturing seasonal and diurnal precipitation over the mountain, 35 while both it and the 4-km simulation demonstrate superior performance in the western 36 Amazon Basin, based on the comparison to the gridded precipitation products and gauge 37 data. Dynamic factors, primarily low-level jet and terrain-induced uplift, are the key drivers 38 for precipitation and MCS genesis along the east slope of the Andes, while thermodynamic 39 factors control the precipitation and MCS activity in the western Amazon Basin and over el-40 evated mountainous regions. The study suggests aspects of the model needing improvement 41 and the choice of better model configurations for future regional climate projections. 42

⁴³ Plain Language Summary

We ran high-resolution model simulations at a 3-km grid spacing with two planetary 44 boundary layer schemes (ACM2 and MYNN) for a 6-year period to investigate precipitation 45 and storm patterns in the Peruvian central Andes region. Other datasets including a 4-km 46 simulation produced by National Center for Atmospheric Research, three gridded precipi-47 tation products, and rain gauge data in Peru and Brazil were collected for comparison and 48 evaluation. We found that all km-scale simulations capture the overall patterns of precipi-49 tation and storms at both seasonal and sub-daily time scales, although some discrepancies 50 exist in precipitation intensity and storm details. Compared to the gridded precipitation 51 products and gauge data, the 3-km simulation using MYNN scheme generally outperforms 52 the other simulations in capturing seasonal and diurnal precipitation over the mountain, 53 while both it and the 4-km simulation demonstrate superior performance in the western 54 Amazon Basin. Low-level wind and terrain-induced uplift is the key driver for precipitation 55 and storm genesis along the Andes' eastern slopes, while factors associated with vertical 56 structures of temperature and humidity control the precipitation and storm activity in the 57 western Amazon Basin and mountain regions. The study suggests aspects of model im-58 provement and better model configurations for future regional climate projections. 59

60 1 Introduction

The Peruvian Central Andes, characterized by complex topography and unique clima-61 tological conditions such as the South American low-level jet (SALLJ), plays a vital role 62 in influencing local and regional weather patterns and hydrological cycles (Marengo et al., 63 2002; Vernekar et al., 2003; Vera et al., 2006; Romatschke & Houze Jr, 2010; Drenkhan 64 et al., 2015; Espinoza et al., 2015; Jones, 2019; Poveda et al., 2020; Arias et al., 2021). 65 The precipitation in the Peruvian Central Andes exhibits substantial spatial and temporal 66 variability, driven by multi-scale atmospheric circulations and localized forcing such as to-67 pography (Mohr et al., 2014; Junquas et al., 2018; Chavez et al., 2020; Anselmo et al., 2021). 68 Mesoscale convective systems (MCSs), which are organized clusters of thunderstorms, often 69 accompany heavy precipitation, hail, and strong winds (Houze Jr, 2004, 2018; R. S. Schu-70 macher & Rasmussen, 2020). As a major source of precipitation in numerous regions (Salio 71

et al., 2007; Li et al., 2020; Roca & Fiolleau, 2020; R. S. Schumacher & Rasmussen, 2020; 72 Anselmo et al., 2021; H. Hu et al., 2021; Kukulies et al., 2021; M. Zhao, 2022; Paccini 73 & Stevens, 2023), MCSs can cause severe flooding, landslides, and other natural disasters, 74 thereby posing significant threats to human safety and infrastructure. As shown in Figure 75 10 of the study by Feng et al. (2021), MCSs can contribute to over 60% of the annual 76 precipitation in the Peruvian Central Andes. Understanding and predicting the behaviors 77 of precipitation and MCSs in the Peruvian Central Andes region are therefore crucial, and 78 understanding the potential impacts of climate change on MCSs is equally important. Re-79 search findings in this area can significantly shape water management practices, disaster 80 preparedness, climate change adaptation strategies, and enhance the resilience of local com-81 munities and economies to weather-related hazards in a changing climate (Martínez et al., 82 2008; Vergara et al., 2011; Drenkhan et al., 2015; Gonzalez et al., 2019). 83

The current understanding of precipitation and MCSs in the Andes and its surrounding 84 regions, however, is limited by the scarcity of public observational databases, especially the 85 scarcity of upper-air radiosonde observations in the region (Condom et al., 2020). State-of-86 the-art global climate models, such as those participating in the Coupled Model Intercompar-87 ison Project Phase 6 (CMIP6) program (Juckes et al., 2020), provide invaluable information 88 on large-scale climate changes over South America. However, limited by available comput-89 ing resources, the resolutions of these global climate models are too coarse (mostly at grid 90 spacings of ~ 100 km) to resolve local orography and weather phenomena that are important 91 for precipitation production (e.g., MCSs) (Giorgi, 2019; Juckes et al., 2020; Kendon et al., 92 2021). Numerous studies have highlighted the added value of convection-permitting models 93 (CPMs, typically at a grid spacing of less than 4 km) for simulating precipitation and MCSs 94 in different regions worldwide (A. Prein et al., 2013; Fosser et al., 2015; Sun et al., 2016; 95 Gao et al., 2017; Karki et al., 2017; Liu et al., 2017; Stratton et al., 2018; Zhu et al., 2018; 96 Berthou et al., 2020; Fumière et al., 2020; Guo et al., 2020; Kouadio et al., 2020; Lind et 97 al., 2020; A. F. Prein et al., 2020; Li et al., 2021; Halladay et al., 2023; Paccini & Stevens, 98 2023). CPMs can significantly improve the representation of land surface conditions includ-99 ing complex topography as well as mesoscale and convective-scale dynamics. Most notably, 100 deep convection can be represented explicitly in CPMs, rather than being parameterized 101 using cumulus schemes which is a major source of uncertainty in quantitative precipitation 102 forecasting. 103

For example, Sun et al. (2016) found that a 4-km regional climate simulation for the 104 U.S. Great Plains more successfully reproduced the magnitude of extreme precipitation and 105 the diurnal cycle of precipitation than a corresponding 25-km simulation. The 4-km grid also 106 more realistically simulated the low-level jet and related atmospheric circulations important 107 for low-level moisture transport. A. F. Prein et al. (2020) presented a CPM climate simula-108 tion over North America at a 4-km grid spacing that was able to capture key characteristics 109 of observed MCSs such as size, precipitation rate, propagation speed, and lifetime, though an 110 underestimate of MCS frequency in the central US during late summer was noted. Paccini 111 and Stevens (2023) demonstrated that simulations at convection-permitting grid spacings 112 (2.5-5.0 km) improved the distribution of precipitation intensity as well as the represen-113 tation of rainfall diurnal cycle over the Amazon Basin. Better representation of organized 114 convective systems played a key role in improving the precipitation simulations. Halladay et 115 al. (2023) presented a CPM regional climate simulation using the Met Office Unified Model 116 at a 4.5-km resolution for South America covering the period of 1998–2007. They found 117 significant improvements in the representation of precipitation in terms of its diurnal cycle, 118 frequency, and sub-daily intensity distribution. To date, CPM regional climate simulations 119 targeting South America remain limited in number (e.g., V. Schumacher et al., 2020; Bet-120 tolli et al., 2021; Lavin-Gullon et al., 2021; Junquas et al., 2022; Dominguez et al., 2023; 121 Halladay et al., 2023; Paccini & Stevens, 2023). Among these, Halladay et al. (2023) and 122 Paccini and Stevens (2023) are the two recent studies over South America covering part of 123 the Peruvian Central Andes region, however, their research is primarily focused on weather 124

phenomena specific to the Amazonia region. Hence, CPM regional climate simulations and
 associated research for the Peruvian Central Andes region are still needed.

In light of the lack of long-term reliable observations and insufficient understanding of the role of climate change in precipitation and MCSs in the Peruvian Central Andes region, the present study employs convection-permitting simulations and available precipitation products to probe into the characteristics and mechanisms of precipitation and MCSs in this region. This study will also provide information on the feasibility of using CPM simulations for climate change assessments, particularly in terms of precipitation and MCSs in the Peruvian Central Andes region.

The remainder of this paper is organized as follows: Section 2 describes the datasets employed in this study, along with the model configuration of CPM simulations. In Section 3, the characteristics of precipitation and MCSs are presented and discussed. A summary is offered in Section 4.

¹³⁸ 2 Data and Method

2.1 Observational data

For the evaluation of simulated precipitation, three global gridded precipitation datasets 140 are utilized: the half-hourly Integrated Multi-satellitE Retrievals for GPM (IMERG) at 0.1° 141 $\times 0.1^{\circ}$ resolution (Huffman et al., 2019), the half-hourly NOAA Climate Prediction Center 142 (CPC) MORPHing Technique (CMORPH) with a grid spacing of approximately 8 km (Joyce 143 et al., 2004), and the 3-hourly Multi-Source Weighted-Ensemble Precipitation (MSWEP) 144 version 2, also at $0.1^{\circ} \times 0.1^{\circ}$ resolution (Beck et al., 2019). Gauge stations incorporated by 145 IMERG and MSWEP are very sparse in our study region (Huffman et al., 2019; Beck et 146 al., 2019), and CMOPRH does not integrate rain gauge data into its precipitation estimates 147 (Joyce et al., 2004). Monthly precipitation data from approximately 400 rain gauge stations 148 in Peru (red dots in Fig. 1, Aybar et al., 2020) are utilized for the evaluation of monthly 149 precipitation. These datasets have been employed in previous simulation evaluations by this 150 research team (Chen et al., 2022; Huang et al., 2023). Additionally, hourly precipitation 151 data from 10 rain gauge stations within the study region, mainly in the western Amazon 152 Basin of Brazil (magenta dots in Fig. 1, accessible at https://bdmep.inmet.gov.br), have 153 been collected for the specific evaluation of diurnal cycle of precipitation. 154

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2.2 Model configuration

The simulations conducted in this study utilize the Weather Research and Forecasting 156 (WRF) model with two one-way nested domains, and their configurations are similar to 157 those described by Huang et al. (2023), which are summarized in Table 1. The outer domain 158 (d01) covers the entirety of South America with a horizontal grid spacing of 15 km, and 159 the inner domain (d02) specifically targets the Peruvian central Andes region with a 3-km 160 horizontal grid spacing (Fig. 1). The hourly, 0.25° ECMWF atmospheric reanalysis version 161 5 (ERA5) data (Hersbach et al., 2020) are used for initial and boundary conditions. Our 162 previous short-term sensitivity tests (Huang et al., 2023) revealed a pronounced sensitivity 163 of simulated precipitation in the Peruvian central Andes region to the choice of planetary 164 boundary layer (PBL) schemes, which can be attributed to differences in free-troposphere 165 mixing in the presence of clouds (X.-M. Hu et al., 2023). We will evaluate whether the 166 performance of CPMs in simulating precipitation and MCSs is similar to our short-term 167 sensitivity study (Huang et al., 2023). Consequently, this study includes two simulations, 168 each employing a different PBL scheme: ACM2 and MYNN level 2.5 based on our previous 169 sensitivity tests (Huang et al., 2023) (Table 1). Limited by computational resources, the 170 simulations cover the period of 2014-2019 with the initial year (2014) serving as the spin-up 171 period, primarily for the land surface model. Hereafter, the two simulations are referred to 172 as WRF3km_ACM2 and WRF3km_MYNN, respectively. 173

Additionally, a simulation with a grid spacing of 4 km, covering the entire South Amer-174 ica (Dominguez et al., 2023), produced by the South America Affinity Group (SAAG) led 175 by National Center for Atmospheric Research (NCAR), is also collected, and the simu-176 lation dataset is available at https://ral.ucar.edu/projects/south-america-affinity 177 -group-saag/model-output. Hereafter, this dataset is referred to as WRF4km_SAAG. The 178 WRF4km_SAAG simulation covers a 22-year period (Jan 2000 – Dec 2021) and also uses 179 0.25° ERA5 reanalysis data for boundary conditions (Dominguez et al., 2023). The main 180 physics parameterizations used are: YSU PBL scheme (Hong & Lim, 2006), Thompson mi-181 crophysics scheme (Thompson et al., 2008), RRTMG radiation scheme (Iacono et al., 2008), 182 and the Noah-MP land surface model (Niu et al., 2011) with an activated Miguez-Macho-Fan 183 groundwater scheme (Miguez-Macho et al., 2007; Barlage et al., 2021). 184

To facilitate comparison among the observational and simulated datasets at various resolutions, CMORPH, MSWEP, and the simulated fields are regridded to match the IMERG grid $(0.1^{\circ} \times 0.1^{\circ})$ utilizing the "patch recovery" technique, a method previously employed by Sun et al. (2016) and Huang et al. (2023). The time period analyzed in this study spans 2015 through 2019, encompassing a total of five years.



Model d02 (3-km), rain gauges in Peru & Brazil, study regions

Figure 1. Terrain height (shaded, m) in the 3-km domain with the locations of rain gauges in Peru (red dots) and Brazil (magenta dots). The blue rectangle indicates the region of Figs. 2 and 4. The orange rectangle indicates the region of Figs. 7, 9, 12, and 13.

Table 1.	Summary of	WRF3km_ACM2	2 and WRF3km_MYNN ^{a}
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	domain 1 $(d01)$	domain 2 $(d02)$
Model	WRF V4.2.1 (Ska	amarock et al., 2019)
Initial and boundary conditions	ERA5 hourly reanalys	sis (Hersbach et al., 2020)
Simulation period	2014–2019 with 201	4 as the spin-up period
Grid spacing	$15 \mathrm{km}$	$3~{ m km}$
Spectral nudging	On (Huang et al., 2023)	Off
Cumulus	Tiedtke (Tiedtke, 1989)	Off
Planetary boundary layer	MYNN level 2.5 (Nakanishi & N	Niino, 2009) or ACM2 (Pleim, 2007)
Microphysics	Thompson (The	ompson et al., 2008)
Land surface model	Unified Noah (Ek et al., 2003)	
Surface layer scheme	revised MM5 Monin-Ob	ukhov (Jiménez et al., 2012)
Longwave and shortwave radiation	RRTMG (Iac	cono et al., 2008)

^aMore details can be referred to Huang et al. (2023).

¹⁹⁰ 2.3 MCS identification

Python package Tracking and Object-Based Analysis of Clouds (TOBAC, Heikenfeld et 191 al., 2019) is adopted to identify and track MCSs based on the observed and simulated hourly 192 precipitation datasets. In this study, MCSs are identified using a precipitation threshold of 193 5 mm h^{-1} , which is commonly used in previous studies (Schwartz et al., 2017; A. F. Prein 194 et al., 2017, 2020; Hwang et al., 2023). An object is characterized as a spatially and 195 temporally contiguous precipitation region with a minimum area of 1000 km^2 , approxi-196 mating a horizontal scale on the order of 100 km (https://glossary.ametsoc.org/wiki/ 197 Mesoscale_convective_system). Utilizing the TOBAC output, various MCS characteris-198 tics are calculated, including hourly mean precipitation, hourly peak precipitation, hourly 199 precipitation volume, MCS size, duration, and propagation speed. 200

201 3 Results

3.1 Precipitation characteristics

Prior to the investigation of MCS characteristics, the simulation of climatological precipitation features such as seasonal and diurnal distributions are evaluated using the three gridded precipitation products in conjunction with rain gauge data.

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3.1.1 Seasonal precipitation

In terms of the spatial distribution of seasonally averaged precipitation (Fig. 2), the 207 gridded precipitation products IMERG, CMORPH, and MSWEP show consistent seasonal 208 variations in precipitation distribution, as well as the four notable hotspots along the 209 east slope of the Andes where precipitation can exceed 16 mm day^{-1} in austral summer 210 (December-January-February, DJF). From northeast to southwest, the precipitation ex-211 hibits a distinct "strong-weak-strong-weak" spatial pattern. Specifically, it is high over the 212 western Amazon Basin, weakens over the transition between the basin and the foothills 213 of the Andes, increases again along the east slope of the Andes, and then weakens once 214 more over the mountains. The three simulations (Figs. 2d1-f4) successfully reproduce the 215 spatial distributions and seasonal variations of precipitation. The WRF3km_ACM2 simu-216 lation, which demonstrated superior performance in precipitation amount in our previous 217 short-term sensitivity experiments (Huang et al., 2023), yields lower precipitation in com-218 parison to the three gridded precipitation products and the other two simulations. This 219 discrepancy is particularly noticeable in the southeastern region of the domain, where the 220 precipitation is less than 6 mm day⁻¹ during the summer season (DJF) and less than 3 221 mm day⁻¹ in other seasons (Figs. 2d1–d4). The WRF4km_SAAG simulation exhibits more 222 precipitation compared to the other simulations particularly over the mountainous region, 223 where the precipitation exceeds 6 mm day^{-1} during the summer season (DJF) and is over 3 224 mm dav^{-1} in other seasons (Figs. 2f1-f4). A comparison between the gridded precipitation 225 products, the simulations, and the rain gauge data (primarily located over the mountainous 226 region) confirms the overestimate by WRF4km_SAAG (Fig. 3). Among the three gridded 227 precipitation products compared to the rain gauge data, IMERG has the lowest absolute 228 value of bias $(0.16 \text{ mm day}^{-1})$ and root mean square error $(\text{RMSE} = 1.60 \text{ mm day}^{-1})$, and 229 the highest correlation coefficient (0.85) (Fig. 3). Regarding the three simulations, although 230 WRF4km_SAAG has a relatively high correlation with the rain gauge data, with a correla-231 tion coefficient of 0.82, it also exhibits the largest bias (1.19 mm day⁻¹) and RMSE (2.53) 232 $mm day^{-1}$) among all gridded and simulated precipitation data (Fig. 3). Huang et al. (2023) 233 showed that WRF3km_ACM2 simulates monthly precipitation that is the closest to that of 234 the rain gauges in February, 2019, which is also seen in Fig. 3. However, WRF3km_ACM2 235 underestimates the peaks of monthly precipitation in 2016 and 2017. The monthly pre-236 cipitation amount of the WRF3km_MYNN simulation falls between WRF4km_SAAG and 237 WRF3km_ACM2, and the correlation coefficient of WRF3km_MYNN with the rain gauge 238

- data is 0.79, which is also between those of WRF4km_SAAG (0.82) and WRF3km_ACM2
- ²⁴⁰ (0.75) (Fig. 3).



Figure 2. Seasonally averaged precipitation (shaded, mm day⁻¹) for the period of 2015–2019 of (a1–a4) IMERG, (b1–b4) CMORPH, (c1–c4) MSWEP, (d1–d4) WRF3km_ACM2, (e1–e4) WRF3km_MYNN, and (f1–f4) WRF4km_SAAG. (a1–f1) DJF: December-January-February, (a2–f2) MAM: March-April-May, (a3–f3) JJA: June-July-August, and (a4–f4) SON: September-October-November. The black contour in each panel represents 1-km terrain elevation.



Figure 3. Time series of monthly precipitation (in mm day⁻¹) from rain gauges in Peru within the 3-km domain (Fig. 1), and corresponding data from IMERG, CMORPH, MSWEP, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG at rain gauge locations. The averaged bias, root mean square error (RMSE), and correlation coefficient between the gridded precipitation products or simulations and the rain gauge data are included in the legend.

Overall, the three simulations broadly capture the spatiotemporal pattern of precipitation at a seasonal scale, but biases in precipitation do exist. Among the simulations of precipitation, WRF3km_MYNN generally outperforms the other two simulations in the Peruvian Central Andes in a combined consideration of bias, RMSE, and correlation coefficient compared with the rain gauge data.

3.1.2 Diurnal cycle of precipitation

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The diurnal precipitation peak times of IMERG, CMORPH, and the three simulations 247 are shown in Fig. 4. The MSWEP is not included due to its coarser temporal resolu-248 tion (three-hourly). As for IMERG and CMORPH, the diurnal precipitation peak time 249 exhibits three distinct belts from the western Amazon Basin to the Andes mountains with a 250 northwest-to-southeast orientation, and this is consistent across all seasons (Figs. 4a1-b4). 251 All three simulations generally reproduce this pattern (Figs. 4c1–e4). While the gridded 252 precipitation products IMERG and CMORPH may have certain biases in precipitation in-253 tensity, their diurnal precipitation peak time should be reliable. Using the diurnal precipita-254 tion peak time in IMERG as a reference, the seasonal average pattern correlation coefficients 255 with it are 0.900 for CMORPH, 0.856 for WRF3km_ACM2, 0.877 for WRF3km_MYNN, and 256

0.896 for WRF4km_SAAG. The higher correlation coefficient in WRF4km_SAAG is probably due to its larger model domain at a 4-km grid spacing, while the 3-km WRF runs have
a much smaller domain nested within a 15-km grid.

To gain a clearer view of the diurnal precipitation, three regions (represented by blue 260 polygons in Fig. 4) are selected to compute the mean diurnal precipitation over the western 261 Amazon Basin, the Andes foothills, and the mountains, respectively (Fig. 5). Because 262 the spatial distributions of diurnal precipitation peak time are similar across all seasons, 263 only the annual-averaged hourly precipitation as a function of local time is shown in Fig. 264 265 5. The precipitation peak time over the western Amazon Basin primarily occurs between \sim 12–17 LST (Local Standard Time) with the maximum average precipitation of \sim 0.40 and 266 $\sim 0.34 \text{ mm h}^{-1}$ in IMERG and CMORPH, respectively (Fig. 5c). The three simulations are 267 able to capture the peak time period in this region. However, in comparison to IMERG, 268 the simulation WRF3km_ACM2 underestimates the average precipitation with a maximum 269 of $\sim 0.28 \text{ mm h}^{-1}$, while WRF3km_MYNN and WRF4km_SAAG overestimate it with the 270 maximum values of ~ 0.54 and ~ 0.49 mm h⁻¹, respectively (Fig. 5c). When compared to the 271 rain gauge data in Brazil (primarily in the western Amazon Basin region, Figs. 1 and 4a), the 272 magnitudes of precipitation in WRF3km_MYNN and WRF4km_SAAG are closer to the rain 273 gauge data than to IMERG (Fig. 6). IMERG actually underestimates the maximum average 274 precipitation by $\sim 20\%$ when compared to the rain gauge data (Fig. 6). Taking the rain 275 gauge data as a reference, the RMSEs for the annual average diurnal precipitation are about 276 $0.054, 0.074, 0.094, 0.051, \text{ and } 0.037 \text{ mm h}^{-1}$ and their corresponding correlation coefficients 277 are around 0.932, 0.891, 0.861, 0.893, and 0.950 for IMERG, CMORPH, WRF3km_ACM2, 278 WRF3km_MYNN, and WRF4km_SAAG, respectively. This suggests that WRF3km_MYNN 279 and especially WRF4km_SAAG perform well in simulating the diurnal cycle of precipitation 280 over the western Amazon Basin with smaller RMSEs and higher correlations. Similarly, the 281 three simulations reproduce the precipitation peak time periods in the foothill and mountain 282 regions, which occur approximately during 0–7 and 13–19 LST, respectively (Fig. 4). Both 283 WRF3km_MYNN and WRF4km_SAAG generally have larger average precipitation in these 284 two regions compared to IMERG, CMORPH, and WRF3km_ACM2 (Figs. 5a and b). Given 285 the lower RMSE for monthly precipitation in WRF3km_MYNN compared to rain gauge data 286 in Peru (Fig. 3), the intensity bias of diurnal precipitation in WRF3km_MYNN should be 287 smaller than that in WRF4km_SAAG over the mountain region. It should be noted that 288 two distinct precipitation peaks are shown in the foothill region (Fig. 5b). This dual-peak 289 pattern is associated with the specific region selected for calculation, which includes the 290 transition zone of precipitation from the Andean foothills to the western Amazon Basin. 291

Overall, the three simulations successfully capture the spatiotemporal patterns of pre-292 cipitation at a sub-daily scale, but biases in precipitation amounts are evident. When 293 taking into account both the spatial distribution and intensity of diurnal precipitation, 294 WRF3km_MYNN generally outperforms the other two simulations in the mountain re-295 gion. Both WRF3km_MYNN and particularly WRF4km_SAAG demonstrate superior per-296 formance in the western Amazon region. X.-M. Hu et al. (2023) found that during the 297 morning, the free atmosphere cloud decks dissipate much faster in the simulation using the 298 YSU PBL scheme than the simulation using the ACM2 PBL scheme, leading to more surface 299 radiative heating and convective instability therefore more precipitation in the simulation 300 using the YSU PBL scheme. The cloud cover results in less precipitation in the simulation 301 using the ACM2 PBL scheme. 302



Figure 4. Precipitation peak time (shaded, Local Standard Time, LST) in each season calculated from (a1–a4) IMERG, (b1–b4) CMORPH, (c1–c4) WRF3km_ACM2, (d1–d4) WRF3km_MYNN, and (e1–e4) WRF4km_SAAG. The white contour in each panel represents 1-km terrain elevation. The blue polygons in each panel indicate the regions utilized for diurnal precipitation calculation shown in Fig. 5. The magenta dots in (a1) mark the locations of the hourly rain gauge data in Brazil.



Figure 5. Averaged diurnal precipitation (mm h⁻¹) in the (a) mountain, (b) foothill, and (c) plain regions shown in Fig. 4 from IMERG, CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG.



Figure 6. Averaged diurnal precipitation (mm h⁻¹) of rain gauges in Brazil shown in Fig. 4a1 for each season from IMERG, CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG.

303 3.2 MCS characteristics

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The earlier evaluations show that the three WRF simulations effectively reproduce the main features of precipitation at both seasonal and sub-daily time scales in the Peruvian Central Andes region. In the following section, the characteristics of MCSs in this region are examined.

3.2.1 Spatiotemporal distribution and propagation

309 Only the MCSs generated within the region depicted by the orange rectangle in Fig. 1 are considered. This specified region is smaller than the 3-km simulation domain to reduce 310 the influence of domain boundaries on the analysis. The spatial distributions of seasonal 311 MCS genesis frequency in Fig. 7 reveal that the genesis hotspots for MCSs are along the 312 east slope of the Andes and over the western Amazon Basin. These locations coincide 313 with the precipitation hotspots (Fig. 2), and MCSs can account for up to 50% of annual 314 precipitation in some of these hotspots (not shown), which is also revealed in Feng et al. 315 (2021). All three simulations produce spatiotemporal evolutions of MCSs that are consistent 316 with IMERG and CMORPH, but WRF3km_ACM2 notably underestimates the MCS genesis 317 frequency (Fig. 7). The lower frequency is linked to the underestimate of precipitation in 318 WRF3km_ACM2 (Figs. 2, 3, 5 and 6) and the use of a fixed threshold of 5 mm h^{-1} for 319 MCS identification. The differences in MCS frequency are more apparent in the time series 320 in Fig. 8. Specifically, the MCS frequency in WRF3km_ACM2 is generally lower than in the 321 other datasets, especially during the warm seasons of 2016 and 2019 (Fig. 8a). Conversely, 322 WRF3km_MYNN and WRF4km_SAAG display 5-year average MCS frequencies of about 323 200 in January and February (Fig. 8b) and the frequency peaks at around 250 in 2019 324 (Fig. 8a). These two simulations generally exhibit higher MCS frequencies than IMERG 325 and CMORPH during the warm season, exceeding their frequencies by about 20 and 50 326 $(\sim 10\%$ and $\sim 33\%)$ in January and February, respectively (Fig. 8b). However, during the 327 cold season (June and July), WRF3km_MYNN and WRF4km_SAAG simulate about 10 328 fewer MCSs per month compared to IMERG and CMORPH (Fig. 8b). 329



Figure 7. Spatial distribution of MCS genesis frequency (in counts) in $1^{\circ} \times 1^{\circ}$ bin in each season for (a1–a4) IMERG, (b1–b4) CMORPH, (c1–c4) WRF3km_ACM2, (d1–d4) WRF3km_MYNN, and (e1–e4) WRF4km_SAAG. The magenta contour in each panel represents 1-km terrain elevation.



Figure 8. Frequency (in counts) of MCS genesis for (a) each individual month from 2015 to 2019 and (b) the average for each month over the 5-year period for IMERG, CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG.



Figure 9. Spatial distribution of the diurnal MCS genesis frequency (in counts) in $1^{\circ} \times 1^{\circ}$ bin for (a1-a4) IMERG, (b1-b4) CMORPH, (c1-c4) WRF3km_ACM2, (d1-d4) WRF3km_MYNN, and (e1-e4) WRF4km_SAAG. The magenta contour in each panel represents 1-km terrain elevation. The Local Standard Time (LST) here is UTC - 5 h based on the longitude of 75°W. The blue rectangles in a1-e1 and a3-e3 indicate the regions to create wind roses shown in Fig. 10.

Based on the IMERG and CMORPH data, MCSs along the east slope of the Andes 330 start to initiate during nighttime hours (18–00 LST, see Figs. 9a4 and b4) and reach a peak 331 in genesis frequency in the early morning (00–06 LST, see Figs. 9a1 and b1). In contrast, 332 the western Amazon Basin sees a concentration of MCS genesis in the afternoon (12–18 333 LST, Figs. 9a3 and b3). All three simulations successfully replicate these diurnal MCS 334 genesis hotspots at terrain notches and over the Amazon Basin. However, WRF3km_ACM2 335 noticeably underestimates the frequency of MCSs in both the east slope of the Andes and 336 the western Amazon Basin regions (Figs. 9c1-e4). 337

To examine MCS propagation patterns in the Peruvian Central Andes, MCS propaga-338 tion direction and speed in the three notable hotspots along the east slope of the Andes and 339 one over the western Amazon Basin are calculated and displayed in the form of wind roses 340 (Fig. 10). It should be noted that the spokes in each wind rose plot indicate the direction 341 towards which MCSs move. The concentric circles in each wind rose plot are divided into 342 16 sectors at intervals of 22.5° , and each sector would represent a probability of 6.25% if 343 the distribution of MCS propagation were uniform. In observational datasets IMERG and 344 CMORPH, MCSs originating along the Andean east slope mainly propagate parallel to the 345 mountain range (Figs. 10a and b), and the probability of southeastward propagation exceeds 346 10% in both the northern and southern hotspots in IMERG (Fig. 10a). This behavior likely 347 arises from the natural barrier posed by the high, steep Andean slopes. Over the western 348 Amazon Basin, westward propagation dominates with a probability close to 10% in IMERG 349 data (Fig. 10a), which is close to the motion of downwind-developing MCSs estimated by 350 the method proposed by Corfidi (2003) considering the influence of cold-pool factors (not 351 shown). All three simulations can replicate these dominant MCS propagation character-352 istics, although discrepancies in specific directional angles, probabilities, and speeds exist 353 (Fig. 10). For instance, WRF3km_ACM2 shows a notably higher northwestward propaga-354 tion probability both along the east slope of the Andes and over the western Amazon Basin, 355 peaking at probabilities above 15%, a higher value than observed in IMERG (Figs. 10a 356 and c). Northwestward propagation is also prevalent along the east slope of the Andes, as 357 seen in WRF4km_SAAG (Fig. 10e). Compared to WRF3km_ACM2, the WRF4km_SAAG 358 simulation, similar to IMERG (Fig. 10a), exhibits a broader directional spread over the 359 western Amazon Basin, ranging from southward to northwestward, with the highest prob-360 ability of $\sim 10\%$ in the west-northwestward direction (Fig. 10e). WRF3km_MYNN closely 361 aligns with IMERG for MCS propagation along the Andean slope but veers more south-362 westward over the Amazon Basin (Fig. 10d). Additionally, all three simulations simulate 363 higher probabilities for MCS propagation speeds exceeding 65 km h^{-1} compared to IMERG 364 and CMORPH, implying an overestimate of MCS propagation speed in the simulations. 365 However, it should be noted that IMERG and CMORPH also have uncertainties, especially 366 in CMORPH, whose MCS propagation direction has a large difference from IMERG and all 367 simulations (Fig. 10). 368

Overall, although specific discrepancies exist in the MCS genesis frequency and propagation speed, the WRF simulations generally replicate the observed spatiotemporal patterns at both seasonal and diurnal scales and the propagation of MCSs in the Peruvian Central Andes and western Amazon.



Figure 10. Wind roses for MCS propagation in the hotspots along the east slope of the Andes and in the western Amazon Basin shown in Fig. 9 for (a) IMERG, (b) CMORPH, (c) WRF3km_ACM2, (d) WRF3km_MYNN, and (e) WRF4km_SAAG. The concentric circles in each panel indicate the probability (5, 10, 15, and 20%) of propagation direction, divided into 16 sectors at intervals of 22.5°. The colors within the circles represent the MCS moving speed classes, segmented into intervals of 10 km h⁻¹. The magenta contour in each panel represents the 1-km terrain elevation.

373 3.2.2 Statistics of MCS properties

In this section, MCS properties are statistically examined to identify main differences in 374 MCSs among IMERG, CMORPH and all simulations. Properties of MCSs, such as hourly 375 mean precipitation, peak hourly precipitation, size, duration, hourly precipitation volume 376 (equals hourly mean precipitation \times area), and moving speed, are displayed for IMERG, 377 CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG using violin plots 378 (Fig. 11). The MCS properties are generally consistent between IMERG and CMORPH, as 379 well as among the three simulations themselves, as shown in Fig. 11. However, a significant 380 discrepancy exists between the gridded precipitation products, IMERG and CMORPH, and 381 the simulations, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG, particularly in 382 MCS precipitation intensity, including both mean and peak hourly precipitation (Figs. 11a 383 and b). The interquartile range (25th to 75th percentiles) for the mean hourly precipitation 384 in IMERG and CMORPH spans $\sim 8-11$ mm h⁻¹, centering around a median value of ~ 9 385 mm h^{-1} . In contrast, all simulations exhibit a higher interquartile range, covering $\sim 13-19$ 386 mm h^{-1} , and center around median values of about 16 mm h^{-1} (Fig. 11a). The differences 387 between the gridded precipitation products and simulations are also evident in peak hourly 388 precipitation rates. Specifically, the 25th, 50th (median), and 75th percentiles for IMERG 389 are approximately 14, 20, and 28 mm h^{-1} , respectively, and for CMORPH, they are around 390 14, 18, and 24 mm h^{-1} . In contrast, these percentiles are notably higher in the simulations: 391 for WRF3km_ACM2, they are about 35, 46, and 59 mm h⁻¹; for WRF3km_MYNN, they are 392 approximately 38, 48, and 60 mm h^{-1} ; and for WRF4km_SAAG, the values are around 40, 393 51, and 64 mm h^{-1} (Fig. 11b). This suggests that the simulations tend to overestimate the 394 median of peak hourly precipitation by more than 130% compared to the IMERG. Regard-395 ing MCS size, IMERG and CMORPH show 25th to 75th percentile ranges of approximately 396 4700 to 12000 km², with median sizes close to 7000 km² (Fig. 11c). However, the simu-397 lations generally produce smaller MCS sizes, with 25th to 75th percentile ranges spanning 398 about 3000 to 7000 $\rm km^2$ and median sizes around 4000 $\rm km^2$. Despite the smaller sizes, the 399 simulations exhibit higher precipitation intensity (Fig. 11a). Consequently, the simulated 400 and observed hourly precipitation volumes are relatively similar (Fig. 11e). Specifically, the 401 25th to 75th percentile ranges in the simulated and observed hourly precipitation volumes 402 are approximately 0.04 to 0.11 km³ h⁻¹, with median volumes of around 0.065 km³ h⁻¹ 403 (Fig. 11e). Meanwhile, all datasets exhibit a median MCS duration of 3 hours (Fig. 11d). 404 However, the simulations generally produce higher MCS movement speeds, with a median 405 of ~ 36 km h⁻¹, compared to the observed median speeds of ~ 20 km h⁻¹ in IMERG and 406 CMORPH (Fig. 11f), which aligns with the findings presented in Fig. 10. 407

Overall, statistical analyses of MCS properties reveal that the simulations generally 408 overestimate both mean and peak hourly precipitation rates associated with MCSs, and 409 simulate smaller MCS sizes but similar hourly precipitation volumes compared to gridded 410 precipitation products. All datasets agree on a median MCS duration of 3 hours, though 411 simulated MCSs tend to move faster. It should be noted that the discrepancies between the 412 simulations and the gridded precipitation products may also arise from the uncertainties 413 and low effective resolutions of the gridded precipitation products (Guilloteau & Foufoula-414 Georgiou, 2020), thereby emphasizing the need for more reliable observational products. 415



Figure 11. Violin plot of MCS properties including MCS (a) hourly mean precipitation, (b) hourly peak precipitation, (c) size, (d) duration, (e) hourly precipitation volume, and (f) moving speed for IMERG, CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG. The white circles in box-and-whisker plots represent the average value of samples. The distributions and medians of the gridded precipitation products and simulations are significantly different at the 0.05 level, except for MCS duration comparisons between CMORPH and WRF3km_ACM2 or WRF3km_MYNN.

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3.2.3 Diurnal dynamic and thermodynamic factors

⁴¹⁷ Despite noted differences in MCS precipitation intensity, frequency, and movement ⁴¹⁸ speed, all three simulations, particularly WRF3km_MYNN, successfully replicate key spa-⁴¹⁹ tiotemporal distributions and evolution of MCSs across multiple scales. In the subsequent ⁴²⁰ section, diurnal variations of dynamic and thermodynamic fields from the 3-km simulations ⁴²¹ WRF3km_MYNN and WRF3km_ACM2 are used to understand the mechanisms underlying ⁴²² MCS genesis in this region.

From the DJF-seasonal mean hourly horizontal wind fields at 850 hPa in WRF3km_MYNN 423 and WRF3km_ACM2 shown in Figs. 12 and 13, we can see that the mean winds in the ex-424 amined region on the east of the Andes are predominantly northwesterly, influenced mainly 425 by the steep high Andean terrain that blocks the northeasterly SALLJ and turns the flows 426 into northwesterly. However, the mean wind speed in WRF3km_MYNN ($\sim 3.9 \text{ m s}^{-1}$) is 427 closer to that in ERA5 ($\sim 4.6 \text{ m s}^{-1}$, not shown) than that in WRF3km_ACM2 ($\sim 2.6 \text{ m}$ 428 s⁻¹). In WRF3km_MYNN, wind convergence (divergence $< -1 \times 10^{-6} \text{ s}^{-1}$) is primarily 429 found along the east slope of the Andes and over the western Amazon Basin between 00-06430 LST (Figs. 12a-g). Such enhancement of convergence and precipitation in the early morn-431

ing hours near the LLJ terminus (Fig. 14a) can be mostly explained by the boundary layer
inertial oscillation theory (Blackadar, 1957; Xue et al., 2018).

Starting from 07 LST, the convergence zones begin to contract and become concentrated 434 within the basin area around the latitude of 10° S between 12–15 LST (Figs. 12h-p). From 435 16 LST, convergence gradually expands and eventually covers both the Andean slope and 436 the basin regions again (Figs. 12q-x). Such distribution and evolution of wind convergence 437 in WRF3km_MYNN are consistent with those in ERA5 (not shown). The diurnal variations 438 in wind convergence and horizontal wind speeds along the east slope of the Andes (Figs. 12 439 440 and 14a) are consistent with the diurnal variation of MCS genesis in the region, where the frequency of MCSs begins to increase between 18–00 LST and peaks between 00–06 LST 441 (Fig. 9). This suggests that MCS activity and precipitation along the eastern Andean slope 442 are mainly driven by dynamical forcings, such as the uplift of moist air by SALLJ and by the 443 mountain-range-parallel northwesterly flows when they encounter the terrain notches near 444 the precipitation hotspots. In WRF3km_ACM2 (Fig. 13), the area of the wind convergence 445 (divergence $< -1 \times 10^{-6} \text{ s}^{-1}$) first decreases and then increases from 00 to 23 LST, which is 446 consistent with that in WRF3km_MYNN. However, in WRF3km_ACM2 (Fig. 13), the wind 447 convergence (divergence $< -1 \times 10^{-6} \text{ s}^{-1}$) primarily covers the east slope of the Andes and 448 part of the western Amazon Basin between 00–06 LST (Figs. 13a–g). The horizontal wind 449 speeds associated with LLJ are also weaker in WRF3km_ACM2 than in WRF3km_MYNN 450 (Fig. 14). There are few convergence zones in the study region between 12–15 LST (Figs. 451 13h-p). It is consistent with the weaker precipitation ((Figs. 2, 5, and 6) and fewer MCS 452 geneses (Fig. 9) over the western Amazon Basin in WRF3km_ACM2. 453



Figure 12. Diurnal horizontal winds at 850 hPa averaged over the DJF months from 2015 to 2019 in WRF3km_MYNN. In order to see the convergence region clearly, the full wind field is decomposed into two components: Thick vectors represent the time-area-averaged wind in the blue dashed box shown in (a), and thin vectors represent the deviation of the full wind field from the time-area-averaged wind. The orange dot-filled areas indicate the regions with wind divergence less than -1×10^{-6} s⁻¹. The magenta contour in each panel represents 1-km terrain elevation. The Local Standard Time (LST) here is UTC -5 h based on the longitude of 75°W.



Figure 13. As in Fig. 12, but for WRF3km_ACM2.



Figure 14. Height-time cross-section of area-averaged horizontal wind speeds (m s⁻¹) in the regions of (a and c) northern MCS genesis hotspot along the east slope of the Andes and (b and d) the hotspot over the western Amazon Basin (blue rectangles shown in Fig. 9) in (a and b) WRF3km_MYNN and (c and d) WRF3km_ACM2, respectively.

For the western Amazon Basin, convergence is consistently present throughout the day 454 in WRF3km_MYNN (Fig. 12) and ERA5 (not shown). Despite this, MCSs predominantly 455 form between 12–18 LST (Fig. 9), indicating that dynamic convergence associated with low-456 level flows is not the most dominant driver of MCS activity in this region. Thermodynamic 457 forcing likely plays even more important roles in triggering and supporting a majority of 458 MCSs. To further understand the underlying mechanisms, vertical cross-sections of diurnal 459 vertical velocity at the latitude of 10° S are examined, along with maximum convective 460 available potential energy (CAPE) and maximum convective inhibition (CIN) (Figs. 15 and 461 16).462

In WRF3km_MYNN, during the early morning hours (00–06 LST), strong updrafts 463 are observed on the Andean east slope, mainly attributed to enhanced low-level flows (Fig. 464 14a) and associated terrain lifting, although the CAPE values are moderate, ranging from 465 approximately 500 to 1000 J kg⁻¹ (Figs. 15a–g). In the western Amazon Basin, CAPE is 466 comparable, but CIN is noticeably higher (up to $\sim 160 \text{ J kg}^{-1}$) (Figs. 15a–g), inhibiting 467 the triggering of significant convection despite the convergence. Starting at 07 LST, both 468 CAPE and CIN undergo diurnal changes in the basin due to solar radiative heating. CAPE 469 rises to 1200–1600 J kg⁻¹, while CIN approaches zero between 10–15 LST (Figs. 15h–p). 470 Consequently, updraft frequency in the basin increases during this period. During 11–13 471 LST (Figs. 151-n), updrafts shift from the Andean slope to the smaller mountains to the 472 east (around $74^{\circ}W$) with a low CAPE between 400–800 J kg⁻¹, showing the importance of 473 even small terrains here. In contrast, despite maximum CAPE values on the Andean slopes 474 up to 1600 J kg⁻¹ (Figs. 15n–p), updrafts in this region decline, which is largely attributed 475 to divergence in this region associated with enhanced convection upstream over the basin 476 (Figs. 12k-p). Although CAPE starts to decrease and CIN begins to rise after 16 LST, 477 updrafts can persist for a while due to the presence of existing convection and relatively 478 high prior CAPE (> 800 J kg⁻¹, Figs. 15q–u) and previous convection trigger effect. Hence, 479 MCSs in the western Amazon Basin are predominantly influenced by thermodynamic factors. 480 Additionally, updrafts are observed at elevations around 4 km during 12–18 LST over the 481 mountains, aligning with the evolution of CAPE and precipitation in the regions (Figs. 15m-482 s and Fig. 5a). It suggests that thermodynamic factors also have a significant influence on 483 precipitation over these elevated terrains. In fact, over major mountain ranges, afternoon 484 convection is often prevalent, such as over the Rocky Mountains (e.g., Carbone & Tuttle, 485 2008; Sun et al., 2016; Y. Zhao et al., 2023). 486

For the WRF3km_ACM2 simulation (Fig. 16), the diurnal evolution of updrafts, CAPE 487 and CIN are basically consistent with those in WRF3km_MYNN (Fig. 15). However, there 488 exist obvious differences in their magnitudes. From 00 to 07 LST, CAPE in WRF3km_ACM2 489 is around 400 J kg⁻¹ (Figs. 16a–h), which is \sim 100–500 J kg⁻¹ smaller than that of 490 WRF3km_MYNN (Figs. 15a-h). In the meanwhile, CIN in WRF3km_ACM2 is mostly between 80 and 160 J kg⁻¹ and can be up to 200 J kg⁻¹ over the western Amazon Basin, 491 492 which is about 40 J kg⁻¹ higher than that of WRF3km_MYNN (Figs. 16a–h and 15a– 493 h). Therefore, the triggering of updrafts is more inhibited in WRF3km_ACM2, which is 494 consistent with the weaker updrafts in WRF3km_ACM2. Between 08–15 LST, CAPE in 495 WRF3km_ACM2 starts to increase, but it is lower than 1200 J kg^{-1} and mostly around 800 496 J kg⁻¹ over the western Amazon Basin (Figs. 16i–p), about 400 J kg⁻¹ smaller than that in 497 WRF3km_MYNN (Figs. 15i-p). Moreover, CIN is also generally higher in WRF3km_ACM2 498 than in WRF3km_MYNN in this period. Thus, there are much fewer updrafts over the west-499 ern Amazon Basin in WRF3km_ACM2 (Figs. 16i-p). Therefore, the lower CAPE and higher 500 CIN along with the weaker LLJ and fewer convergence zones in WRF3km_ACM2 result in 501 weaker precipitation and fewer MCSs than WRF3km_MYNN. These differences were also 502 found in our previous short-term simulation study (Huang et al., 2023), and analyses in 503 X.-M. Hu et al. (2023) show that the differences in the strength of vertical mixing within 504 the PBL and entrainment flux at the PBL top in different PBL schemes impact the vertical 505 transportation of moisture and momentum. This affects cloud formation and cloud frac-506 tion, ultimately influencing surface radiative heating, CAPE and precipitation (Huang et 507

- al., 2023; X.-M. Hu et al., 2023). Sensitivity experiments in X.-M. Hu et al. (2023) suggest
- that the stronger free-troposphere mixing in ACM2 scheme is the primary factor responsible
- $_{\tt 510}$ $\,$ for the discrepancies in the vertical thermodynamic structure and simulated precipitation
- ⁵¹¹ between the simulations using different PBL schemes.



Figure 15. Vertical cross-section of vertical velocity (shaded, in units of m s⁻¹) along the latitude of 10°S in WRF3km_MYNN. The black curves represent the terrain height (km), and the blue and magenta curves represent CAPE (J kg⁻¹) and CIN(10⁻¹ J kg⁻¹), respectively. The unit of CIN in 10^{-1} J kg⁻¹ is used here to make CIN more visible. The Local Standard Time (LST) here is UTC - 5 h based on the longitude of 75°W.



Figure 16. As in Fig. 15, but for WRF3km_ACM2.

512 4 Summary

To investigate the precipitation and MCSs in the Peruvian Central Andes, a region with 513 complex terrain, two CPM regional climate simulations are run using the WRF model and 514 two PBL schemes, namely ACM2 and MYNN, over a 6-year period (2014–2019) with the first 515 year treated as a spin-up period. These simulations are at a grid spacing of 15 km covering 516 the entire South America and a nested convection-permitting grid spacing of 3 km covering 517 the Peruvian central Andes region. The ERA5 reanalysis data are used to provide the lateral 518 boundary conditions for the 15-km gird. These two CPM simulations combined with the 519 SAAG 4-km simulation covering the entire South America and using the YSU PBL scheme, 520 rain gauge data in Peru and Brazil, and three gridded global precipitation datasets, are used 521 to study the characteristics of precipitation and MCSs in the Peruvian central Andes region 522 and evaluate the capability of models in replicating key observed characteristics. This study 523 provides the evidence on the feasibility of CPM simulations thus configured for projecting 524 the potential impacts of climate change on precipitation and MCSs in this region while 525 pointing out certain deficiencies. The major results are summarized as follows. 526

(1) All three simulations, the two 3-km simulations (WRF3km_ACM2 and WRF3km_MYNN) 527 and the 4-km simulation (WRF4km_SAAG), broadly capture the seasonal spatiotemporal 528 patterns of precipitation, particularly the hotspots associated with the prevailing winds and 529 terrain features along the east slope of the Peruvian Central Andes, although some biases 530 in specific precipitation values are present. Among the simulations, WRF3km_MYNN gen-531 erally outperforms the other two simulations over the mountain regions compared to the 532 gridded precipitation products and available rain gauge data. Meanwhile, WRF3km_MYNN 533 and WRF4km_SAAG display comparable performance in the western Amazon Basin region. 534

(2) The three simulations also effectively replicate the sub-daily spatiotemporal patterns
of precipitation, but biases in precipitation intensity are evident. When taking into account
both the spatial distribution and intensity of diurnal precipitation, WRF3km MYNN generally outperforms the other two simulations in the mountain region. Both WRF3km MYNN
and particularly WRF4km SAAG demonstrate superior performance in the western Amazon region when compared to gridded precipitation products and available rain gauge data
in Brazil.

(3) The simulations generally replicate the observed spatiotemporal patterns and prop-542 agation of MCSs, particularly along the east slope of the Peruvian Central Andes and 543 over the western Amazon Basin, across both seasonal and diurnal time scales. However, 544 specific discrepancies exist in MCS genesis frequency and movement speed. For instance, 545 WRF3km_ACM2 notably underestimates the frequency of MCSs, particularly during the 546 warm seasons of 2016 and 2019. Conversely, WRF3km_MYNN and WRF4km_SAAG tend 547 to overestimate MCS frequency during the warm season. Additionally, all three simulations 548 consistently depict higher frequencies of MCSs with higher moving speeds than those ob-549 served in IMERG and CMORPH, highlighting areas for model improvement. Nonetheless, 550 uncertainties do exist with the IMERG and CMORPH precipitation estimate products, and 551 more robust precipitation observations are needed to obtain more reliable evaluations. 552

(4) Statistical analyses of MCS properties reveal that the simulations generally overestimate both mean and peak hourly precipitation intensity associated with the MCSs, and
produce smaller MCS sizes but similar total hourly precipitation volumes compared to the
gridded precipitation products. Moreover, all datasets agree on a median MCS duration of
~3 hours within the study area, and the simulations generally produce faster MCS moving
speeds compared to the gridded precipitation products.

(5) Analyses of the diurnal variations in dynamic and thermodynamic parameters in dicate that dynamic factors, mainly LLJ-terrain-induced uplift of moisture and energy, are
 the principal drivers for MCS genesis along the east slopes of the Andes. While in the west ern Amazon Basin, MCSs predominantly form in the afternoon and are largely governed by

thermodynamic factors, specifically solar radiation-induced diurnal changes in CAPE and 563 CIN. The lower CAPE and higher CIN along with weaker convergence in WRF3km_ACM2 564 result in weaker precipitation and fewer MCSs than in WRF3km_MYNN. These differences 565 are attributed to the differences in vertical mixing within the PBL and especially entrain-566 ment flux at the PBL top in different PBL schemes. They impact the vertical transportation 567 of moisture and momentum, then cloud formation and cloud fraction, and ultimately sur-568 face radiative heating, CAPE, and precipitation, analyzed previously based on shorter-term 569 simulations (Huang et al., 2023; X.-M. Hu et al., 2023). Besides, similar thermodynamic 570 effects are observed to be the dominant influence on precipitation over elevated mountains. 571

In summary, the investigation of precipitation and MCS characteristics in the Peru-572 vian Central Andes in this study offers valuable insights into both observed patterns and 573 convection-permitting regional climate simulation performances. The findings not only en-574 hance our understanding of the specific precipitation and MCS characteristics within this 575 region, but also document the differences between observations and the WRF simulations, 576 which can inform future model improvements. It should be noted that the discrepancies 577 between the gridded precipitation products and the simulations may also arise from the 578 uncertainties and low effective resolutions of the gridded precipitation products (Guilloteau 579 & Foufoula-Georgiou, 2020), thereby emphasizing the need for more reliable observational 580 products. Despite the presence of biases, the CPM simulations effectively capture the fun-581 damental mechanisms that govern precipitation and convective systems in the Peruvian 582 Central Andes region. It suggests the feasibility of CPM simulations for projecting the po-583 tential impacts of climate change on precipitation and MCSs in the region, thereby providing 584 critical input for tailored climate adaptation strategies in this region, especially after bias 585 correction/calibration of the model projections. Two future climate simulations have been 586 conducted using the same model configuration as WRF3km_MYNN, focusing on two shared 587 socioeconomic pathway (SSP) scenarios, SSP2-4.5 and SSP5-8.5, that represent the medium 588 and high emission scenarios, respectively. The choice of the WRF3km_MYNN configuration 589 was based on the evaluations of the historical simulations reported in Huang et al. (2023), 590 X.-M. Hu et al. (2023), and this study. These simulations are driven by a bias-corrected 591 global dataset, derived from a CMIP6 multi-model ensemble (Xu et al., 2021). The SAAG 592 future simulation is running as well using a pseudo global warming approach and targeting 593 a warming level of $\sim 2.5^{\circ}$ C in the period of 2060–2080 over South America (Dominguez et 594 al., 2023). Projected changes in precipitation and MCSs in the Peruvian Central Andes 595 region, based on these CPM simulations, will be analyzed and reported in the future. 596

⁵⁹⁷ Open Research Section

ERA5 reanalysis data are available at https://doi.org/10.5065/BH6N-5N20. GPM 598 IMERG Final Precipitation dataset is available at https://doi.org/10.5067/GPM/IMERGDF/ 599 DAY/06 (last access: 12 November 2020). CMORPH dataset is available at https:// 600 ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0/CRT/8km-30min (last access: 12 November 601 2020). MSWEP dataset is available at http://www.gloh2o.org/mswep (last access: 17 602 July 2021). The rain gauge data in Peru are available at https://piscoprec.github.io/ 603 webPISCO/en/raingauges (last access: 18 July 2021). The rain gauge data in Brazil are 604 available at https://bdmep.inmet.gov.br (last access: 19 January 2023). The SAAG 605 4-km simulation dataset is available at https://ral.ucar.edu/projects/south-america 606 -affinity-group-saag/model-output (last access: 18 July 2022). The model outputs are too large to be publicly archived. Please contact the corresponding author for more 608 information. 609

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Characteristics of Precipitation and Mesoscale Convective Systems over the Peruvian Central Andes in Multi 5-Year Convection-Permitting Simulations

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15 Key Points:

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16	•	Characteristics of precipitation and MCSs in the Peruvian Central Andes are inves-
17		tigated based on convection-permitting simulations.
18	•	WRF3km_MYNN outperforms in simulating mountain precipitation; both it and
19		WRF4km_SAAG show superior performance in western Amazon.
20	•	Dynamic factors dominate precipitation and MCSs on the Andean east slope, while

Dynamic factors dominate precipitation and MCSs on the Andean east slope, while
 thermodynamic factors are dominant in western Amazon Basin.

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22 Abstract

Using the Weather Research and Forecasting (WRF) model with two planetary boundary 23 layer schemes, ACM2 and MYNN, convection-permitting model (CPM) regional climate 24 simulations were conducted for a 6-year period at a 15-km grid spacing covering entire 25 South America and a nested convection-permitting 3-km grid spacing covering the Peruvian 26 central Andes region. These two CPM simulations along with a 4-km simulation covering 27 South America produced by National Center for Atmospheric Research, three gridded global 28 precipitation datasets, and rain gauge data in Peru and Brazil, are used to document the 29 characteristics of precipitation and MCSs in the Peruvian central Andes region. Results 30 show that all km-scale simulations generally capture the spatiotemporal patterns of pre-31 cipitation and MCSs at both seasonal and diurnal scales, although biases exist in aspects 32 such as precipitation intensity and MCS frequency, size, propagation speed, and associated 33 precipitation intensity. The 3-km simulation using MYNN scheme generally outperforms 34 the other simulations in capturing seasonal and diurnal precipitation over the mountain, 35 while both it and the 4-km simulation demonstrate superior performance in the western 36 Amazon Basin, based on the comparison to the gridded precipitation products and gauge 37 data. Dynamic factors, primarily low-level jet and terrain-induced uplift, are the key drivers 38 for precipitation and MCS genesis along the east slope of the Andes, while thermodynamic 39 factors control the precipitation and MCS activity in the western Amazon Basin and over el-40 evated mountainous regions. The study suggests aspects of the model needing improvement 41 and the choice of better model configurations for future regional climate projections. 42

⁴³ Plain Language Summary

We ran high-resolution model simulations at a 3-km grid spacing with two planetary 44 boundary layer schemes (ACM2 and MYNN) for a 6-year period to investigate precipitation 45 and storm patterns in the Peruvian central Andes region. Other datasets including a 4-km 46 simulation produced by National Center for Atmospheric Research, three gridded precipi-47 tation products, and rain gauge data in Peru and Brazil were collected for comparison and 48 evaluation. We found that all km-scale simulations capture the overall patterns of precipi-49 tation and storms at both seasonal and sub-daily time scales, although some discrepancies 50 exist in precipitation intensity and storm details. Compared to the gridded precipitation 51 products and gauge data, the 3-km simulation using MYNN scheme generally outperforms 52 the other simulations in capturing seasonal and diurnal precipitation over the mountain, 53 while both it and the 4-km simulation demonstrate superior performance in the western 54 Amazon Basin. Low-level wind and terrain-induced uplift is the key driver for precipitation 55 and storm genesis along the Andes' eastern slopes, while factors associated with vertical 56 structures of temperature and humidity control the precipitation and storm activity in the 57 western Amazon Basin and mountain regions. The study suggests aspects of model im-58 provement and better model configurations for future regional climate projections. 59

60 1 Introduction

The Peruvian Central Andes, characterized by complex topography and unique clima-61 tological conditions such as the South American low-level jet (SALLJ), plays a vital role 62 in influencing local and regional weather patterns and hydrological cycles (Marengo et al., 63 2002; Vernekar et al., 2003; Vera et al., 2006; Romatschke & Houze Jr, 2010; Drenkhan 64 et al., 2015; Espinoza et al., 2015; Jones, 2019; Poveda et al., 2020; Arias et al., 2021). 65 The precipitation in the Peruvian Central Andes exhibits substantial spatial and temporal 66 variability, driven by multi-scale atmospheric circulations and localized forcing such as to-67 pography (Mohr et al., 2014; Junquas et al., 2018; Chavez et al., 2020; Anselmo et al., 2021). 68 Mesoscale convective systems (MCSs), which are organized clusters of thunderstorms, often 69 accompany heavy precipitation, hail, and strong winds (Houze Jr, 2004, 2018; R. S. Schu-70 macher & Rasmussen, 2020). As a major source of precipitation in numerous regions (Salio 71

et al., 2007; Li et al., 2020; Roca & Fiolleau, 2020; R. S. Schumacher & Rasmussen, 2020; 72 Anselmo et al., 2021; H. Hu et al., 2021; Kukulies et al., 2021; M. Zhao, 2022; Paccini 73 & Stevens, 2023), MCSs can cause severe flooding, landslides, and other natural disasters, 74 thereby posing significant threats to human safety and infrastructure. As shown in Figure 75 10 of the study by Feng et al. (2021), MCSs can contribute to over 60% of the annual 76 precipitation in the Peruvian Central Andes. Understanding and predicting the behaviors 77 of precipitation and MCSs in the Peruvian Central Andes region are therefore crucial, and 78 understanding the potential impacts of climate change on MCSs is equally important. Re-79 search findings in this area can significantly shape water management practices, disaster 80 preparedness, climate change adaptation strategies, and enhance the resilience of local com-81 munities and economies to weather-related hazards in a changing climate (Martínez et al., 82 2008; Vergara et al., 2011; Drenkhan et al., 2015; Gonzalez et al., 2019). 83

The current understanding of precipitation and MCSs in the Andes and its surrounding 84 regions, however, is limited by the scarcity of public observational databases, especially the 85 scarcity of upper-air radiosonde observations in the region (Condom et al., 2020). State-of-86 the-art global climate models, such as those participating in the Coupled Model Intercompar-87 ison Project Phase 6 (CMIP6) program (Juckes et al., 2020), provide invaluable information 88 on large-scale climate changes over South America. However, limited by available comput-89 ing resources, the resolutions of these global climate models are too coarse (mostly at grid 90 spacings of ~ 100 km) to resolve local orography and weather phenomena that are important 91 for precipitation production (e.g., MCSs) (Giorgi, 2019; Juckes et al., 2020; Kendon et al., 92 2021). Numerous studies have highlighted the added value of convection-permitting models 93 (CPMs, typically at a grid spacing of less than 4 km) for simulating precipitation and MCSs 94 in different regions worldwide (A. Prein et al., 2013; Fosser et al., 2015; Sun et al., 2016; 95 Gao et al., 2017; Karki et al., 2017; Liu et al., 2017; Stratton et al., 2018; Zhu et al., 2018; 96 Berthou et al., 2020; Fumière et al., 2020; Guo et al., 2020; Kouadio et al., 2020; Lind et 97 al., 2020; A. F. Prein et al., 2020; Li et al., 2021; Halladay et al., 2023; Paccini & Stevens, 98 2023). CPMs can significantly improve the representation of land surface conditions includ-99 ing complex topography as well as mesoscale and convective-scale dynamics. Most notably, 100 deep convection can be represented explicitly in CPMs, rather than being parameterized 101 using cumulus schemes which is a major source of uncertainty in quantitative precipitation 102 forecasting. 103

For example, Sun et al. (2016) found that a 4-km regional climate simulation for the 104 U.S. Great Plains more successfully reproduced the magnitude of extreme precipitation and 105 the diurnal cycle of precipitation than a corresponding 25-km simulation. The 4-km grid also 106 more realistically simulated the low-level jet and related atmospheric circulations important 107 for low-level moisture transport. A. F. Prein et al. (2020) presented a CPM climate simula-108 tion over North America at a 4-km grid spacing that was able to capture key characteristics 109 of observed MCSs such as size, precipitation rate, propagation speed, and lifetime, though an 110 underestimate of MCS frequency in the central US during late summer was noted. Paccini 111 and Stevens (2023) demonstrated that simulations at convection-permitting grid spacings 112 (2.5-5.0 km) improved the distribution of precipitation intensity as well as the represen-113 tation of rainfall diurnal cycle over the Amazon Basin. Better representation of organized 114 convective systems played a key role in improving the precipitation simulations. Halladay et 115 al. (2023) presented a CPM regional climate simulation using the Met Office Unified Model 116 at a 4.5-km resolution for South America covering the period of 1998–2007. They found 117 significant improvements in the representation of precipitation in terms of its diurnal cycle, 118 frequency, and sub-daily intensity distribution. To date, CPM regional climate simulations 119 targeting South America remain limited in number (e.g., V. Schumacher et al., 2020; Bet-120 tolli et al., 2021; Lavin-Gullon et al., 2021; Junquas et al., 2022; Dominguez et al., 2023; 121 Halladay et al., 2023; Paccini & Stevens, 2023). Among these, Halladay et al. (2023) and 122 Paccini and Stevens (2023) are the two recent studies over South America covering part of 123 the Peruvian Central Andes region, however, their research is primarily focused on weather 124

phenomena specific to the Amazonia region. Hence, CPM regional climate simulations and
 associated research for the Peruvian Central Andes region are still needed.

In light of the lack of long-term reliable observations and insufficient understanding of the role of climate change in precipitation and MCSs in the Peruvian Central Andes region, the present study employs convection-permitting simulations and available precipitation products to probe into the characteristics and mechanisms of precipitation and MCSs in this region. This study will also provide information on the feasibility of using CPM simulations for climate change assessments, particularly in terms of precipitation and MCSs in the Peruvian Central Andes region.

The remainder of this paper is organized as follows: Section 2 describes the datasets employed in this study, along with the model configuration of CPM simulations. In Section 3, the characteristics of precipitation and MCSs are presented and discussed. A summary is offered in Section 4.

¹³⁸ 2 Data and Method

2.1 Observational data

For the evaluation of simulated precipitation, three global gridded precipitation datasets 140 are utilized: the half-hourly Integrated Multi-satellitE Retrievals for GPM (IMERG) at 0.1° 141 $\times 0.1^{\circ}$ resolution (Huffman et al., 2019), the half-hourly NOAA Climate Prediction Center 142 (CPC) MORPHing Technique (CMORPH) with a grid spacing of approximately 8 km (Joyce 143 et al., 2004), and the 3-hourly Multi-Source Weighted-Ensemble Precipitation (MSWEP) 144 version 2, also at $0.1^{\circ} \times 0.1^{\circ}$ resolution (Beck et al., 2019). Gauge stations incorporated by 145 IMERG and MSWEP are very sparse in our study region (Huffman et al., 2019; Beck et 146 al., 2019), and CMOPRH does not integrate rain gauge data into its precipitation estimates 147 (Joyce et al., 2004). Monthly precipitation data from approximately 400 rain gauge stations 148 in Peru (red dots in Fig. 1, Aybar et al., 2020) are utilized for the evaluation of monthly 149 precipitation. These datasets have been employed in previous simulation evaluations by this 150 research team (Chen et al., 2022; Huang et al., 2023). Additionally, hourly precipitation 151 data from 10 rain gauge stations within the study region, mainly in the western Amazon 152 Basin of Brazil (magenta dots in Fig. 1, accessible at https://bdmep.inmet.gov.br), have 153 been collected for the specific evaluation of diurnal cycle of precipitation. 154

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2.2 Model configuration

The simulations conducted in this study utilize the Weather Research and Forecasting 156 (WRF) model with two one-way nested domains, and their configurations are similar to 157 those described by Huang et al. (2023), which are summarized in Table 1. The outer domain 158 (d01) covers the entirety of South America with a horizontal grid spacing of 15 km, and 159 the inner domain (d02) specifically targets the Peruvian central Andes region with a 3-km 160 horizontal grid spacing (Fig. 1). The hourly, 0.25° ECMWF atmospheric reanalysis version 161 5 (ERA5) data (Hersbach et al., 2020) are used for initial and boundary conditions. Our 162 previous short-term sensitivity tests (Huang et al., 2023) revealed a pronounced sensitivity 163 of simulated precipitation in the Peruvian central Andes region to the choice of planetary 164 boundary layer (PBL) schemes, which can be attributed to differences in free-troposphere 165 mixing in the presence of clouds (X.-M. Hu et al., 2023). We will evaluate whether the 166 performance of CPMs in simulating precipitation and MCSs is similar to our short-term 167 sensitivity study (Huang et al., 2023). Consequently, this study includes two simulations, 168 each employing a different PBL scheme: ACM2 and MYNN level 2.5 based on our previous 169 sensitivity tests (Huang et al., 2023) (Table 1). Limited by computational resources, the 170 simulations cover the period of 2014-2019 with the initial year (2014) serving as the spin-up 171 period, primarily for the land surface model. Hereafter, the two simulations are referred to 172 as WRF3km_ACM2 and WRF3km_MYNN, respectively. 173

Additionally, a simulation with a grid spacing of 4 km, covering the entire South Amer-174 ica (Dominguez et al., 2023), produced by the South America Affinity Group (SAAG) led 175 by National Center for Atmospheric Research (NCAR), is also collected, and the simu-176 lation dataset is available at https://ral.ucar.edu/projects/south-america-affinity 177 -group-saag/model-output. Hereafter, this dataset is referred to as WRF4km_SAAG. The 178 WRF4km_SAAG simulation covers a 22-year period (Jan 2000 – Dec 2021) and also uses 179 0.25° ERA5 reanalysis data for boundary conditions (Dominguez et al., 2023). The main 180 physics parameterizations used are: YSU PBL scheme (Hong & Lim, 2006), Thompson mi-181 crophysics scheme (Thompson et al., 2008), RRTMG radiation scheme (Iacono et al., 2008), 182 and the Noah-MP land surface model (Niu et al., 2011) with an activated Miguez-Macho-Fan 183 groundwater scheme (Miguez-Macho et al., 2007; Barlage et al., 2021). 184

To facilitate comparison among the observational and simulated datasets at various resolutions, CMORPH, MSWEP, and the simulated fields are regridded to match the IMERG grid $(0.1^{\circ} \times 0.1^{\circ})$ utilizing the "patch recovery" technique, a method previously employed by Sun et al. (2016) and Huang et al. (2023). The time period analyzed in this study spans 2015 through 2019, encompassing a total of five years.



Model d02 (3-km), rain gauges in Peru & Brazil, study regions

Figure 1. Terrain height (shaded, m) in the 3-km domain with the locations of rain gauges in Peru (red dots) and Brazil (magenta dots). The blue rectangle indicates the region of Figs. 2 and 4. The orange rectangle indicates the region of Figs. 7, 9, 12, and 13.

Table 1.	Summary of	WRF3km_ACM2	2 and WRF3km_MYNN ^{a}
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	domain 1 $(d01)$	domain 2 $(d02)$	
Model	WRF V4.2.1 (Skamarock et al., 2019)		
Initial and boundary conditions	ERA5 hourly reanalysis (Hersbach et al., 2020)		
Simulation period	2014-2019 with 2014 as the spin-up period		
Grid spacing	$15 \mathrm{km}$	$3~{ m km}$	
Spectral nudging	On (Huang et al., 2023)	Off	
Cumulus	Tiedtke (Tiedtke, 1989)	Off	
Planetary boundary layer	MYNN level 2.5 (Nakanishi & N	Niino, 2009) or ACM2 (Pleim, 2007)	
Microphysics	Thompson (The	ompson et al., 2008)	
Land surface model	Unified Noah	(Ek et al., 2003)	
Surface layer scheme	revised MM5 Monin-Ob	ukhov (Jiménez et al., 2012)	
Longwave and shortwave radiation	RRTMG (Iacono et al., 2008)		

^aMore details can be referred to Huang et al. (2023).

¹⁹⁰ 2.3 MCS identification

Python package Tracking and Object-Based Analysis of Clouds (TOBAC, Heikenfeld et 191 al., 2019) is adopted to identify and track MCSs based on the observed and simulated hourly 192 precipitation datasets. In this study, MCSs are identified using a precipitation threshold of 193 5 mm h^{-1} , which is commonly used in previous studies (Schwartz et al., 2017; A. F. Prein 194 et al., 2017, 2020; Hwang et al., 2023). An object is characterized as a spatially and 195 temporally contiguous precipitation region with a minimum area of 1000 km^2 , approxi-196 mating a horizontal scale on the order of 100 km (https://glossary.ametsoc.org/wiki/ 197 Mesoscale_convective_system). Utilizing the TOBAC output, various MCS characteris-198 tics are calculated, including hourly mean precipitation, hourly peak precipitation, hourly 199 precipitation volume, MCS size, duration, and propagation speed. 200

201 3 Results

3.1 Precipitation characteristics

Prior to the investigation of MCS characteristics, the simulation of climatological precipitation features such as seasonal and diurnal distributions are evaluated using the three gridded precipitation products in conjunction with rain gauge data.

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3.1.1 Seasonal precipitation

In terms of the spatial distribution of seasonally averaged precipitation (Fig. 2), the 207 gridded precipitation products IMERG, CMORPH, and MSWEP show consistent seasonal 208 variations in precipitation distribution, as well as the four notable hotspots along the 209 east slope of the Andes where precipitation can exceed 16 mm day^{-1} in austral summer 210 (December-January-February, DJF). From northeast to southwest, the precipitation ex-211 hibits a distinct "strong-weak-strong-weak" spatial pattern. Specifically, it is high over the 212 western Amazon Basin, weakens over the transition between the basin and the foothills 213 of the Andes, increases again along the east slope of the Andes, and then weakens once 214 more over the mountains. The three simulations (Figs. 2d1-f4) successfully reproduce the 215 spatial distributions and seasonal variations of precipitation. The WRF3km_ACM2 simu-216 lation, which demonstrated superior performance in precipitation amount in our previous 217 short-term sensitivity experiments (Huang et al., 2023), yields lower precipitation in com-218 parison to the three gridded precipitation products and the other two simulations. This 219 discrepancy is particularly noticeable in the southeastern region of the domain, where the 220 precipitation is less than 6 mm day⁻¹ during the summer season (DJF) and less than 3 221 mm day⁻¹ in other seasons (Figs. 2d1–d4). The WRF4km_SAAG simulation exhibits more 222 precipitation compared to the other simulations particularly over the mountainous region, 223 where the precipitation exceeds 6 mm day^{-1} during the summer season (DJF) and is over 3 224 mm dav^{-1} in other seasons (Figs. 2f1-f4). A comparison between the gridded precipitation 225 products, the simulations, and the rain gauge data (primarily located over the mountainous 226 region) confirms the overestimate by WRF4km_SAAG (Fig. 3). Among the three gridded 227 precipitation products compared to the rain gauge data, IMERG has the lowest absolute 228 value of bias $(0.16 \text{ mm day}^{-1})$ and root mean square error $(\text{RMSE} = 1.60 \text{ mm day}^{-1})$, and 229 the highest correlation coefficient (0.85) (Fig. 3). Regarding the three simulations, although 230 WRF4km_SAAG has a relatively high correlation with the rain gauge data, with a correla-231 tion coefficient of 0.82, it also exhibits the largest bias (1.19 mm day⁻¹) and RMSE (2.53) 232 $mm day^{-1}$) among all gridded and simulated precipitation data (Fig. 3). Huang et al. (2023) 233 showed that WRF3km_ACM2 simulates monthly precipitation that is the closest to that of 234 the rain gauges in February, 2019, which is also seen in Fig. 3. However, WRF3km_ACM2 235 underestimates the peaks of monthly precipitation in 2016 and 2017. The monthly pre-236 cipitation amount of the WRF3km_MYNN simulation falls between WRF4km_SAAG and 237 WRF3km_ACM2, and the correlation coefficient of WRF3km_MYNN with the rain gauge 238

- data is 0.79, which is also between those of WRF4km_SAAG (0.82) and WRF3km_ACM2
- ²⁴⁰ (0.75) (Fig. 3).



Figure 2. Seasonally averaged precipitation (shaded, mm day⁻¹) for the period of 2015–2019 of (a1–a4) IMERG, (b1–b4) CMORPH, (c1–c4) MSWEP, (d1–d4) WRF3km_ACM2, (e1–e4) WRF3km_MYNN, and (f1–f4) WRF4km_SAAG. (a1–f1) DJF: December-January-February, (a2–f2) MAM: March-April-May, (a3–f3) JJA: June-July-August, and (a4–f4) SON: September-October-November. The black contour in each panel represents 1-km terrain elevation.



Figure 3. Time series of monthly precipitation (in mm day⁻¹) from rain gauges in Peru within the 3-km domain (Fig. 1), and corresponding data from IMERG, CMORPH, MSWEP, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG at rain gauge locations. The averaged bias, root mean square error (RMSE), and correlation coefficient between the gridded precipitation products or simulations and the rain gauge data are included in the legend.

Overall, the three simulations broadly capture the spatiotemporal pattern of precipitation at a seasonal scale, but biases in precipitation do exist. Among the simulations of precipitation, WRF3km_MYNN generally outperforms the other two simulations in the Peruvian Central Andes in a combined consideration of bias, RMSE, and correlation coefficient compared with the rain gauge data.

3.1.2 Diurnal cycle of precipitation

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The diurnal precipitation peak times of IMERG, CMORPH, and the three simulations 247 are shown in Fig. 4. The MSWEP is not included due to its coarser temporal resolu-248 tion (three-hourly). As for IMERG and CMORPH, the diurnal precipitation peak time 249 exhibits three distinct belts from the western Amazon Basin to the Andes mountains with a 250 northwest-to-southeast orientation, and this is consistent across all seasons (Figs. 4a1-b4). 251 All three simulations generally reproduce this pattern (Figs. 4c1–e4). While the gridded 252 precipitation products IMERG and CMORPH may have certain biases in precipitation in-253 tensity, their diurnal precipitation peak time should be reliable. Using the diurnal precipita-254 tion peak time in IMERG as a reference, the seasonal average pattern correlation coefficients 255 with it are 0.900 for CMORPH, 0.856 for WRF3km_ACM2, 0.877 for WRF3km_MYNN, and 256

0.896 for WRF4km_SAAG. The higher correlation coefficient in WRF4km_SAAG is probably due to its larger model domain at a 4-km grid spacing, while the 3-km WRF runs have
a much smaller domain nested within a 15-km grid.

To gain a clearer view of the diurnal precipitation, three regions (represented by blue 260 polygons in Fig. 4) are selected to compute the mean diurnal precipitation over the western 261 Amazon Basin, the Andes foothills, and the mountains, respectively (Fig. 5). Because 262 the spatial distributions of diurnal precipitation peak time are similar across all seasons, 263 only the annual-averaged hourly precipitation as a function of local time is shown in Fig. 264 265 5. The precipitation peak time over the western Amazon Basin primarily occurs between \sim 12–17 LST (Local Standard Time) with the maximum average precipitation of \sim 0.40 and 266 $\sim 0.34 \text{ mm h}^{-1}$ in IMERG and CMORPH, respectively (Fig. 5c). The three simulations are 267 able to capture the peak time period in this region. However, in comparison to IMERG, 268 the simulation WRF3km_ACM2 underestimates the average precipitation with a maximum 269 of $\sim 0.28 \text{ mm h}^{-1}$, while WRF3km_MYNN and WRF4km_SAAG overestimate it with the 270 maximum values of ~ 0.54 and ~ 0.49 mm h⁻¹, respectively (Fig. 5c). When compared to the 271 rain gauge data in Brazil (primarily in the western Amazon Basin region, Figs. 1 and 4a), the 272 magnitudes of precipitation in WRF3km_MYNN and WRF4km_SAAG are closer to the rain 273 gauge data than to IMERG (Fig. 6). IMERG actually underestimates the maximum average 274 precipitation by $\sim 20\%$ when compared to the rain gauge data (Fig. 6). Taking the rain 275 gauge data as a reference, the RMSEs for the annual average diurnal precipitation are about 276 $0.054, 0.074, 0.094, 0.051, \text{ and } 0.037 \text{ mm h}^{-1}$ and their corresponding correlation coefficients 277 are around 0.932, 0.891, 0.861, 0.893, and 0.950 for IMERG, CMORPH, WRF3km_ACM2, 278 WRF3km_MYNN, and WRF4km_SAAG, respectively. This suggests that WRF3km_MYNN 279 and especially WRF4km_SAAG perform well in simulating the diurnal cycle of precipitation 280 over the western Amazon Basin with smaller RMSEs and higher correlations. Similarly, the 281 three simulations reproduce the precipitation peak time periods in the foothill and mountain 282 regions, which occur approximately during 0–7 and 13–19 LST, respectively (Fig. 4). Both 283 WRF3km_MYNN and WRF4km_SAAG generally have larger average precipitation in these 284 two regions compared to IMERG, CMORPH, and WRF3km_ACM2 (Figs. 5a and b). Given 285 the lower RMSE for monthly precipitation in WRF3km_MYNN compared to rain gauge data 286 in Peru (Fig. 3), the intensity bias of diurnal precipitation in WRF3km_MYNN should be 287 smaller than that in WRF4km_SAAG over the mountain region. It should be noted that 288 two distinct precipitation peaks are shown in the foothill region (Fig. 5b). This dual-peak 289 pattern is associated with the specific region selected for calculation, which includes the 290 transition zone of precipitation from the Andean foothills to the western Amazon Basin. 291

Overall, the three simulations successfully capture the spatiotemporal patterns of pre-292 cipitation at a sub-daily scale, but biases in precipitation amounts are evident. When 293 taking into account both the spatial distribution and intensity of diurnal precipitation, 294 WRF3km_MYNN generally outperforms the other two simulations in the mountain re-295 gion. Both WRF3km_MYNN and particularly WRF4km_SAAG demonstrate superior per-296 formance in the western Amazon region. X.-M. Hu et al. (2023) found that during the 297 morning, the free atmosphere cloud decks dissipate much faster in the simulation using the 298 YSU PBL scheme than the simulation using the ACM2 PBL scheme, leading to more surface 299 radiative heating and convective instability therefore more precipitation in the simulation 300 using the YSU PBL scheme. The cloud cover results in less precipitation in the simulation 301 using the ACM2 PBL scheme. 302



Figure 4. Precipitation peak time (shaded, Local Standard Time, LST) in each season calculated from (a1–a4) IMERG, (b1–b4) CMORPH, (c1–c4) WRF3km_ACM2, (d1–d4) WRF3km_MYNN, and (e1–e4) WRF4km_SAAG. The white contour in each panel represents 1-km terrain elevation. The blue polygons in each panel indicate the regions utilized for diurnal precipitation calculation shown in Fig. 5. The magenta dots in (a1) mark the locations of the hourly rain gauge data in Brazil.



Figure 5. Averaged diurnal precipitation (mm h⁻¹) in the (a) mountain, (b) foothill, and (c) plain regions shown in Fig. 4 from IMERG, CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG.



Figure 6. Averaged diurnal precipitation (mm h⁻¹) of rain gauges in Brazil shown in Fig. 4a1 for each season from IMERG, CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG.

303 3.2 MCS characteristics

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The earlier evaluations show that the three WRF simulations effectively reproduce the main features of precipitation at both seasonal and sub-daily time scales in the Peruvian Central Andes region. In the following section, the characteristics of MCSs in this region are examined.

3.2.1 Spatiotemporal distribution and propagation

309 Only the MCSs generated within the region depicted by the orange rectangle in Fig. 1 are considered. This specified region is smaller than the 3-km simulation domain to reduce 310 the influence of domain boundaries on the analysis. The spatial distributions of seasonal 311 MCS genesis frequency in Fig. 7 reveal that the genesis hotspots for MCSs are along the 312 east slope of the Andes and over the western Amazon Basin. These locations coincide 313 with the precipitation hotspots (Fig. 2), and MCSs can account for up to 50% of annual 314 precipitation in some of these hotspots (not shown), which is also revealed in Feng et al. 315 (2021). All three simulations produce spatiotemporal evolutions of MCSs that are consistent 316 with IMERG and CMORPH, but WRF3km_ACM2 notably underestimates the MCS genesis 317 frequency (Fig. 7). The lower frequency is linked to the underestimate of precipitation in 318 WRF3km_ACM2 (Figs. 2, 3, 5 and 6) and the use of a fixed threshold of 5 mm h^{-1} for 319 MCS identification. The differences in MCS frequency are more apparent in the time series 320 in Fig. 8. Specifically, the MCS frequency in WRF3km_ACM2 is generally lower than in the 321 other datasets, especially during the warm seasons of 2016 and 2019 (Fig. 8a). Conversely, 322 WRF3km_MYNN and WRF4km_SAAG display 5-year average MCS frequencies of about 323 200 in January and February (Fig. 8b) and the frequency peaks at around 250 in 2019 324 (Fig. 8a). These two simulations generally exhibit higher MCS frequencies than IMERG 325 and CMORPH during the warm season, exceeding their frequencies by about 20 and 50 326 $(\sim 10\%$ and $\sim 33\%)$ in January and February, respectively (Fig. 8b). However, during the 327 cold season (June and July), WRF3km_MYNN and WRF4km_SAAG simulate about 10 328 fewer MCSs per month compared to IMERG and CMORPH (Fig. 8b). 329



Figure 7. Spatial distribution of MCS genesis frequency (in counts) in $1^{\circ} \times 1^{\circ}$ bin in each season for (a1–a4) IMERG, (b1–b4) CMORPH, (c1–c4) WRF3km_ACM2, (d1–d4) WRF3km_MYNN, and (e1–e4) WRF4km_SAAG. The magenta contour in each panel represents 1-km terrain elevation.



Figure 8. Frequency (in counts) of MCS genesis for (a) each individual month from 2015 to 2019 and (b) the average for each month over the 5-year period for IMERG, CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG.



Figure 9. Spatial distribution of the diurnal MCS genesis frequency (in counts) in $1^{\circ} \times 1^{\circ}$ bin for (a1-a4) IMERG, (b1-b4) CMORPH, (c1-c4) WRF3km_ACM2, (d1-d4) WRF3km_MYNN, and (e1-e4) WRF4km_SAAG. The magenta contour in each panel represents 1-km terrain elevation. The Local Standard Time (LST) here is UTC - 5 h based on the longitude of 75°W. The blue rectangles in a1-e1 and a3-e3 indicate the regions to create wind roses shown in Fig. 10.

Based on the IMERG and CMORPH data, MCSs along the east slope of the Andes 330 start to initiate during nighttime hours (18–00 LST, see Figs. 9a4 and b4) and reach a peak 331 in genesis frequency in the early morning (00–06 LST, see Figs. 9a1 and b1). In contrast, 332 the western Amazon Basin sees a concentration of MCS genesis in the afternoon (12–18 333 LST, Figs. 9a3 and b3). All three simulations successfully replicate these diurnal MCS 334 genesis hotspots at terrain notches and over the Amazon Basin. However, WRF3km_ACM2 335 noticeably underestimates the frequency of MCSs in both the east slope of the Andes and 336 the western Amazon Basin regions (Figs. 9c1-e4). 337

To examine MCS propagation patterns in the Peruvian Central Andes, MCS propaga-338 tion direction and speed in the three notable hotspots along the east slope of the Andes and 339 one over the western Amazon Basin are calculated and displayed in the form of wind roses 340 (Fig. 10). It should be noted that the spokes in each wind rose plot indicate the direction 341 towards which MCSs move. The concentric circles in each wind rose plot are divided into 342 16 sectors at intervals of 22.5° , and each sector would represent a probability of 6.25% if 343 the distribution of MCS propagation were uniform. In observational datasets IMERG and 344 CMORPH, MCSs originating along the Andean east slope mainly propagate parallel to the 345 mountain range (Figs. 10a and b), and the probability of southeastward propagation exceeds 346 10% in both the northern and southern hotspots in IMERG (Fig. 10a). This behavior likely 347 arises from the natural barrier posed by the high, steep Andean slopes. Over the western 348 Amazon Basin, westward propagation dominates with a probability close to 10% in IMERG 349 data (Fig. 10a), which is close to the motion of downwind-developing MCSs estimated by 350 the method proposed by Corfidi (2003) considering the influence of cold-pool factors (not 351 shown). All three simulations can replicate these dominant MCS propagation character-352 istics, although discrepancies in specific directional angles, probabilities, and speeds exist 353 (Fig. 10). For instance, WRF3km_ACM2 shows a notably higher northwestward propaga-354 tion probability both along the east slope of the Andes and over the western Amazon Basin, 355 peaking at probabilities above 15%, a higher value than observed in IMERG (Figs. 10a 356 and c). Northwestward propagation is also prevalent along the east slope of the Andes, as 357 seen in WRF4km_SAAG (Fig. 10e). Compared to WRF3km_ACM2, the WRF4km_SAAG 358 simulation, similar to IMERG (Fig. 10a), exhibits a broader directional spread over the 359 western Amazon Basin, ranging from southward to northwestward, with the highest prob-360 ability of $\sim 10\%$ in the west-northwestward direction (Fig. 10e). WRF3km_MYNN closely 361 aligns with IMERG for MCS propagation along the Andean slope but veers more south-362 westward over the Amazon Basin (Fig. 10d). Additionally, all three simulations simulate 363 higher probabilities for MCS propagation speeds exceeding 65 km h^{-1} compared to IMERG 364 and CMORPH, implying an overestimate of MCS propagation speed in the simulations. 365 However, it should be noted that IMERG and CMORPH also have uncertainties, especially 366 in CMORPH, whose MCS propagation direction has a large difference from IMERG and all 367 simulations (Fig. 10). 368

Overall, although specific discrepancies exist in the MCS genesis frequency and propagation speed, the WRF simulations generally replicate the observed spatiotemporal patterns at both seasonal and diurnal scales and the propagation of MCSs in the Peruvian Central Andes and western Amazon.



Figure 10. Wind roses for MCS propagation in the hotspots along the east slope of the Andes and in the western Amazon Basin shown in Fig. 9 for (a) IMERG, (b) CMORPH, (c) WRF3km_ACM2, (d) WRF3km_MYNN, and (e) WRF4km_SAAG. The concentric circles in each panel indicate the probability (5, 10, 15, and 20%) of propagation direction, divided into 16 sectors at intervals of 22.5°. The colors within the circles represent the MCS moving speed classes, segmented into intervals of 10 km h⁻¹. The magenta contour in each panel represents the 1-km terrain elevation.

373 3.2.2 Statistics of MCS properties

In this section, MCS properties are statistically examined to identify main differences in 374 MCSs among IMERG, CMORPH and all simulations. Properties of MCSs, such as hourly 375 mean precipitation, peak hourly precipitation, size, duration, hourly precipitation volume 376 (equals hourly mean precipitation \times area), and moving speed, are displayed for IMERG, 377 CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG using violin plots 378 (Fig. 11). The MCS properties are generally consistent between IMERG and CMORPH, as 379 well as among the three simulations themselves, as shown in Fig. 11. However, a significant 380 discrepancy exists between the gridded precipitation products, IMERG and CMORPH, and 381 the simulations, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG, particularly in 382 MCS precipitation intensity, including both mean and peak hourly precipitation (Figs. 11a 383 and b). The interquartile range (25th to 75th percentiles) for the mean hourly precipitation 384 in IMERG and CMORPH spans $\sim 8-11$ mm h⁻¹, centering around a median value of ~ 9 385 mm h^{-1} . In contrast, all simulations exhibit a higher interquartile range, covering $\sim 13-19$ 386 mm h^{-1} , and center around median values of about 16 mm h^{-1} (Fig. 11a). The differences 387 between the gridded precipitation products and simulations are also evident in peak hourly 388 precipitation rates. Specifically, the 25th, 50th (median), and 75th percentiles for IMERG 389 are approximately 14, 20, and 28 mm h^{-1} , respectively, and for CMORPH, they are around 390 14, 18, and 24 mm h^{-1} . In contrast, these percentiles are notably higher in the simulations: 391 for WRF3km_ACM2, they are about 35, 46, and 59 mm h⁻¹; for WRF3km_MYNN, they are 392 approximately 38, 48, and 60 mm h^{-1} ; and for WRF4km_SAAG, the values are around 40, 393 51, and 64 mm h^{-1} (Fig. 11b). This suggests that the simulations tend to overestimate the 394 median of peak hourly precipitation by more than 130% compared to the IMERG. Regard-395 ing MCS size, IMERG and CMORPH show 25th to 75th percentile ranges of approximately 396 4700 to 12000 km², with median sizes close to 7000 km² (Fig. 11c). However, the simu-397 lations generally produce smaller MCS sizes, with 25th to 75th percentile ranges spanning 398 about 3000 to 7000 $\rm km^2$ and median sizes around 4000 $\rm km^2$. Despite the smaller sizes, the 399 simulations exhibit higher precipitation intensity (Fig. 11a). Consequently, the simulated 400 and observed hourly precipitation volumes are relatively similar (Fig. 11e). Specifically, the 401 25th to 75th percentile ranges in the simulated and observed hourly precipitation volumes 402 are approximately 0.04 to 0.11 km³ h⁻¹, with median volumes of around 0.065 km³ h⁻¹ 403 (Fig. 11e). Meanwhile, all datasets exhibit a median MCS duration of 3 hours (Fig. 11d). 404 However, the simulations generally produce higher MCS movement speeds, with a median 405 of ~ 36 km h⁻¹, compared to the observed median speeds of ~ 20 km h⁻¹ in IMERG and 406 CMORPH (Fig. 11f), which aligns with the findings presented in Fig. 10. 407

Overall, statistical analyses of MCS properties reveal that the simulations generally 408 overestimate both mean and peak hourly precipitation rates associated with MCSs, and 409 simulate smaller MCS sizes but similar hourly precipitation volumes compared to gridded 410 precipitation products. All datasets agree on a median MCS duration of 3 hours, though 411 simulated MCSs tend to move faster. It should be noted that the discrepancies between the 412 simulations and the gridded precipitation products may also arise from the uncertainties 413 and low effective resolutions of the gridded precipitation products (Guilloteau & Foufoula-414 Georgiou, 2020), thereby emphasizing the need for more reliable observational products. 415



Figure 11. Violin plot of MCS properties including MCS (a) hourly mean precipitation, (b) hourly peak precipitation, (c) size, (d) duration, (e) hourly precipitation volume, and (f) moving speed for IMERG, CMORPH, WRF3km_ACM2, WRF3km_MYNN, and WRF4km_SAAG. The white circles in box-and-whisker plots represent the average value of samples. The distributions and medians of the gridded precipitation products and simulations are significantly different at the 0.05 level, except for MCS duration comparisons between CMORPH and WRF3km_ACM2 or WRF3km_MYNN.

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3.2.3 Diurnal dynamic and thermodynamic factors

⁴¹⁷ Despite noted differences in MCS precipitation intensity, frequency, and movement ⁴¹⁸ speed, all three simulations, particularly WRF3km_MYNN, successfully replicate key spa-⁴¹⁹ tiotemporal distributions and evolution of MCSs across multiple scales. In the subsequent ⁴²⁰ section, diurnal variations of dynamic and thermodynamic fields from the 3-km simulations ⁴²¹ WRF3km_MYNN and WRF3km_ACM2 are used to understand the mechanisms underlying ⁴²² MCS genesis in this region.

From the DJF-seasonal mean hourly horizontal wind fields at 850 hPa in WRF3km_MYNN 423 and WRF3km_ACM2 shown in Figs. 12 and 13, we can see that the mean winds in the ex-424 amined region on the east of the Andes are predominantly northwesterly, influenced mainly 425 by the steep high Andean terrain that blocks the northeasterly SALLJ and turns the flows 426 into northwesterly. However, the mean wind speed in WRF3km_MYNN ($\sim 3.9 \text{ m s}^{-1}$) is 427 closer to that in ERA5 ($\sim 4.6 \text{ m s}^{-1}$, not shown) than that in WRF3km_ACM2 ($\sim 2.6 \text{ m}$ 428 s⁻¹). In WRF3km_MYNN, wind convergence (divergence $< -1 \times 10^{-6} \text{ s}^{-1}$) is primarily 429 found along the east slope of the Andes and over the western Amazon Basin between 00-06430 LST (Figs. 12a-g). Such enhancement of convergence and precipitation in the early morn-431

ing hours near the LLJ terminus (Fig. 14a) can be mostly explained by the boundary layer
inertial oscillation theory (Blackadar, 1957; Xue et al., 2018).

Starting from 07 LST, the convergence zones begin to contract and become concentrated 434 within the basin area around the latitude of 10° S between 12–15 LST (Figs. 12h-p). From 435 16 LST, convergence gradually expands and eventually covers both the Andean slope and 436 the basin regions again (Figs. 12q-x). Such distribution and evolution of wind convergence 437 in WRF3km_MYNN are consistent with those in ERA5 (not shown). The diurnal variations 438 in wind convergence and horizontal wind speeds along the east slope of the Andes (Figs. 12 439 440 and 14a) are consistent with the diurnal variation of MCS genesis in the region, where the frequency of MCSs begins to increase between 18–00 LST and peaks between 00–06 LST 441 (Fig. 9). This suggests that MCS activity and precipitation along the eastern Andean slope 442 are mainly driven by dynamical forcings, such as the uplift of moist air by SALLJ and by the 443 mountain-range-parallel northwesterly flows when they encounter the terrain notches near 444 the precipitation hotspots. In WRF3km_ACM2 (Fig. 13), the area of the wind convergence 445 (divergence $< -1 \times 10^{-6} \text{ s}^{-1}$) first decreases and then increases from 00 to 23 LST, which is 446 consistent with that in WRF3km_MYNN. However, in WRF3km_ACM2 (Fig. 13), the wind 447 convergence (divergence $< -1 \times 10^{-6} \text{ s}^{-1}$) primarily covers the east slope of the Andes and 448 part of the western Amazon Basin between 00–06 LST (Figs. 13a–g). The horizontal wind 449 speeds associated with LLJ are also weaker in WRF3km_ACM2 than in WRF3km_MYNN 450 (Fig. 14). There are few convergence zones in the study region between 12–15 LST (Figs. 451 13h-p). It is consistent with the weaker precipitation ((Figs. 2, 5, and 6) and fewer MCS 452 geneses (Fig. 9) over the western Amazon Basin in WRF3km_ACM2. 453



Figure 12. Diurnal horizontal winds at 850 hPa averaged over the DJF months from 2015 to 2019 in WRF3km_MYNN. In order to see the convergence region clearly, the full wind field is decomposed into two components: Thick vectors represent the time-area-averaged wind in the blue dashed box shown in (a), and thin vectors represent the deviation of the full wind field from the time-area-averaged wind. The orange dot-filled areas indicate the regions with wind divergence less than -1×10^{-6} s⁻¹. The magenta contour in each panel represents 1-km terrain elevation. The Local Standard Time (LST) here is UTC -5 h based on the longitude of 75°W.



Figure 13. As in Fig. 12, but for WRF3km_ACM2.



Figure 14. Height-time cross-section of area-averaged horizontal wind speeds (m s⁻¹) in the regions of (a and c) northern MCS genesis hotspot along the east slope of the Andes and (b and d) the hotspot over the western Amazon Basin (blue rectangles shown in Fig. 9) in (a and b) WRF3km_MYNN and (c and d) WRF3km_ACM2, respectively.

For the western Amazon Basin, convergence is consistently present throughout the day 454 in WRF3km_MYNN (Fig. 12) and ERA5 (not shown). Despite this, MCSs predominantly 455 form between 12–18 LST (Fig. 9), indicating that dynamic convergence associated with low-456 level flows is not the most dominant driver of MCS activity in this region. Thermodynamic 457 forcing likely plays even more important roles in triggering and supporting a majority of 458 MCSs. To further understand the underlying mechanisms, vertical cross-sections of diurnal 459 vertical velocity at the latitude of 10° S are examined, along with maximum convective 460 available potential energy (CAPE) and maximum convective inhibition (CIN) (Figs. 15 and 461 16).462

In WRF3km_MYNN, during the early morning hours (00–06 LST), strong updrafts 463 are observed on the Andean east slope, mainly attributed to enhanced low-level flows (Fig. 464 14a) and associated terrain lifting, although the CAPE values are moderate, ranging from 465 approximately 500 to 1000 J kg⁻¹ (Figs. 15a–g). In the western Amazon Basin, CAPE is 466 comparable, but CIN is noticeably higher (up to $\sim 160 \text{ J kg}^{-1}$) (Figs. 15a–g), inhibiting 467 the triggering of significant convection despite the convergence. Starting at 07 LST, both 468 CAPE and CIN undergo diurnal changes in the basin due to solar radiative heating. CAPE 469 rises to 1200–1600 J kg⁻¹, while CIN approaches zero between 10–15 LST (Figs. 15h–p). 470 Consequently, updraft frequency in the basin increases during this period. During 11–13 471 LST (Figs. 151-n), updrafts shift from the Andean slope to the smaller mountains to the 472 east (around $74^{\circ}W$) with a low CAPE between 400–800 J kg⁻¹, showing the importance of 473 even small terrains here. In contrast, despite maximum CAPE values on the Andean slopes 474 up to 1600 J kg⁻¹ (Figs. 15n–p), updrafts in this region decline, which is largely attributed 475 to divergence in this region associated with enhanced convection upstream over the basin 476 (Figs. 12k-p). Although CAPE starts to decrease and CIN begins to rise after 16 LST, 477 updrafts can persist for a while due to the presence of existing convection and relatively 478 high prior CAPE (> 800 J kg⁻¹, Figs. 15q–u) and previous convection trigger effect. Hence, 479 MCSs in the western Amazon Basin are predominantly influenced by thermodynamic factors. 480 Additionally, updrafts are observed at elevations around 4 km during 12–18 LST over the 481 mountains, aligning with the evolution of CAPE and precipitation in the regions (Figs. 15m-482 s and Fig. 5a). It suggests that thermodynamic factors also have a significant influence on 483 precipitation over these elevated terrains. In fact, over major mountain ranges, afternoon 484 convection is often prevalent, such as over the Rocky Mountains (e.g., Carbone & Tuttle, 485 2008; Sun et al., 2016; Y. Zhao et al., 2023). 486

For the WRF3km_ACM2 simulation (Fig. 16), the diurnal evolution of updrafts, CAPE 487 and CIN are basically consistent with those in WRF3km_MYNN (Fig. 15). However, there 488 exist obvious differences in their magnitudes. From 00 to 07 LST, CAPE in WRF3km_ACM2 489 is around 400 J kg⁻¹ (Figs. 16a–h), which is \sim 100–500 J kg⁻¹ smaller than that of 490 WRF3km_MYNN (Figs. 15a-h). In the meanwhile, CIN in WRF3km_ACM2 is mostly between 80 and 160 J kg⁻¹ and can be up to 200 J kg⁻¹ over the western Amazon Basin, 491 492 which is about 40 J kg⁻¹ higher than that of WRF3km_MYNN (Figs. 16a–h and 15a– 493 h). Therefore, the triggering of updrafts is more inhibited in WRF3km_ACM2, which is 494 consistent with the weaker updrafts in WRF3km_ACM2. Between 08–15 LST, CAPE in 495 WRF3km_ACM2 starts to increase, but it is lower than 1200 J kg^{-1} and mostly around 800 496 J kg⁻¹ over the western Amazon Basin (Figs. 16i–p), about 400 J kg⁻¹ smaller than that in 497 WRF3km_MYNN (Figs. 15i-p). Moreover, CIN is also generally higher in WRF3km_ACM2 498 than in WRF3km_MYNN in this period. Thus, there are much fewer updrafts over the west-499 ern Amazon Basin in WRF3km_ACM2 (Figs. 16i-p). Therefore, the lower CAPE and higher 500 CIN along with the weaker LLJ and fewer convergence zones in WRF3km_ACM2 result in 501 weaker precipitation and fewer MCSs than WRF3km_MYNN. These differences were also 502 found in our previous short-term simulation study (Huang et al., 2023), and analyses in 503 X.-M. Hu et al. (2023) show that the differences in the strength of vertical mixing within 504 the PBL and entrainment flux at the PBL top in different PBL schemes impact the vertical 505 transportation of moisture and momentum. This affects cloud formation and cloud frac-506 tion, ultimately influencing surface radiative heating, CAPE and precipitation (Huang et 507

- al., 2023; X.-M. Hu et al., 2023). Sensitivity experiments in X.-M. Hu et al. (2023) suggest
- that the stronger free-troposphere mixing in ACM2 scheme is the primary factor responsible
- $_{\tt 510}$ $\,$ for the discrepancies in the vertical thermodynamic structure and simulated precipitation
- ⁵¹¹ between the simulations using different PBL schemes.



Figure 15. Vertical cross-section of vertical velocity (shaded, in units of m s⁻¹) along the latitude of 10°S in WRF3km_MYNN. The black curves represent the terrain height (km), and the blue and magenta curves represent CAPE (J kg⁻¹) and CIN(10⁻¹ J kg⁻¹), respectively. The unit of CIN in 10^{-1} J kg⁻¹ is used here to make CIN more visible. The Local Standard Time (LST) here is UTC - 5 h based on the longitude of 75°W.



Figure 16. As in Fig. 15, but for WRF3km_ACM2.

512 4 Summary

To investigate the precipitation and MCSs in the Peruvian Central Andes, a region with 513 complex terrain, two CPM regional climate simulations are run using the WRF model and 514 two PBL schemes, namely ACM2 and MYNN, over a 6-year period (2014–2019) with the first 515 year treated as a spin-up period. These simulations are at a grid spacing of 15 km covering 516 the entire South America and a nested convection-permitting grid spacing of 3 km covering 517 the Peruvian central Andes region. The ERA5 reanalysis data are used to provide the lateral 518 boundary conditions for the 15-km gird. These two CPM simulations combined with the 519 SAAG 4-km simulation covering the entire South America and using the YSU PBL scheme, 520 rain gauge data in Peru and Brazil, and three gridded global precipitation datasets, are used 521 to study the characteristics of precipitation and MCSs in the Peruvian central Andes region 522 and evaluate the capability of models in replicating key observed characteristics. This study 523 provides the evidence on the feasibility of CPM simulations thus configured for projecting 524 the potential impacts of climate change on precipitation and MCSs in this region while 525 pointing out certain deficiencies. The major results are summarized as follows. 526

(1) All three simulations, the two 3-km simulations (WRF3km_ACM2 and WRF3km_MYNN) 527 and the 4-km simulation (WRF4km_SAAG), broadly capture the seasonal spatiotemporal 528 patterns of precipitation, particularly the hotspots associated with the prevailing winds and 529 terrain features along the east slope of the Peruvian Central Andes, although some biases 530 in specific precipitation values are present. Among the simulations, WRF3km_MYNN gen-531 erally outperforms the other two simulations over the mountain regions compared to the 532 gridded precipitation products and available rain gauge data. Meanwhile, WRF3km_MYNN 533 and WRF4km_SAAG display comparable performance in the western Amazon Basin region. 534

(2) The three simulations also effectively replicate the sub-daily spatiotemporal patterns
of precipitation, but biases in precipitation intensity are evident. When taking into account
both the spatial distribution and intensity of diurnal precipitation, WRF3km MYNN generally outperforms the other two simulations in the mountain region. Both WRF3km MYNN
and particularly WRF4km SAAG demonstrate superior performance in the western Amazon region when compared to gridded precipitation products and available rain gauge data
in Brazil.

(3) The simulations generally replicate the observed spatiotemporal patterns and prop-542 agation of MCSs, particularly along the east slope of the Peruvian Central Andes and 543 over the western Amazon Basin, across both seasonal and diurnal time scales. However, 544 specific discrepancies exist in MCS genesis frequency and movement speed. For instance, 545 WRF3km_ACM2 notably underestimates the frequency of MCSs, particularly during the 546 warm seasons of 2016 and 2019. Conversely, WRF3km_MYNN and WRF4km_SAAG tend 547 to overestimate MCS frequency during the warm season. Additionally, all three simulations 548 consistently depict higher frequencies of MCSs with higher moving speeds than those ob-549 served in IMERG and CMORPH, highlighting areas for model improvement. Nonetheless, 550 uncertainties do exist with the IMERG and CMORPH precipitation estimate products, and 551 more robust precipitation observations are needed to obtain more reliable evaluations. 552

(4) Statistical analyses of MCS properties reveal that the simulations generally overestimate both mean and peak hourly precipitation intensity associated with the MCSs, and
produce smaller MCS sizes but similar total hourly precipitation volumes compared to the
gridded precipitation products. Moreover, all datasets agree on a median MCS duration of
~3 hours within the study area, and the simulations generally produce faster MCS moving
speeds compared to the gridded precipitation products.

(5) Analyses of the diurnal variations in dynamic and thermodynamic parameters in dicate that dynamic factors, mainly LLJ-terrain-induced uplift of moisture and energy, are
 the principal drivers for MCS genesis along the east slopes of the Andes. While in the west ern Amazon Basin, MCSs predominantly form in the afternoon and are largely governed by

thermodynamic factors, specifically solar radiation-induced diurnal changes in CAPE and 563 CIN. The lower CAPE and higher CIN along with weaker convergence in WRF3km_ACM2 564 result in weaker precipitation and fewer MCSs than in WRF3km_MYNN. These differences 565 are attributed to the differences in vertical mixing within the PBL and especially entrain-566 ment flux at the PBL top in different PBL schemes. They impact the vertical transportation 567 of moisture and momentum, then cloud formation and cloud fraction, and ultimately sur-568 face radiative heating, CAPE, and precipitation, analyzed previously based on shorter-term 569 simulations (Huang et al., 2023; X.-M. Hu et al., 2023). Besides, similar thermodynamic 570 effects are observed to be the dominant influence on precipitation over elevated mountains. 571

In summary, the investigation of precipitation and MCS characteristics in the Peru-572 vian Central Andes in this study offers valuable insights into both observed patterns and 573 convection-permitting regional climate simulation performances. The findings not only en-574 hance our understanding of the specific precipitation and MCS characteristics within this 575 region, but also document the differences between observations and the WRF simulations, 576 which can inform future model improvements. It should be noted that the discrepancies 577 between the gridded precipitation products and the simulations may also arise from the 578 uncertainties and low effective resolutions of the gridded precipitation products (Guilloteau 579 & Foufoula-Georgiou, 2020), thereby emphasizing the need for more reliable observational 580 products. Despite the presence of biases, the CPM simulations effectively capture the fun-581 damental mechanisms that govern precipitation and convective systems in the Peruvian 582 Central Andes region. It suggests the feasibility of CPM simulations for projecting the po-583 tential impacts of climate change on precipitation and MCSs in the region, thereby providing 584 critical input for tailored climate adaptation strategies in this region, especially after bias 585 correction/calibration of the model projections. Two future climate simulations have been 586 conducted using the same model configuration as WRF3km_MYNN, focusing on two shared 587 socioeconomic pathway (SSP) scenarios, SSP2-4.5 and SSP5-8.5, that represent the medium 588 and high emission scenarios, respectively. The choice of the WRF3km_MYNN configuration 589 was based on the evaluations of the historical simulations reported in Huang et al. (2023), 590 X.-M. Hu et al. (2023), and this study. These simulations are driven by a bias-corrected 591 global dataset, derived from a CMIP6 multi-model ensemble (Xu et al., 2021). The SAAG 592 future simulation is running as well using a pseudo global warming approach and targeting 593 a warming level of $\sim 2.5^{\circ}$ C in the period of 2060–2080 over South America (Dominguez et 594 al., 2023). Projected changes in precipitation and MCSs in the Peruvian Central Andes 595 region, based on these CPM simulations, will be analyzed and reported in the future. 596

⁵⁹⁷ Open Research Section

ERA5 reanalysis data are available at https://doi.org/10.5065/BH6N-5N20. GPM 598 IMERG Final Precipitation dataset is available at https://doi.org/10.5067/GPM/IMERGDF/ 599 DAY/06 (last access: 12 November 2020). CMORPH dataset is available at https:// 600 ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0/CRT/8km-30min (last access: 12 November 601 2020). MSWEP dataset is available at http://www.gloh2o.org/mswep (last access: 17 602 July 2021). The rain gauge data in Peru are available at https://piscoprec.github.io/ 603 webPISCO/en/raingauges (last access: 18 July 2021). The rain gauge data in Brazil are 604 available at https://bdmep.inmet.gov.br (last access: 19 January 2023). The SAAG 605 4-km simulation dataset is available at https://ral.ucar.edu/projects/south-america 606 -affinity-group-saag/model-output (last access: 18 July 2022). The model outputs are too large to be publicly archived. Please contact the corresponding author for more 608 information. 609

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