Top-of-Atmosphere Radiation Budget and Cloud Radiative Effects Over the Tibetan Plateau and Adjacent Monsoon Regions From CMIP6 Simulations

Jiadong Li1,2, Zhian Sun3, Yimin Liu1, Qinglong You4, Guoxing Chen4, and Qing Bao1

1State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China, 2Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science and Technology, Nanjing, China, 3Science to Services, Science and Innovation Group, Australian Bureau of Meteorology, Melbourne, Vic, Australia, 4Department of Atmospheric and Oceanic Sciences & Institute of Atmospheric Sciences, Fudan University, Shanghai, China

Abstract This study investigates the top-of-atmosphere (TOA) radiation budget ($R_T$) and cloud radiative effects (CREs) over the Tibetan Plateau (TP) and adjacent Asian monsoon regions including Eastern China (EC) and South Asia (SA) using the Coupled Model Intercomparison Project 6 (CMIP6) simulations. Considerable simulation biases occur but specific causes differ in these regions. Most models underestimate the intensity of annual mean $R_T$ and cloud radiative cooling effect over the TP, and the $R_T$ during the cold-warm transition period is hard to capture. The biases in surface temperature and cloud fractions substantially contribute to cloud-radiation biases over the western and eastern TP, respectively. Over EC, the intensity of $R_T$ and cloud radiative cooling effect is seriously underestimated especially in the springtime when the model spread is large, and their biases are closely related to less low-middle cloud fractions and weaker ascending motion. Over SA, simulation biases mainly arise from longwave radiative components associated with less high cloud fraction and weaker convection, with the large model spread in the summertime. The annual cycles of $R_T$ and CREs over EC and SA can be well reproduced by most models, while the summertime peak of the net CRE over the TP occurs later than the observation. The $R_T$ and its simulation bias strongly depend on the cloud radiative cooling effect over EC and SA. Our results demonstrate that contemporary climate models still have obvious difficulties in representing various complex cloud-radiation processes in Asian monsoon regions.

1. Introduction

The Tibetan Plateau (TP), the largest and highest plateau in the world, strongly influences Asian climate and global circulation (Flohn, 1957; Liu et al., 2020; Wang, Duan, & Wu, 2014; Wu et al., 2007, 2015; Xu et al., 2015; Yanai et al., 1992; Yeh et al., 1957). Eastern China (EC) and South Asia (SA), adjacent to the TP, have significant features of the Asian monsoon climate such as remarkable seasonal variation of circulation, precipitation, and cloud fractions (Ding & Chan, 2005; Luo et al., 2009; Tao & Chen, 1987; Webster et al., 1998; Zhao et al., 2019). These three subregions are integral parts of the whole Asian monsoon region, and regional surface temperature, precipitation, and cloud-radiation processes are very sensitive to current climate change (Ma et al., 2021; Turner & Annamalai, 2012; B. Wang et al., 2020; You et al., 2020). Understanding and predicting the Asian monsoon climate is of great scientific and societal importance owing to its huge impact on the population of a large region and sustainable socio-economic development. Clouds play a vital role in the Earth’s energy balance and the water cycle. The cloud-radiation process is one of the major uncertainties in current climate simulations and predictions (Boucher et al., 2013; Stephens, 2005; Webb et al., 2017). A reasonable projection for the TP and Asian monsoon climate, therefore, highly depends on an in-depth understanding of cloud-radiation processes and their improvement in climate models (B. Wang et al., 2020; T. Zhou et al., 2016).

Complex topography, various surface types, and strong land-sea contrast are distributed in the TP and adjacent Asian monsoon regions, where circulation and cloud-radiation processes exhibit pronounced subregional features (Wu et al., 2007, 2015; Yang et al., 2014). The top-of-atmosphere (TOA) outgoing longwave radiation (OLR) over the TP is lower than that of adjacent low-elevation regions (X. Zhou et al., 2009). The
comprehension effect from the TP topography significantly reduces the geometric thickness of clouds and alters their vertical structure (Luo et al., 2011; H. Wang et al., 2011; Yan et al., 2016). Deep convective clouds occur frequently in the eastern TP in summer (Fu et al., 2020; Luo et al., 2011). EC, to the east of the TP, is a subtropical monsoon region where large amounts of low-middle clouds occur and reflect more shortwave radiation (J. Li et al., 2019; W.-C. Wang et al., 2004; Yu et al., 2004). Considerable spring-summer rainfall is also distributed over EC (Ding et al., 2005; He et al., 2008; Wan & Wu, 2007). SA, to the south of the TP, is a tropical monsoon region where strong convective activities and high clouds with large cloud optical depth prevail, which can produce large upward shortwave radiation and cooling effect at TOA (Rajeevan & Srinivasan, 2000; Saud et al., 2016). It is noteworthy that cloud-radiation characteristics over EC and SA exhibit remarkable differences, such as dominant cloud types and seasonal cycle of cloud and precipitation (J. Li et al., 2017; Luo et al., 2009; Yu et al., 2001; B. Zhang et al., 2020). These differences in cloud-radiation characteristics very likely lead to the uneven regional distribution of atmospheric radiative heating and surface-atmosphere energy over the TP and adjacent Asian monsoon regions. The uneven geographical distribution of surface-atmosphere energy is the basic force driving atmospheric dynamics and thermal states (Trenberth et al., 2009; Webster et al., 1998). Hence, it is critical to investigate key cloud-radiation characteristics and identify their subregional differences over the TP and adjacent Asian monsoon regions for improving cloud-radiation parameterizations and reducing their uncertainties in climate models.

Although current state-of-art climate models can generally capture the global distribution and intensity of major cloud-radiation properties (Dolinar et al., 2014; Flato et al., 2013; Wild et al., 2013), considerable biases in cloud-radiation simulation still exit over Asian monsoon regions (Flato et al., 2013; Lauer & Hamilton, 2013; J. Li et al., 2009; J.-L. F. Li et al., 2013; Wang, Yang, & Wu, 2014). These biases contribute to current difficulties in simulation and prediction of the Asian monsoon climate to a high degree (Boo et al., 2011; Sperber et al., 2013; B. Wang et al., 2020; T. Zhou et al., 2016). In present climate models, TOA radiation budget and cloud radiative effects (CREs) are key evaluation metrics (Flato et al., 2013). A reasonable TOA radiation budget is a basic requirement for climate models to well reproduce climate system stability and internal feedback and it is strongly modulated by CREs (Trenberth et al., 2009). CREs represent bulk cloud radiative roles in the surface-atmosphere system and are composed of longwave and shortwave CREs, with radiative cooling and warming roles, respectively (Allan, 2011; Ramanathan et al., 1987). Many climate models underestimated the intensity of the cloud radiative cooling effect over EC (Wang, Yang, & Wu, 2014; Y. Zhang & Li, 2013) and this poor model reproducibility is partly attributed to parameterization difficulties in complex topography, cloud macrophysical and microphysical processes (Y. Zhang et al., 2015; Y. Zhou et al., 2019). The work by J. Li et al. (2019) showed that the spring cloud radiative cooling effect over EC is closely associated with regional ascending motion and water vapor convergence, indicating that simulation biases of CREs are sensitive to regional circulation conditions. Notably, model evaluation studies of key cloud-radiation characteristics remain sparse for the TP and SA regions, although observational analyses were conducted for the two regions (Saud et al., 2016; Yu et al., 2001; Zhao et al., 2019). Moreover, most of the existing model studies paid little attention to the comparison and identification of spatial differences in CREs and the TOA radiation budget and underlying influencing factors over the TP and adjacent EC and SA.

Recently, simulated data from the Coupled Model Intercomparison Project Phase 6 (CMIP6) were released (Eyring et al., 2016). Compared with previous CMIP5 data, spatial resolution and physical processes are significantly improved for climate models participating in CMIP6 (Eyring et al., 2016; Furtado et al., 2016; Kay et al., 2016; Taylor et al., 2012). The CMIP6 simulation was extended to Dec. 2014 and is close to current Clouds and the Earth's Radiant Energy System (CERES) Energy Balanced and Filled (EBAF) satellite retrievals (Loeb et al., 2018), which is the most reliable TOA cloud-radiation satellite dataset so far. Thus, the comparison of CMIP6 data with CERES-EBAF satellite observations can provide a new opportunity to further evaluate and understand cloud-radiation processes over the above Asian monsoon climatic regions.

As for cloud-radiation issues over the TP and adjacent Asian monsoon regions, those of particular interest for the climatic community are (1) how well spatiotemporal features of the TOA radiation budget and CREs are reproduced by the CMIP6 models in annual mean, seasonal and interannual scales; (2) how subregional systematic biases in the simulated TOA radiation budget and CREs are identified and how the reasons for their biases are examined, and (3) the attempt to understand the role of CREs in the TOA radiation budget.
The purpose of this study is to address the abovementioned issues and provide valuable clues for understanding and improving cloud-radiation processes over the TP and adjacent Asian monsoon regions. The paper is organized as follows: Section 2 describes the data and method, Section 3 presents the simulated annual mean states, Section 4 examines the simulated seasonal and interannual variation, Section 5 analyzes the possible causes of simulation biases, and Section 6 gives the conclusion and discussion.

2. Data and Methods

2.1. CMIP6 AMIP Simulations

Atmospheric Model Intercomparison Project (AMIP) simulations from 27 CMIP6 models are used as model results in this study and the model information is listed in Table 1. The AMIP experiment is driven by observed sea surface temperature and sea ice concentration, prescribed greenhouse gases, aerosol, solar, and other forcing terms and is designed to evaluate climate model performance and climate variability (Eyring et al., 2016). Monthly AMIP simulations range from 1979 to 2014. Nine of 27 AMIP models provide CALIPSO satellite simulator output, including total, high-, middle-, and low-cloud fraction data. There are several ensembles for each AMIP model experiment and only run 1 is used in this study.

2.2. Reference Data

2.2.1. Satellite-Derived Data

Monthly CERES-EBAF Ed4.1 data are used to evaluate TOA radiation fluxes and CREs (Loeb et al., 2018, 2020). These data include the TOA incident shortwave radiative flux, outgoing shortwave and longwave radiative fluxes under clear-sky and all-sky conditions, and other details (e.g., retrieval algorithm, process methods, data uncertainties, etc.) that can be referred to from the CERES-EBAF website (http://ceres.larc.nasa.gov). CERES-EBAF is the most reliable data set for TOA radiative fluxes and CREs to date and is widely used as observation to measure the Earth’s radiation balance, cloud roles and their climatic variability. The latest CERES-EBAF Ed4.1 data have a consistent definition of clear-sky fluxes such as those of climate models and can be used to make a proper comparison with the results from climate models (Loeb et al., 2020).

The CERES-EBAF data span from March 2000 to the present day have a spatial resolution of 1° latitude by 1° longitude. In addition, cloud water path from Terra and Aqua MODIS (Collection 6.1 level-3) (King et al., 2013) data are used as reference data to roughly evaluate model counterparts.

To better understand the simulated CREs, the general circulation model (GCM) oriented CALIPSO Cloud data (CALIPSO-GOCCP; herein GOCCP) is used for comparison with the simulated column cloud fraction in the CMIP6 AGCMs that provide CALIPSO satellite simulator output. The GOCCP data span from June 2006 to October 2019 and include the global column total, high-, middle-, and low-cloud fraction data (Chepfer et al., 2010). The GOCCP data have a horizontal resolution of 2° latitude by 2° longitude.

2.2.2. Meteorological Data

The meteorological variables for characterizing the regional atmospheric circulation and surface air temperature (Ts) are obtained from the ERA-Interim reanalysis (spatial resolution of 1.0°) available from January 1979 to the present day (Dee et al., 2011). Monthly precipitation data, with a spatial resolution of 2.5°, are obtained from the Global Precipitation Climatology Project (GPCP; Adler et al., 2003). Despite

| Model ID | Model name       | Spatial resolution (Lat × Lon: degree) |
|----------|------------------|----------------------------------------|
| 1        | ACCESS-CM2       | 1.25 × 1.875                           |
| 2        | ACCESS-ESM1-5    | 1.25 × 1.875                           |
| 3        | BCC-CSM2-MR      | 1.1215 × 1.125                         |
| 4        | BCC-ESM1         | 2.7906 × 2.8125                        |
| 5        | CanESM5          | 2.7906 × 2.8125                        |
| 6        | CAMS-CSM1-0      | 1.1215 × 1.125                         |
| 7        | CESM2*           | 0.9424 × 1.25                          |
| 8        | CNRM-CM6-1       | 1.40 × 1.40625                         |
| 9        | CNRM-CM6-1-HR    | 0.5 × 0.5                               |
| 10       | CNRM-ESM2-1*     | 1.40 × 1.40625                         |
| 11       | ESM1-0*          | 1.0 × 1.0                               |
| 12       | FGOALS-f3-L      | 1.0 × 1.25                              |
| 13       | FGOALS-g3        | 2.0 × 2.025                             |
| 14       | GFDL-AM4         | 1.0 × 1.25                              |
| 15       | GISS-E2-1        | 1.0 × 2.5                               |
| 16       | HadGEM3-GC31-LL  | 1.25 × 1.875                           |
| 17       | HadGEM3-GC31-MM* | 0.555 × 0.8333                         |
| 18       | INM-CM5-0        | 2.0 × 1.5                               |
| 19       | IPSL-CM6a-LR*    | 1.2676 × 2.5                           |
| 20       | KACE-1-0-G       | 1.25 × 1.875                           |
| 21       | MIROC6*          | 1.4007 × 1.40625                       |
| 22       | MRI-ESM2-0*      | 1.1214 × 1.125                         |
| 23       | MPI-ESM1-2-HR    | 0.935 × 0.9375                         |
| 24       | NEM3             | 1.865 × 1.875                          |
| 25       | NorESM2-LM*      | 1.8947 × 2.5                           |
| 26       | SAM0-UNICON      | 0.9424 × 1.25                          |
| 27       | UKESM1-0-LL*     | 1.25 × 1.875                           |

The model with an asterisk has the satellite simulator output.
some uncertainties, the ERA-Interim and GPCP data show very good performance in reproducing regional wind fields, atmospheric moisture, and precipitation over Asian monsoon and TP regions (D.-Q. Huang et al., 2016; Simmons et al., 2014). In this study, CERES satellite retrievals, ERA-Interim meteorological fields, GPCP precipitation, and GOCCP data are used as observational data.

2.3. Methods

2.3.1. Definition of Key Concepts

The TOA radiation budget ($R_T$) is the difference between the TOA net incident shortwave radiation (ASR) and OLR, and it represents the net TOA energy of the surface-atmosphere system (Trenberth et al., 2009, 2015). The intensity of $R_T$ is highly dependent on cloud radiative roles. Generally, the cloud radiative cooling (warming) role weakens (intensifies) the intensity of $R_T$.

The CREs are defined as the difference in radiative fluxes at TOA between clear-sky and all-sky conditions (Allan, 2011; Ramanathan, 1987), and include longwave and shortwave CREs (herein, LWCRE and SWCRE). The net CRE (NCRE) is the arithmetic sum of LWCRE and SWCRE. These terms effectively measure the immense role of clouds in the atmosphere-surface system and are therefore widely used in researches on model evaluation, climatic variability, and uncertainties (Boucher et al., 2013).

Note that the sign of SWCRE is negative and its decrease in absolute values denotes that the effect of clouds on shortwave radiation is weaker. The same applies to NCRE except for high surface albedo regions. The abbreviations of the variable names used in this study are listed in Table 2.

2.3.2. Evaluation Metrics

To evaluate the climatological states of CMIP6 simulations, statistical metrics including domain overall mean (bias), relative bias (RB), spatial (pattern) temporal correlation, standard deviation, and root-mean-square error (RMSE) are used to represent model reproducibility compared with observed states. These statistical metrics are commonly used in model assessment (Pincus et al., 2008; Taylor, 2001; Wang, Yang, & Wu, 2014), and their use and formulas are listed under the supporting information. To clearly represent simulation skills of CMIP6 AMIP models, we used a simplified square Taylor diagram to quantitatively show simulated spatial similarity and biases and the model spread degree.

In this study, the 500-hPa vertical velocity and surface temperature from the CMIP6 simulations are compared to ERA-Interim data to understand the roles of atmospheric ascending motion and surface thermal state in CREs and $R_T$.

2.3.3. Data Treatment

The observational and simulated data during 2001–2014 are extracted to analyze climatological annual mean, seasonal, and interannual variation. GOCCP and corresponding model data during 2007–2014 are used to investigate simulated biases of cloud fractions and CREs. The run one in each model AMIP ensemble is selected. The multi-model ensemble (MME) is based on the equal-weighted average of individual models. To obtain MME and facilitate intercomparison among models, AMIP simulations are regridded into a common horizontal resolution of 1.0° latitude by 1.25° longitude via bilinear interpolation.

In this study, the domain of TP is specified as 27.5°–37.5°N and 80°–100°E, and adjacent East China (EC) and SA monsoon regions are set in an area of 22°–32°N and 102°–122°E and 15.5°–25.5°N and 80°–100°E, respectively (Figure 1c).

3. Annual Mean States

3.1. Observational States

3.1.1. Geographical Distribution of Annual Mean Cloud-Radiation Variables

Figure 1 presents the global distribution of annual mean $R_T$. The zonal variation of $R_T$ is small in the Southern Hemisphere but large in the Northern Hemisphere due to its larger land area and more complex topography. The large NCRE is mainly located in the Pacific and Atlantic stratus regions, midlatitude storm
track regions, EC, and South Ocean. The $R_T$ in most parts of the TP is up to 10 W m$^{-2}$ and is the strongest positive $R_T$ in land areas of the same latitude (Figure 1a). Over the TP, the OLR and surface temperature (not shown) are lower relative to adjacent regions (Figure 2b). Subtropical EC lies downstream of the TP, with a negative $R_T$ from −40 to −20 W m$^{-2}$ and the largest cloud radiative cooling effect up to −60 W m$^{-2}$ at the same latitudes (Figures 1a–1b). Over EC and south flank of the TP, the strong negative $R_T$ coincides with large ASR, total cloud fraction (TCF), and NCRE (SWCRE) (Figures 1b, 2a, 2d, and 2f), indicating that regional $R_T$ is strongly related to the cloud radiative cooling role in the two regions. South Asian regions to the south of the TP are tropical monsoon regions where the obvious positive $R_T$ and negative NCRE occur. Although there is considerable amount of TCF, the offset between LWCRE and SWCRE makes the intensity of NCRE over SA and the TP weaker than that over EC (Figures 1b, and 2–2f). Over SA, the TOA net incident shortwave radiation (ASR) is larger than those over EC and TP due to its lower latitude (Figure 2a). These results demonstrate the pronounced subregional differences of cloud-radiation features over the TP and adjacent Asian monsoon regions.

### 3.1.2. Domain-Averaged Values of TOA Cloud-Radiation Variables

Table 3 lists annual mean values of domain average TOA radiative fluxes and CREs. The annual mean $R_T$ over EC, SA, and the TP are −12.0, 28.8, and 7.7 W m$^{-2}$, respectively. The ASR over EC and the TP are
The latitude of the TP is the highest but its TOA incident shortwave radiation is the lowest among these three regions. The OLR over the TP is 220.3 W m\(^{-2}\) and is much lower than those over EC (243.6 W m\(^{-2}\)) and SA (253.1 W m\(^{-2}\)). The relatively lower OLR over the TP is directly responsible for its remarkable positive \(R_T\). The RSUT, SWCRE and NCRE over EC are 142.6, –83.3, and –48.6 W m\(^{-2}\), respectively, and their intensity is much larger than the counterparts over SA and the TP.

3.2. Simulated Annual Mean States

3.2.1. Simulated Annual Mean States of \(R_T\)

Figure 3 shows the geographical distribution of annual mean \(R_T\) simulated from CMIP6 AMIP models. Over the TP, most models can capture the \(R_T\) distribution, especially positive \(R_T\) value over the central and eastern TP and negative \(R_T\) value over the south flank of the TP, but somewhat underestimate the \(R_T\) over the western TP (Figure 3). The regional mean biases of \(R_T\), ASR, and OLR in MME are –4.0, –10.1, and –6.1 W m\(^{-2}\), respectively, and their pattern correlation coefficients (PCCs) are 0.48, 0.66, and 0.94, respectively, over the TP (Table 4). The domain-mean OLR bias is 60% of the ASR over the TP, and ASR is mainly responsible for regional mean bias and spatial pattern of \(R_T\) in many models. In particular, the seriously underestimated \(R_T\) over the western TP is directly linked to the underestimated ASR in CanESM5, CNRM-CM6-1, CNRM-ESM2-1, FGOALS-g3, and MIROC6 (Figure S1), and their PCCs are less than 0.2 over the TP (Figure 5h).

Over EC, most models can roughly represent the spatial pattern of \(R_T\) but seriously underestimate its magnitude (Figure 3). The regional mean \(R_T\) in MME over EC is 1.0 W m\(^{-2}\) and its intensity is much lower than the observational value of –12.0 W m\(^{-2}\) (Figure 4a). As listed in Table 4, the regional mean value and RB of ASR in MME over EC are 15.0 W m\(^{-2}\) and 6.5%, respectively, and much larger than the counterparts (2.0 W m\(^{-2}\) and 0.8%) of OLR. The annual mean OLR bias averaged over EC is only 13.3% of the ASR bias. This indicates that the simulated weaker \(R_T\) is mainly attributed to the overestimated ASR. Over EC, regional mean \(R_T\) in ACCESS-ESM1-5 (–14.0 W m\(^{-2}\)), CAMS-CSM1-0 (–7.4 W m\(^{-2}\)), GISS-E2-1-G (–16.4 W m\(^{-2}\)), and MRI-ESM2-0 (–14.3 W m\(^{-2}\)) are relatively close to the observation and their absolute RBs are less than 40% (Figure 4a). Meanwhile, these four models also reproduced well the regional mean ASR over EC, with absolute RBs less than 30% (Figure 4b). ACCESS-ESM1-5 (0.81), CanESM5 (0.80), and CESM2 (0.81) have higher PCCs of \(R_T\) than MME (0.76; Figures 3 and 5a). Note that the sign of regional mean \(R_T\) in CanESM5 and BCC-ESM1 is positive, suggesting that the two models actually cannot reasonably represent \(R_T\) over EC (Figure 4a). The PCCs of \(R_T\) in FGOALS-g3 and IPSL-CM6A-LR are only 0.17 and –0.02, respectively, and they even produced evident positive \(R_T\) over EC (Figures 3m, 3s, and 5a) as a result of their larger biases and poor spatial reproducibility of ASR (Figures 5b and S1). This further demonstrates that the spatial pattern of \(R_T\) in these AMIP models is mainly related to that of the simulated ASR.

Over SA, most models can reproduce the positive \(R_T\) although the simulated \(R_T\) intensity is weaker than the observation (Figure 3). The regional mean \(R_T\) and RB in MME are 26.0 W m\(^{-2}\) and –9.6% (Table 4), respectively. Most models can reproduce well the spatial patterns of \(R_T\) and ASR over SA, with PCCs over 0.7 (Figures 5d–5e). The regional mean biases of ASR and OLR in MME are 0.6 and 3.4 W m\(^{-2}\), respectively, but the ASR bias is only 17.6% of the OLR bias, showing that the underestimated \(R_T\) over SA is mainly caused by the underestimated OLR (Table 4). The PCC of OLR in MME is 0.83, which is lower than the ASR (0.95) and \(R_T\) (0.94) over SA (Table 4). The low PCCs of OLR in some models (e.g., ACCESS-ESM1-5, E3SM-1-0, LI ET AL.
HadGEM3-GC31-LL, MPI-ESM1-2-HR) are less than 0.4 (Figure 5f) and their poor reproducibility may be related to the unreasonable location of the tropical strong convection over SA (Figure S3).

Note that MME can reproduce better the spatial pattern of RT, OLR, and ASR, with higher PCCs compared with those in individual models over the above three regions (Figures 5, S1, and S3).

3.2.2. Simulated Annual Mean States of CREs

Figure 6 shows the geographical distribution of annual mean NCRE simulated from CMIP6 AMIP models. Over the TP, most models can reproduce the large NCRE over the eastern TP and south flank of the TP (Figure 6). Most models can represent well the spatial pattern of NCRE (SWCRE; Figures 6 and S6), with the PCC of 0.87 (0.92) in MME (Figures 8g–8h), but have relatively worse reproducibility for LWCRE (Figure S5), with the PCC of 0.61 in MME (Figure 8i). Most models underestimate the intensity of NCRE, especially over the western TP (Figure 6). The regional mean NCRE in MME is −17.5 W m⁻² (Figure 7g). The regional mean biases of NCRE, SWCRE, and LWCRE in MME over the TP are 7.2, 11.2, and −3.9 W m⁻² (Table 4), respectively, suggesting that the weak simulated NCRE arises mainly from underestimating the strength of SWCRE. By comparison, ACCESS-CM2, HadGEM3-GC31-LL, HadGEM3-GC31-MM, and UKESM1-0-LL have better simulation skills regarding the PCCs and RMSEs of CREs (Figures 8g–8i).

Over EC, most models can represent large negative NCRE, but underestimated the intensity of NCRE (Figure 6). The regional mean value of NCRE in MME is −48.6 W m⁻² (Figure 7a). Many models fail to capture the regional center of NCRE over southwestern China (Figure 6), resulting in their poor PCCs of NCRE (Figure 8a), and the PCC of NCRE in MME is 0.59 (Table 4). As shown in Figures 7b–7c and Table 4, the regional mean biases of SWCRE and LWCRE in MME are 22.0 W m⁻² and −10.4 W m⁻² averaged over EC, respectively. Although the underestimated LWCRE makes a substantial contribution to the NCRE bias, the underestimated intensity of SWCRE still accounts for the majority of the NCRE bias and.

| Table 3 | Annual Mean Top-Of-Atmosphere (TOA) Radiation Fluxes and Cloud Radiative Effects (CREs) From CERES-EBAF Averaged Over Eastern China (EC: 22°–32°N, 102°–122°E), South Asia (SA: 15.5°–25.5°N, 80°–100°E) and the Tibetan Plateau (TP: 27.5°–37.5°N, 80°–100°E) |
|---------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
|         | EC | SA | TP |
| RSDT    | 374.1 | 391.1 | 356.4 |
| ASR     | 231.6 | 281.9 | 228.0 |
| RSUT    | 142.6 | 109.3 | 128.4 |
| OLR     | 243.6 | 253.1 | 220.3 |
| RT      | −12.0 | 28.8 | 7.7 |
| LWCRE   | 34.6 | 37.8 | 28.3 |
| SWCRE   | −83.3 | −50.1 | −53.0 |
| NCRE    | −48.6 | −12.3 | −24.7 |

Units: W m⁻².
determines the sign of NCRE over EC. The spatial pattern and PCCs of simulated NCRE in models are also very similar to their SWCRE (Figures 6, 8a–8b, and S6). The PCCs of SWCRE and LWCRE in MME are 0.52 and 0.31 over EC, respectively (Table 4). The PCCs of NCRE in CESM2, ACCESS-ESM1-5, MRI-ESM2-0, MPI-ESM1-2-HR, and NESM3 are larger than MME (Figure 8a), and these models can capture the regional center of NCRE over southwestern China (Figure 6). Compared to other models, CESM2 and MPI-ESM1-2-HR can reproduce better NCRE over EC (Figure 6), with PCCs of 0.73 and 0.67, respectively (Figure 8a).

Over SA, unlike EC and the TP, most models overestimate the intensity of cloud radiative cooling effect (Figure 6) and the regional mean NCRE ($-18.6$ W m$^{-2}$) in MME is stronger than the observation ($-12.3$ W m$^{-2}$; Figure 7d; Table 4). As listed in Table 4, regional mean biases of SWCRE and LWCRE in MME are 3.0 and $-9.3$ W m$^{-2}$ averaged over SA, respectively. The overestimated NCRE is mainly attributed to the underestimated LWCRE. Most models can reproduce the spatial pattern of NCRE (LWCRE and SWCRE) over SA (Figures 6, S5, and S6). The MME can substantially improve simulated $R_T$ and NCRE, and their longwave and shortwave counterparts, especially for their spatial distribution. The PCCs of $R_T$, ASR, and OLR (NCRE, SWCRE, and LWCRE)
of MME are higher than most individual models (Figures 5 and 8). In Figures 5 and 8, the center RMSE is used to measure the spatial pattern biases and the spread degree of grids shows the spread degree of multi-model results. The model spreads of \( R_T \) and ASR over the TP are much larger than the counterparts over EC and SA (Figures 5a, 5d, and 5g). The model spreads of NCRE and SWCRE are relatively larger over EC and SA. Notice that the spread pattern of simulated \( R_T \) (NCRE) is very close to that of ASR (SWCRE) over EC and the TP regions. Moreover, the spread degree of OLR (LWCRE) is very large over SA (Figures 5f and 8f), reflecting that various simulated convection intensity and distribution occur in CMIP6 AMIP models. Note that although the absolute contribution of LWCRE to NCRE is relatively small over SA (Table 4), the spread degree of simulated LWCRE is very large over EC where current climate models probably have big differences in reproducing cloud height and cloud vertical distribution (H. Zhang & Jing, 2016). Moreover, clear-sky components also substantially contribute to the CRE biases (Figures S2, S4, S5, and S6). As listed in Table 4, the annual mean OLRCS biases are \(-8.4, -5.9, \text{ and } -10.0\) W m\(^{-2}\) averaged over EC, SA, and the TP, respectively, and their magnitudes are larger than the counterparts of OLR (2.0, 3.4, and \(-6.1\) W m\(^{-2}\)). The RSUTCS bias (21.4 W m\(^{-2}\)) averaged over the TP is also obviously larger than the RSUT bias (10.2 W m\(^{-2}\)). The clear-sky radiation biases are closely related to land surface model biases and also make a significant contribution to the climatic simulation (Y. Huang & Ramaswamy, 2008; Y. Huang et al., 2007). Thus, clear-sky radiation biases are equally striking over EC and the TP with complex surface states.

It is noteworthy that ACCESS-CM2 and its coupled counterpart (ACCESS-ESM1-5) show some differences in the spatial pattern and intensity of NCRE over EC (Figures 6a, 6b, and 7a). These simulation differences are very likely caused by different parameters setting in physical processes. Compared with their respective high-resolution versions (CNRM-CM6-1-HR and HadGEM3-GC31-MM), CNRM-CM6-1 and HadGEM3-GC31-LL with lower resolution have similar performances in spatial patterns of \( R_T \) and NCRE over the above three regions. Over EC, the PCCs of \( R_T \) and NCRE in HadGEM3-GC31-MM are 0.71 and 0.53, respectively, and higher than the counterparts (0.55 and 0.40) in HadGEM3-GC31-LL (Figures 5a and 5b). Over the TP, the PCCs of \( R_T \) and NCRE in HadGEM3-GC31-MM are 0.90 and 0.72, respectively, and are higher than those (0.86 and 0.43) in HadGEM3-GC31-LL (Figures 5g and 8g). This demonstrates that some high-resolution models have better performance with the improvement of fine-topography and relevant subgrid cloud processes (Haarsma et al., 2016).

### 4. Annual Cycle and Interannual Variation

#### 4.1. Observational Annual Cycle

Figures 7, 9, and 11 show observational annual cycles of regional mean \( R_T \), NCRE and their shortwave and longwave components averaged over three regions. The positive \( R_T \) over SA and the TP first occur in March and over EC in April, and then the positive \( R_T \) stays until September over EC and the TP, and until October over SA (Figures 5a, 5d, and 5g). The \( R_T \) value over SA is larger than those over EC and the TP in most months except for July and August (Figure 5a, 5d, and 5g). It is noteworthy that the sensible heating over the TP becomes positive in March and stays until October (Wu et al., 2007). A similar duration time...
between \( R_T \) and surface sensible heating also indicates that the surface states are key influencing factors for regional \( R_T \) over the TP. The seasonal variation range of OLR over EC and the TP is much weaker than that over SA (Figures S7c, 9c, 9f, 9i). The intensity of NCRE and SWCRE over EC is much larger than that over SA and TP in most months, especially in December–March (Figures S7d, S7e, and 11) when large amounts of low-middle clouds occur (J. Li et al., 2017; Pan et al., 2015). Over SA, the maximum \( R_T \) intensity occurs in May (April), before the monsoon onset month (June), and the intensity of CREs (NCRE, SWCRE, and LWCRE) is at its peak in July when the summer monsoon erupts (Figures S7a, S7d–S7f, and 11). Compared with May, the convection intensity and cloud fractions increase quickly but the intensity of ASR and OLR decrease over SA in June and July (summer monsoon period), when the convection and the CREs become stronger than those before the onset of monsoon (B. Zhang et al., 2020).

4.2. Simulated Annual Cycle

4.2.1. Simulated Annual Cycle of \( R_T \)

Figure 9 shows the simulated annual cycles of \( R_T \), ASR, and OLR averaged over three regions. Over the TP, most models overestimate the negative \( R_T \) from December to February but simulate well the \( R_T \) intensity from May to November (Figure 9g). Notably, most models and MME cannot reproduce the positive \( R_T \) in March (Figure 9g). Nonetheless, several models including ACCESS-CM2, HadGEM3-GC31-MM, and UKESM1-0-LL can succeed in reproducing the positive \( R_T \) over TP in March and its annual cycle (Figure S8a), and their RMSEs of \( R_T \) annual cycle are much smaller than other models (Figure 10a). By comparison, the simulation bias and model spread of \( R_T \) over the TP, mainly contributed by the ASR are larger from February to May than those over EC and SA (Figures 9g–9i and 10g–10i), indicating that the model uncertainty of \( R_T \) is very large during the cold-warm transition period over the TP. In the meantime, the large range of ASR and OLR over the TP from May to June exhibit the large impact of summer monsoon on simulated TOA radiation (Figures 9h–9i).

Over EC, most models can capture well the seasonal ranges of \( R_T \) and ASR and their peaks in July (Figures 9a–9b), and their PCCs of \( R_T \) and ASR are over 0.97 (Figures 10a–10b). However, most models underestimate the intensity of \( R_T \) from October to February and overestimate it from April to August (Figures 9a–9b). The intensity of ASR over EC is underestimated by most models throughout the year while...
the annual cycle of simulated OLR is very close to the observation (Figures 9b–9c). Compared to other models, GFDL-AM4 and MRI-ESM2-0 have better simulation skills in the PCC and RMSE of \( RT_{EC} \) (Figure 10a). Moreover, a similar spread pattern between \( RT \) and ASR shows that the \( RT \) bias and its model spread over EC is dominated by the ASR (Figures 9a–9b and 10a–10b).

Over SA, most models simulate well the annual cycles of \( RT \), ASR, and OLR, and can capture the peak of \( RT \) (ASR) in May (April) and the valley of OLR in July (Figures 9d–9f). Most models overestimate the intensity of ASR and OLR over SA from May to September, and the model spread of ASR and OLR and their biases are very large from May to June (Figures 9e–9f and 10e–10f). Over SA, the intensity of ASR is underestimated from November to April and the OLR is systematically underestimated by the models throughout the year, although seasonal ranges of ASR and OLR are well captured by the models (Figures 9e–9f). Based on the simulation skills of PCC and RMSE, CESM2, GFDL-AM4, and NorESM2-LM are better at \( RT \) over SA.

### 4.2.2. Simulated Annual Cycle of CREs

Figure 11 shows the simulated annual cycle of NCRE and its longwave and shortwave components. Over the TP, most models underestimate the strength of LWCRE and SWCRE from January to July, and NCRE...
from February to May (Figures 11g–11i). The offset between LWCRE and SWCRE over SA makes the simulated NCRE in MME peaks in July, while it occurs in June in the observation. NorESM2-LM can capture the NCRE peak in June over the TP and it has the highest PCC (0.9734) and the smallest RMSE (Figure 12g) in all models. HadGEM3-GC31-LL, HadGEM3-GC31-MM, and CESM2 also have better reproducibility in the NCRE over the TP (Figure 12g). The model spread of NCRE is relatively larger in summertime (Figures 11a, 11d, and 11g).

Over EC, models reproduce large NCRE from February to May, but obviously underestimate its intensity in most months (Figure 11a). The underestimation of the intensity of NCRE and $R_c$ exists simultaneously over EC. As shown in Figures 11b and 11c, the systematic underestimation of simulated LWCRE and SWCRE over EC occurs throughout the year, and the magnitude of underestimated SWCRE is larger than LWCRE, except for July and August when the NCRE in MME is relatively close to the observation. Relatively, MPI-ESM1-2-HR and NorESM2-LM perform better in the intensity of NCRE from February to May and its annual cycle relative to other models (Figures 12a and 58d).

Over SA, most models can capture well the peaks of NCRE, LWCRE, and SWCRE in July, but underestimate the intensity of LWCRE, especially from May to October (Figures 11d–11f), indicating that the convection...
is also weaker compared to the observation. Due to the strong offset between LWCRE and SWCRE biases in the summertime, the simulated NCRE bias over SA is smaller than its longwave and shortwave components. Particularly, ACCESS-ESM1-5 simulates an opposite annual cycle of the NCRE phase relative to the observation (Figure S8e), which is mainly caused by its weaker SWCRE during November–March and in the summertime (not shown). Moreover, HadGEM3-GC31-LL, HadGEM3-GC31-MM, and UKESM1-0-LL also have weaker SWCRE and NCRE in summer (Figure 8e). The model spread of simulated CREs and their biases over SA, especially for biases of NCRE and SWCRE, is very large from May to September (Figures 11d–11f).

The results mentioned above show that the large model spread of the simulated NCRE and SWCRE over EC occurs during the springtime, and the counterparts over SA occur during the summertime. In the same period, large amounts of dominant low-middle and high clouds occur over EC and SA, respectively, and correspond to their strong NCRE and SWCRE. In addition, the intensity of simulated LWCRE and SWCRE and their ratios directly determine whether the intensity of NCRE and its annual cycle over SA are reasonable in these models. Thus, current CMIP6 AMIP models still face considerable uncertainties in reproducing the intensity of TOA CREs in their peak months over the TP and adjacent monsoon regions.

4.3. Interannual Variation

4.3.1. Simulated Time Series of $R_T$ and NCRE

Table 5 lists interannual variation of simulated $R_T$ and NCRE during 2001–2014. Here, STD is used to represent the intensity of interannual variation. There is pronounced interannual variation for $R_T$ and NCRE over three regions. The STDs of observational $R_T$ and NCRE over the TP are 3.64 and 4.67 W m$^{-2}$, respectively, and the counterparts over SA are 4.19 and 3.72 W m$^{-2}$, respectively. The STDs of observational $R_T$ and NCRE over EC, with values of 7.76 and 8.53 W m$^{-2}$, respectively, are almost two times larger than the counterparts over SA and the TP (Table 5), indicating larger interannual variation over EC. Compared with the observation and individual models, the magnitude of interannual variation of $R_T$ and NCRE weakens substantially in MME and most models find it difficult to capture well the interannual variations of $R_T$ and NCRE, only with the temporal correlation coefficients less than 0.2 in MME. By comparison, models have
better interannual reproducibility over EC, with temporal correlation coefficients of 0.19 and 0.20 for $R_T$ and NCRE in MME, respectively, but the counterparts in MME are much lower over SA and the TP (not shown).

4.3.2. Interannual Relationship Between $R_T$ and NCRE

To examine the potential role of NCRE in $R_T$, Table 5 shows the temporal correlation between monthly $R_T$ and NCRE averaged over three regions during 2001–2014. Over EC, the correlation coefficients between $R_T$ and NCRE in the observation and MME are 0.93 and 0.85, respectively, and the temporal correlation coefficients in most models are close to or over 0.85. This demonstrates that the interannual variation of $R_T$ can be well explained by the NCRE. Over SA, the observed and simulated correlation coefficients between $R_T$ and NCRE are 0.73 and 0.67, respectively. Over the TP, although the observed correlation coefficient between $R_T$ and NCRE is 0.75, the simulated counterpart is only 0.42. The model spread of correlation coefficients over the TP is larger than those over EC and SA, and the coefficients in CNRM-CM6-1 and CNRM-ESM2-1 are even less than 0 (not shown). The interannual relationship between $R_T$ and NCRE demonstrate that cloud radiative roles have the dominant role in the $R_T$ variation over EC and SA, and models can well represent this relationship, especially over EC. However, the observed large contribution of clouds to $R_T$ cannot be

Figure 8. Pattern correlation coefficient and standard center RMSE between annual mean CMIP6 AMIP model and observational counterparts for NCRE, SWCRE and LWCRE over EC (Figures 8a–8c), SA (Figures 8d–8f) and the TP (Figures 8g–8i). The standard center RMSE from an individual model is divided by the STD of the observational counterpart. EC, Eastern China; LWCRE, Longwave cloud radiation effect; MME, multi-model mean; NCRE, Net cloud radiation effect; RMSE, root-mean-square error; SA, South Asia; SWCRE, Shortwave cloud radiation effect; TOA, top-of-atmosphere; TP, Tibetan Plateau.
This means that other factors, such as surface states, also have certain effects on \( R_T \) over the TP.

5. Possible Causes for Simulation Biases

In this section, we investigate possible causes for simulation biases of \( R_T \) and CREs in CMIP6 models over the TP and adjacent EC and SA. The spatial distribution of simulation biases of cloud-radiation variables is analyzed first, and the relationship between simulated \( R_T \) and CREs is examined to highlight the role of clouds in simulated \( R_T \) biases. CREs are closely related to cloud fractions being very sensitive to regional circulation conditions and surface states. We further examine the influences of simulated cloud fractions on CREs and potential associations between simulated cloud fraction and meteorological conditions.
5.1. Geographical Distribution of Simulation Biases

Figure 13 shows the geographical distribution of simulated biases of RT, NCRE, and relevant radiative fluxes in MME. Over the central TP and south flank of TP, positive RT bias corresponds to negative biases ASR and RSUT, and positive NCRE (SWCRE) bias, suggesting an overall underestimated cloud radiative cooling effect. Over the western TP, the negative RT bias coincides with the negative biases of ASR and OLR and the positive biases of RSUT (RSUTCS) and NCRE (SWCRE). The cloud-radiation biases exhibit an obvious difference between the western and eastern TP. In this case, the PCC between NCRE (SWCRE) and RT biases is only 0.27 (0.36) over the TP (Figure S9g and S9h), indicating that cloud biases are not responsible for the RT bias over the whole TP. A similar spatial pattern among the biases of RT, RSUT (RSUTCS), OLR (OLRCS), and NCRE (SWCRE) suggest that the surface state biases (e.g., surface temperature and albedo) may substantially contribute to cloud-radiation biases over the western TP.

Over EC, obvious positive RT bias coincides with negative RSUT biases and positive biases of ASR and NCRE (SWCRE), and their maximum bias centers occur nearly over southwestern China. The PCC between...
the biases of NCRE (SWCRE) and $R_T$ is up to 0.93 (0.88) over EC, but the counterpart between LWCRE and $R_T$ is only 0.18 (Figures S9a–S9c). This demonstrates that the spatial pattern of seriously underestimated negative $R_T$ over EC highly depends on that of the weaker cloud radiative cooling effect (SWCRE) in CMIP6 AMIP models.

Over SA, the intensity of LWCRE is underestimated in the whole region (Figure 13i). Note that the spatial pattern of $R_T$ bias is also similar to those of NCRE and SWCRE in the Bay of Bengal (BOB), southern India, and the Indochina Peninsula (Figures 13a, 13g, and 13h). The PCC between the $R_T$ and NCRE biases is 0.85 (Figure S9d), and the PCC between the SWCRE (LWCRE) and $R_T$ biases is 0.63 (0.41) over SA (Figures S9e–S9f). The high spatial correlation suggests that cloud biases account for the $R_T$ bias to a large extent. In addition, the strong CREs and their longwave and shortwave components often coexist with strong convective activities over SA (Hartmann et al., 2001; Kiehl, 1994; J. Li et al., 2017; Rajeevan & Srinivasan, 2000). Thus,
although the underestimated domain-mean positive $RT_{\text{SA}}$ mainly arises from its underestimated cloud warming effect (LWCRE), the spatial pattern bias of $RT$ is also sensitive to regional SWCRE biases in the BOB where strong convection happens frequently.

### Table 5

The Standard Deviation (STD) of Monthly $R_T$ and NCRE From the Observation and CMIP6 MME, Respectively, and the Temporal Correlation Coefficients Between MME and the Observation Averaged Over EC, SA, and the TP During 2001–2014

|             | $R_T$ STD (W m$^{-2}$) | NCRE STD (W m$^{-2}$) | Correlation between $R_T$ and NCRE |
|-------------|------------------------|------------------------|------------------------------------|
|             | OBS | MME | OBS | MME | OBS | MME |
| EC          | 7.76 | 2.14 | 8.53 | 2.43 | 0.93 | 0.85 |
| SA          | 4.19 | 2.19 | 3.72 | 1.58 | 0.73 | 0.67 |
| TP          | 3.64 | 1.19 | 4.67 | 1.04 | 0.75 | 0.42 |

### 5.2. Simulation Biases of Cloud Fractions

Figures S10 and S11 show the geographical distribution of annual mean TCF and high cloud fraction (HCF) in nine CMIP6 AMIP models with satellite simulator output, respectively. In addition to cloud fractions, cloud water path from Terra and Aqua MODIS data are used to roughly evaluate the cloud water path from these nine models (Figures S13 and S14).

In the observation, large amounts of cloud fractions and cloud liquid water path occur over EC, especially over southwestern China where the maximum centers of cloud fractions and cloud liquid water path are very close to that of SWCRE (Figures 2d, S10k, and S13k–S13l). Low-middle
Clouds account for a large proportion of the total clouds over EC (J. Li et al., 2017; Pan et al., 2015). Low-middle clouds mainly consisting of liquid water can strongly reflect the incident shortwave radiation and help cause large SWCRE and NCRE over EC (J. Li et al., 2017, 2019). Lots of high clouds prevail over the eastern TP and SA, especially in summer (Figures S11k, 14e, and 14f), and lead to a certain intensity of LWCRE and SWCRE (Figures 2d–2e).

In the simulation, most models seriously underestimate the annual mean TCF and HCF over EC, SA, and most parts of the TP (Figures 15a–15f). In particular, middle cloud fraction and low cloud fraction (LCF) simulated by most models are lower than the observation performed over EC (not shown), where TCF and HCF in the whole year are almost underestimated (Figures 14a and 14d). The underestimated TCF and the cloud liquid water path over EC coincide well with the identically underestimated strength of SWCRE and NCRE (Figures 15d–15e, 15g, and S13j). The PCC between the annual mean NCRE (SWCRE) and TCF biases in MME is −0.76 (−0.82) over EC (Figures S12a–S12b). This high correspondence in the relationship between TCF and SWCRE (NCRE) biases demonstrates that less cloud fractions directly result in the underestimated intensity of cloud radiative cooling effect over EC. The underestimated LWCRE in annual mean MME corresponds with the less HCF and cloud ice water path over EC and SA (Figures 15f, 15i, and S13v). The correlation coefficients between HCF and LWCRE biases in the annual mean MME are 0.51 and 0.46 over EC and SA, respectively (Figures S12c and S12f), indicating that the LWCRE bias highly relies on the HCF biases in CMIP6 models.

Figure 13. Distribution of annual mean biases of (a–i) $R_T$, ASR, OLR, RSUT, RSUTCS, OLRCS, NCRE, SWCRE, and LWCRE (unit: W m$^{-2}$) during 2001–2014 simulated from CMIP6 AMIP MME. AMIP, Atmospheric Model Intercomparison Project; LWCRE, Longwave cloud radiation effect; MME, multi-model mean; NCRE, Net cloud radiation effect; SWCRE, Shortwave cloud radiation effect.
Over the TP, the underestimated TCF and HCF mainly appear from January to August (Figures 14c and 14f), when the strength of SWCRE and LWCRE is also underestimated. Besides, a late peak month (July) of NCRE in MME mainly occurs in the western TP and is caused by obviously underestimated LWCRE (not shown). As shown in Figures S10 and S11, TCF and HCF are larger over the eastern TP than those over the western TP (Bao et al., 2019), and therefore, clouds exert more influences on the intensity of CReS and their biases over the eastern TP. The correlation coefficient between TCF (HCF) and SWCRE (LWCRE) is $-0.26$ ($0.37$) over the eastern TP, and is significantly higher than the counterparts over the whole TP (Figures S12h and S12i). As for individual models, those models with better-simulated column CFs can better simulate CReS. For instance, CESM2 and UKESM1-0-LL well reproduce LCF over EC and HCF over the eastern TP, and they can also well capture the intensity and spatial pattern of regional SWCRE and LWCRE (not shown). Most models except for CESM2 and MIROC6 underestimate the cloud liquid water path over EC and SA, and this underestimation also corresponds to their individual weaker SWCRE. Relative to the other 8 models, CESM2 performs better in the intensity and spatial pattern of annual mean cloud liquid water path, cloud fractions, and CReS over EC and SA (Figures S10a, S11a, and S13a), demonstrating that CESM2 can capture primary cloud properties over Asian monsoon regions. Cloud ice water paths are seriously underestimated in 9 CMIP6 AMIP models in three target regions and this underestimation is also reflected by their much weaker HCF (Figures S11 and S13). Cloud fractions and cloud water path broadly represent cloud mass content and a large amount of cloud optical depth. Thus, our current results can provide a piece of information for the community regarding cloud-radiation performances over the TP and adjacent Asian monsoon regions in the latest CMIP6 AMIP models. Note that this is only a rough comparison of the cloud water path because there are no satellite simulator counterparts. More cloud properties, such as cloud number concentrations and radius, will be very helpful to further analyze radiation biases, but these outputs did not occur in the CMIP6 AMIP models. Further analysis of cloud properties could be conducted in future special model experiments.

Figure 14. Seasonal cycles of monthly and regional mean (a, b, and c) TCF and (d, e, and f) HCF (unit: %) averaged over EC (Figures 14a and 14d), SA (Figures 14b and 14e), and the TP (Figures 14c and 14f) simulated by nine CMIP6 models with satellite simulator output during 2007–2014. The red and black solid lines denote the observation and MME, respectively. The black box indicates the standard deviation among the models. The number on x-axis is the month number. HCF, High cloud fraction; LCF, Low cloud fraction; MME, multi-model mean; TCF, Total cloud fraction; TP, Tibetan Plateau.
5.3. Simulation Biases of Seasonal Meteorological Conditions

The seasonal variations of circulation and clouds are very obvious over Asian monsoon regions (Ding & Chan, 2005; J. Li et al., 2017; Luo et al., 2009; Webster et al., 1998). Here, we further analyze possible connections between clouds and CREs with some meteorological conditions, especially in winter and summer.

In the observation, a strong ascending motion occurs over the Maritime Continent and EC throughout the year, and over the southern and eastern BOB it occurs in summer (Figures S15a–S15c). The low-level southwestern wind from the BOB reaches EC in winter and the eastern TP in summer (Figures S15b–S15c). The southern wind, west to the west Pacific anti-cycle, also enters EC via the South China Sea. Thus, considerable amounts of water vapor are transported into the eastern TP and EC and work as stable cloud water sources. In the meantime, EC is located in the south of the 200-hPa westerly jet entrance especially in winter (Figure S15b), which is favorable for maintaining the regional low-middle ascending motion and large SWCRE (J. Li et al., 2019; Liang & Wang, 1998).

In comparison, less TCF and weaker SWCRE (NCRE) over EC are more obvious in winter (Figure S16), but less HCF and weaker LWCRE over SA are more obvious in summer (Figure S17). These biases are closely related to the distribution of seasonal circulation biases. In winter, large cold surface temperature bias occurs over the western and central TP (Figure S15b), which is very common in climate models including most CMIP5 models (Flato et al., 2013) and is very likely caused by surface state biases, such as the snow-albedo...
Large surface temperature cold bias generally associated with higher surface albedo over the TP is conducive to the underestimated (overestimated) OLRCS (RSUTCS) (Figures 13c–13d and 15d), especially in winter. Surface temperature cold bias also occurs over northern China. In this case, according to the PV-Θ view (Hoskins, 1991) and the theory of thermal adaptation (Wu et al., 2009; Wu & Liu, 2003), the strong cold bias over the TP helps to induce a low-level anti-cyclonic and high-level cyclonic anomaly surrounding the TP, SA, and EC (Figures 16b and 16e). Thus, the low-level southwesterly and southerly wind in EC is weaker than the observation. Meanwhile, the weaker 200-hPa westerly jet over EC also weakens its pumping role and regional ascending motion (Figure 16e). The simulated weaker low-middle ascending motion does not aid the formation and maintenance of regional low-middle CFs over EC, and causes the underestimated intensity of regional SWCRE and NCRE (J. Li et al., 2019, 2020).

In summer, the surface temperature exhibits obvious warm biases over EC, continental SA, and the central TP (Figure 16c). These warm biases are conducive to low-level westerly wind anomaly over the North Indian Ocean, Indochina Peninsula, South China Sea, and the northwestern Pacific (Figure 16c). In particular, an obvious cyclonic anomaly occurs over northwestern Pacific accompanied by a high-level anti-cyclonic anomaly, indicating a weaker northwestern Pacific high in summer in the CMIP6 AMIP models (Figures 16c and 16f). A weaker ascending motion appears in the southern BOB. The 200-hPa westerly jet over EC is also weaker in summer, which likely results from large-scale heating biases. Compared to the observation, this summer distribution of circulation biases inhibits the regional ascending motion and causes less cloud fractions and weaker LWCRE over EC and southern SA in summer (Figure 14). In addition, AMIP runs are forced by observational SST and sea ice, with no reasonable air-sea interactions, and their main circulation biases come from atmospheric and land processes, probably giving rise to some unavoidable large-scale heating anomaly and regional land-sea thermal contrast biases (Sperber et al., 2013). Note that the abovementioned theory for circulation biases is suitable for large scale simulation biases and not for local-scale biases. For instance, the correspondence between cloud-radiation and vertical motion biases is not good over the Yunnan-Guizhou Plateau and the eastern TP in summer (Figures 16c and 16f). The subgrid atmospheric states and diurnal cloud variations over these regions, where the topography is very complex, are hard to reproduce in global models (G. Chen & Wang, 2016; Y. Zhang et al., 2015), and observational Ts and column cloud fraction data remain largely uncertain (Fu et al., 2020; A. Wang & Zeng, 2012).
Another notable issue is that of the simulated aerosol-radiation-cloud biases in contemporary models. Due to heavy aerosol loading in EC, the model cannot capture the sensitivity of the cloud radius and optical depth to the aerosols (Z. Q. Li et al., 2016; Wu et al., 2016). For instance, many climate models underestimated the aerosol loading and optical depth over EC (Li et al., 2014; Shindell et al., 2013). A lower simulated aerosol optical depth can lead to less upward shortwave radiation at the TOA, and additional simulation uncertainties in cloud radiative properties and lifetime. Because the outputs of CMIP6 AMIP models do not include these variables associated with the cloud-aerosol interaction, detailed analysis cannot be conducted in this study.

6. Summary and Discussion

This study examined TOA $R_T$ and CREs over the TP and adjacent Asian monsoon regions in CMIP6 AMIP simulations. Our results show that specific model performances vary over the TP and adjacent EC and SA. Over the TP, most models roughly represent the distribution of $R_T$ and NCRE but underestimate their intensity. These biases of $R_T$ and NCRE mainly arise from their underestimated shortwave components (ASR and SWCRE). The simulated spatial reproducibility of annual mean $R_T$ over the TP is quite lower, with a spatial correlation of 0.48 in the MME. The simulation bias and model spread of $R_T$ over the TP are larger from February to May, indicating that the simulation uncertainty of $R_T$ is quite large during the cold-warm transition period. Most models fail to reproduce the positive $R_T$ value over the TP in March, except for UKESM1-0-LL, ACCESS-CM2, and HadGEM3-GC31-MM. Although NorESM2-LM, HadGEM3-GC31-LL, HadGEM3-GC31-MM, and CESM2 can succeed in capturing the peak month (June) of NCRE over the TP, most models produce a late NCRE peak in July, relative to the observation. This late NCRE peak month in CMIP6 simulations is more obvious in the western TP.

Over EC, most models seriously underestimate the annual mean intensity of $R_T$ and NCRE. The underestimated intensity of $R_T$ is mainly caused by the overestimated ASR. The cloud radiative cooling effect over EC is seriously underestimated by most models from February to May when the large model spread also occurs. Only some models (e.g., ACCESS-ESM1-5, CESM2, GFDL-AM4, and MPI-ESM1-2-HR) can reasonably capture the spatial pattern and intensity of $R_T$ (NCRE) over EC, but most models still find it difficult to reproduce the center of intensity of NCRE (SWCRE) over southwestern EC.

Over SA, most models can represent well the spatial distribution of $R_T$ and NCRE. In contrast to EC and the TP, the biases of $R_T$ and NCRE are mainly caused by their longwave components. The overestimated (underestimated) OLR (LWCRE) largely accounts for the underestimated (overestimated) intensity of $R_T$ (cloud radiative cooling effect) in CMIP6 models over SA. The largest model spread of CREs occurs especially from May to September. By comparison, most models can capture well the peak months of $R_T$ and CREs over SA.

The MME in CMIP6 models can improve the simulated spatial similarity and biases of $R_T$, NCRE, and their components over the TP and adjacent monsoon regions for the annual mean and seasonal variation states. Even so, most models find it difficult to capture well the interannual variations of $R_T$ and NCRE over the above three regions, with quite low monthly temporal correlations with the observations, and underestimate the interannual intensity of NCRE and $R_T$ over EC. Most models can reproduce well the close interannual relationship between observational NCRE and $R_T$ over EC and SA, especially in the former, further suggesting the vital cloud radiative roles in the TOA $R_T$. However, the majority of the models show very low reproducibility in this interannual relationship over the TP, except for ACCESS-CM2, ACCESS-ESM1-5, MPI-ESM1-2-HR, and UKESM1-0-LL.

It is noteworthy that no single model has the best and most comprehensive simulation skill of $R_T$ and CREs over these three subregions in this study. This simulation difficulty demonstrates the complexity and the various cloud-radiation climatic processes in Asian monsoon regions. Although clouds play substantial roles in determining the intensity of NCRE and $R_T$ over Asian monsoon regions, clear-sky radiation biases are equally alarming, especially over the TP with complex surface states. This study shows that the simulated surface temperature cold bias in CMIP6 models over the central and western TP is conducive to weaker OLR and larger surface albedo, causing larger upward shortwave radiation and weaker ASR (SWCRE). Meanwhile, considerable differences in cloud fractions, CREs, and their model performances also exist between the
western and eastern TP. Further model assessment is therefore needed to well understand the simulation differences in cloud-radiation performances over the western and eastern TP. The underestimated intensity of $R_T$ and NCRE over EC is highly correlated to underestimated low-middle cloud fractions associated with weaker regional ascending motion in current CMIP6 AMIP models. Besides, this underestimated cloud radiative cooling effect is also very likely related to large uncertainties in aerosol-cloud-radiation effects over EC where heavy aerosol loading is distributed (Gettelman & Sherwood, 2016; J. Li et al., 2016; Wu et al., 2016). Over SA, the underestimated HCF and OLR are related to weaker deep convection, which is probably caused by inappropriate convective parameterizations in present climate models. These biases and difficulties of cloud-radiation simulation should be further examined over the TP and adjacent monsoon regions with complex topography using more reliable reanalyzed meteorological and satellite-retrieved data.

**Data Availability Statement**

The authors acknowledge the providers of NASA CERES-EBF and MODIS satellite products and CMIP6 (https://esgf-node.llnl.gov/search/cmip6/) data.

**References**

Adler, R. F., Huffman, G. J., Chang, A., Ferraro, R., Xie, P.-P., Janowiak, J., et al. (2003). The version-2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (1979-Present). *Journal of Hydrometeorology*, 4, 1147–1167. https://doi.org/10.1175/1525-7541(2003)004<1147:tgpcpm2.0.co;2

Allan, R. P. (2011). Combining satellite data and models to estimate cloud radiative effect at the surface and in the atmosphere. *Meteorological Applications*, 18, 324–333. https://doi.org/10.1002/met.285

Bao, S., Letu, H., Zhao, J., Shang, H., Lei, Y., Duan, A., et al. (2019). Spatiotemporal distributions of cloud parameters and their response to meteorological factors over the Tibetan Plateau during 2003-2015 based on MODIS data. *International Journal of Climatology*, 39, 532–543. https://doi.org/10.1002/joc.5826

Boo, K.-O., Martin, G., Sellar, A., Senior, C., & Byun, Y.-H. (2011). Evaluating the East Asian monsoon simulation in climate models. *Journal of Geophysical Research*, 116(D1), D01109. https://doi.org/10.1029/2010JD014737

Boucher, O., Randall, D., Artaxo, P., Bretherton, C., Feingold, G., Forster, P., et al. (2013). Clouds and aerosols. In T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, V. Bex, & P. M. Midgley (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Chen, G., & Wang, W.-C. (2016). An effective approach to evaluate GCM simulated diurnal variation of clouds. *Geophysical Research Letters*, 43, 604–611. https://doi.org/10.1002/2016GL067446

Chen, X., Liu, Y., & Wu, G. (2017). Understanding the surface temperature cold bias in CMIP5 AGCMs over the Tibetan Plateau. *Advances in Atmospheric Sciences*, 34(12), 1447–1460. https://doi.org/10.1007/s00376-017-6326-9

Chepfer, H., Bony, S., Winker, D., Cesana, G., Dufresne, J. L., Minnis, P., et al. (2010). The GCM-Oriented CALIPSO Cloud Product (CALIPSO-GOCCP). *Journal of Geophysical Research*, 115. https://doi.org/10.1029/2009JD012251

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., et al. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 137, 553–597.

Ding, Y., & Chan, J. C. (2005). The East Asian summer monsoon: An overview. *Meteorology and Atmospheric Physics*, 89, 35–73.

Dolinar, E. K., Dong, X., Xi, B., Jiang, J. H., & Su, H. (2014). Evaluation of CMIP5 simulated clouds and TOA radiation budgets using NASA satellite observations. *Climate Dynamics*, 44, 2229–2247. https://doi.org/10.1007/s00382-014-2158-9

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, 9, 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016

Flato, G., Marotzke, J., Aebischer, B., Braconnot, P., Collins, W., et al. (2013). Evaluation of climate models. In T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, & P. M. Midgley (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Flohn, H. (1957). Large-scale aspects of the “summer monsoon” in South and East Asia. *Journal of the Meteorological Society of Japan*, 35A, 180–186. https://doi.org/10.2151/jmsj1923.35a_0_180

Fu, Y., Ma, Y., Zhong, L., Yang, Y., Guo, X., Wang, C., et al. (2020). Land-surface processes and summer-cloud-precipitation characteristics in the Tibetan Plateau and their effects on downstream weather: A review and perspective. *National Science Review*, 7(3), 500–515. https://doi.org/10.1093/nsr/nzw228

Furtado, K., Field, P. R., Boutle, I. A., Morcrette, C. J., & Wilkinson, J. M. (2016). A physically based subgrid parameterization for the production and maintenance of mixed-phase clouds in a General Circulation Model. *Journal of the Atmospheric Sciences*, 73(1), 279–291. https://doi.org/10.1175/Jas-D-15-0021.1

Gettelman, A., & Sherwood, S. C. (2016). Processes responsible for cloud feedback. *Current Climate Change Reports*, 2(4), 179–189. https://doi.org/10.1007/s40641-016-0052-8

Haarsma, R. J., Roberts, M. J., Vidale, P. L., Senior, C. A., Bellucci, A., Bao, Q., et al. (2016). High Resolution Model Intercomparison Project (HighResMIP v1.0) for CMIP6. *Geoscientific Model Development*, 9, 4185–4208. https://doi.org/10.5194/gmd-9-4185-2016

Hartmann, D. L., Moy, L. A., & Fu, Q. (2001). Tropical convection and the energy at the top of the atmosphere. *Journal of Climate*, 14, 4495–4511. https://doi.org/10.1175/1520-0442(2001)014<4495:ctaceb>2.0.co;2

He, J. H., Zhao, P., Zhu, C. W., Zhang, R. H., & Tang, X. (2008). Discussions on the East Asian subtropical monsoon. *Acta Meteorologica Sinica*, 66(5), 683–696.
Hoskins, B. J. (1991). Toward a PV-theta view of the general circulation. Tellus, 43, 27–35. https://doi.org/10.1034/j.1600-0870.1991.t01-3-0005.x

Huang, D.-Q., Zhu, J., Zhang, Y.-C., Huang, Y., & Kuang, X.-Y. (2016). Assessment of summer monsoon precipitation derived from five reanalysis datasets over East Asia. Quarterly Journal of the Royal Meteorological Society, 142(694), 108–119. https://doi.org/10.1002/qj.2634

Huang, Y., & Ramaswamy, V. (2008). Observed and simulated seasonal co-variations of outgoing longwave radiation spectrum and surface temperature. Geophysical Research Letters, 35, L17803. https://doi.org/10.1029/2008GL034859

Huang, X., Ramaswamy, V., Huang, X., Fu, Q., & Bardeen, C. (2007). A strict test in climate modeling with spectrally resolved radiances: GCM simulation versus AIRS observations. Geophysical Research Letters, 34, L24707. https://doi.org/10.1029/2007GL031049

Kay, J. E., Wall, C., Yettelia, V., Medeiros, B., Hannay, C., Caldwell, P., & Blit, C. (2016). Global climate impacts of fixing the Southern Ocean shortwave radiative effect in the Community Earth System Model (CESM). Journal of Climate, 29(12), 4617–4636. https://doi.org/10.1175/JCLI-D-15-0358.1

Kiehl, J. T. (1994). On the observed near cancellation between longwave and shortwave cloud forcing in tropical regions. Journal of Climate, 7, 559–565. https://doi.org/10.1175/1520-0442(1994)007<0559:oancbt>2.0.co;2

King, M. D., Platnick, S., Menzel, W. P., Ackerman, S. A., & Hubanks, P. A. (2013). Spatial and temporal distribution of clouds observed by MODIS onboard the Terra and Aqua satellites. IEEE Transactions on Geoscience and Remote Sensing, 51(7), 3826–3852. https://doi.org/10.1109/tgrs.2012.2227333

Lauer, A., & Hamilton, K. (2013). Simulating climate with Global Models: A comparison of CMIP5 results with CMIP3 and satellite data. Journal of Climate, 26, 3823–3845. https://doi.org/10.1175/jcli-d-12-00451.1

Li, J., Wang, W.-C., Dong, X., & Mao, J. (2017). Cloud-radiation-precipitation associations over the Asian monsoon region: An observational analysis. Climate Dynamics, 49(9), 3237–3255. https://doi.org/10.1007/s00382-016-3509-5

Li, J., Wang, W.-C., Mao, J., Wang, Z., Zeng, G., & Chen, G. (2019). Persistent spring shortwave cloud radiative effect and the associated circulations over Southeastern China. Journal of Climate, 32, 3069–3087. https://doi.org/10.1175/jcli-d-18-0385.1

Li, J., You, Q., & He, B. (2020). Distinctive shortwave cloud radiative effect and its inter-annual variation over Southeastern China. Atmospheric Science Letters, 21, e970. https://doi.org/10.1002/asl.970

Li, J. D., Liu, Y. M., & Wu, G. X. (2009). Cloud Radiative Forcing in Asian Monsoon Region Simulated by IPCC AR4 AMIP Models. Advance in Atmospheric Sciences, 26(5), 923–932

Li, J. D., Wang, W.-C., Sun, Z. A., Wu, G. X., Liao, H., & Liu, Y. M. (2014). Decadal variation of East Asian radiative forcing due to anthropogenic aerosols during 1850–2100 and the role of atmospheric moisture. Climate Research, 61(3), 241–257.

Li, J.-L. F., Waliser, D. E., Stephens, G., Lee, S., L'Ecuyer, T., Kato, S., et al. (2013). Characterizing and understanding radiation budget biases in CMIP3/CMIP5 GCMs, contemporary GCM, and reanalysis. Journal of Geophysical Research: Atmospheres, 118, 8166–8184. https://doi.org/10.1002/jgrd.50378

Li, Z. Q., Liu, W. M., Ramanathan, V., Wu, G., Ding, Y., Manoj, M. G., et al. (2016). Aerosol and monsoon climate interactions over Asia. Reviews of Geophysics, 54(4), 866–892.

Li, Z.-Q., & Wang, W.-C. (1998). Associations between China monsoon rainfall and tropospheric jets. The Quarterly Journal of the Royal Meteorological Society, 124(552), 2597–2623. https://doi.org/10.1002/qj.49712455204

Luo, Y., Zhang, R., Qian, W., Luo, Z., & Hu, X. (2011). Intercomparison of deep convection over the Tibetan Plateau-Asian monsoon region and subtropical North America in boreal summer using CloudSat/CALIPSO data. Journal of Climate, 24(8), 2164–2177. https://doi.org/10.1175/2010JCLI4632.1

Luo, Y., Zhang, R., & Wang, Y. (2009). Comparing occurrences and vertical structures of hydrometeors between eastern China and the Indian monsoon region using CloudSat/CALIPSO data. Journal of Climate, 22, 1052–1064. https://doi.org/10.1175/2008jcli2066.1

Ma, Q., You, Q., Ma, Y., Cao, Y., Zhang, J., Niu, M., & Zhang, Y. (2021). Changes in cloud amount over the Tibetan Plateau and impacts of large-scale circulation. Atmospheric Research, 249, 105332. https://doi.org/10.1016/j.atmosres.2020.105332

Pan, Z., Gong, W., Mao, F., Li, J., Wang, W., Li, C., & Min, Q. (2015). Macrophysical and optical properties of clouds over East Asia measured by CALIPSO. Journal of Geophysical Research: Atmospheres, 120, 11653–11668. https://doi.org/10.1002/2015jd023735

Pincus, R., Bartstone, C. P., Hofmann, J. R. P., Taylor, K. E., & Glecker, P. J. (2008). Evaluating the present-day simulation of clouds, precipitation, and radiation in climate models. Journal of Geophysical Research, 113(D14). https://doi.org/10.1029/2007jd009334

Rajeevan, M., & Srinivasan, J. (2000). Net cloud radiative forcing at the top of the atmosphere in the Asian monsoon region. Journal of Climate, 13(3), 650–657. https://doi.org/10.1175/1520-0442(2000)013<0650:ncrfat>2.0.co;2

Ramanathan, V. (1987). The role of earth radiation budget studies in climate and general circulation research. Journal of Geophysical Research, 92(D4), 4075–4095. https://doi.org/10.1029/jd092id04p04075

Sato, T., Dey, S., Das, S., & Dutta, S. (2016). A satellite-based 13-year climatology of net cloud radiative forcing over the Indian monsoon region. Atmospheric Research, 182, 76–86. https://doi.org/10.1016/j.atmosres.2016.07.017

Shindell, D. T., Lamarque, J.-F., Schulz, M., Flanner, M., Chin, C. M., Young, P. J., et al. (2013). Radiative forcing in the ACCMIP historical and future climate simulations. Atmospheric Chemistry and Physics, 13, 2939–2974. https://doi.org/10.5194/acp-13-2939-2013

Simmons, A. J., Poli, P., Dee, D. P., Berrisford, P., Hersbach, H., Kobayashi, S., & Peubey, C. (2014). Estimating low frequency variability and trends in atmospheric temperature using ERA-Interim. Quarterly Journal of the Royal Meteorological Society, 140, 329–353.

Sperber, K. R., Annamalai, H., Kang, I.-S., Kitoh, A., Koenig-Langmann, D., & Lu, D. (2000). Intercomparison of deep convection over the Tibetan Plateau-Asian monsoon region and tropospheric jets. The Quarterly Journal of the Royal Meteorological Society, 126, 3823–3845. https://doi.org/10.1002/qj.49712455204

Stephens, G. L. (2005). Cloud feedbacks in the climate system: A critical review. Journal of Climate, 18, 237–273. https://doi.org/10.1175/jcli-3243.1

Tao, S. Y., & Chen, L. X. (1987). A review of recent research on the East Asian summer monsoon in China. Monsoon Meteorology, 60–92. Taylor, K. E. (2001). Summarizing multiple aspects of model performance in a single diagram. Journal of Geophysical Research, 106(D7), 7183–7192. https://doi.org/10.1029/2001jd000719

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. Bulletin of the American Meteorological Society, 93, 485–498. https://doi.org/10.1175/bams-d-11-00094.1
