Identifying the error sources in total cloud fraction (CF) simulated by global climate models is essential for improving climate prediction. This study investigates if and how significant the aerosol simulation errors contribute to the model CF biases in the Atmosphere Model Inter-comparison Project (AMIP) simulations of the Coupled Model Inter-comparison Project Phase 5 (CMIP5) models. The aerosol optical depths (AODs) and CFs in 12 CMIP5/AMIP models have been examined and compared with 8-year moderate resolution imaging spectroradiometer (MODIS) satellite observations. The results show that the global-averaged multimodel ensemble mean AOD and CF, which are .14 and 56.2%, are 22.2 and 15.2% lower than those from MODIS, respectively. The simulated relationship between AOD and CF generally agrees with the observation on the global scale but differs on regional scale. Based on the “conditional sampling approach,” the AOD simulation errors that affect the CF biases of the models were separated from the model biases caused by the aerosol–CF errors that are related to dynamics, thermodynamics, and microphysics. It is found that the AOD biases contribution in some regions, such as south Indian Ocean, Asia, Europe, and North Pacific Ocean, cannot be ignored. We also found that with increasing cloud liquid water path the CF does not increase with AOD as sensitively in the CMIP5/AMIP models as in the MODIS observations.

**KEYWORDS**
aerosol simulation error, AMIP project, cloud fraction bias, MODIS, prognostic CF scheme

1 INTRODUCTION

Aerosols can modify the cloud microphysical properties (e.g., cloud droplet number concentration and droplet size) and macrophysical properties (e.g., cloud fraction [CF]), causing significant impacts to the global energy balance and hydrological cycle. Among the cloud variables, CF is of particular importance in terms of the cloud radiative effect because a small change in CF can offset the warming by anthropogenic greenhouse gases (Sekiguchi et al., 2003; Kaufman et al., 2005; George and Wood, 2010; Chuang et al., 2012; Goren and Rosenfeld, 2014). However, there are still large uncertainties in the CF simulations by the global climate models (GCMs) (Stanfield et al., 2014; Dolar et al., 2015; Stanfield et al., 2015) although many improvements in cloud simulations have been made in
Identifying the error sources of CF simulation by GCMs is essential for improving climate prediction. CF is controlled by dynamics, thermodynamics, and cloud microphysics. While recent efforts have been made on improving the representation of cloud dynamics and thermodynamics in GCMs (Su et al., 2013; Yoo et al., 2013; Stanfield et al., 2014; Cheng and Xu, 2015; Huang et al., 2015; Luo et al., 2015; Stanfield et al., 2015), many studies also indicated that cloud microphysics plays an important role in determining the CF. By serving as cloud condensation nuclei (CCN), increased aerosols can result in smaller cloud droplet size, inhibit drizzle events, prolong cloud lifetime, and enhance cloudiness, that is, the “cloud lifetime effect” (Albrecht, 1989). Satellite observations have indicated that increased aerosol concentration can enhance convective CF, which is called the aerosol “invigoration effect” (Koren et al., 2005; Koren et al., 2010). The aerosol “microphysical effect” drives dramatic increase in the anvil coverage at the mature and dissipation stages of the convective clouds as indicated by cloud-resolving model simulation (Fan et al., 2013) and decade-long ground-based measurements (Yan et al., 2014). Satellite observations also show that the CF increases with aerosol concentration in shallow liquid clouds (Kaufman et al., 2005; Myhre et al., 2007), trade wind cumulus (Yuan et al., 2011), deep convective clouds (Koren et al., 2004; Koren et al., 2005), and mixed types of clouds around the world (Kaufman and Koren, 2006). For the observed positive aerosol optical depth (AOD)–CF relationship, it remains an open question whether this can be explained as aerosol effects on CF or meteorological covariation/retrieval contamination (Zhang et al., 2005a; 2005b; Quaas et al., 2009; Twomey et al., 2009; Varnai and Marshak, 2009; Engström and Ekman, 2010; Jeong and Li, 2010; Koren et al., 2010; Quaas et al., 2010; Huang et al., 2011; Grandey et al., 2013; Gryspeerdt et al., 2016), while Koren et al. (2010) applied a more stringent filtering of cloud masking to aerosol retrievals and found a robust positive AOD–CF relationship for deep convective clouds. Ground observations further provide evidence of a strong physical aerosol effect on the CF (Ten Hoeve and Augustine, 2015). Nevertheless, clouds can also dissipate with increased aerosols due to enhanced entrainment at the cloud top or lateral boundary in non-precipitating and modestly precipitating warm clouds (Ackerman et al., 2004; Bretherton et al., 2007). Wet scavenging events may also lead to a negative relationship between aerosols and CF according to model calculations (Quaas et al., 2010).

Previous studies show that GCMs simulations do not agree with the satellite observations regarding the change of CF associated with the change of aerosol (Penner et al., 2006; Myhre et al., 2007; Quaas et al., 2009). One likely reason is that the various complex interactions between aerosols and clouds are not fully and properly characterized in GCMs. In most GCMs, CF is a variable diagnosed by the grid-box mean relative humidity or cloud water (Sundqvist, 1978; Slingo, 1987; Smith, 1990; Bony and Emanuel, 2001), which makes it difficult to represent sub-grid-scale physical processes that link the aerosol properties to the CF. Also, CFs in GCMs are often tuned to achieve good radiative budget as required by steady long-term climate simulation (Rotstayn, 2000; Wilson et al., 2008). The tuning might end up with using aerosol-related parameters without sufficient observational supports and thus cannot well represent the aerosol–cloud interaction in reality. Moreover, large uncertainties of aerosol concentration in current GCM simulations have been reported (Liu et al., 2012; Zhao et al., 2012; Shindell et al., 2013). The biases of global mean AODs from 10 ACCIMP GCMs range between −30 and +20% with most models being too low (Shindell et al., 2013). This implies that even the correct relationship between aerosol and CF is simulated by the GCMs, modelled CF could still be biased.

As indicated above, there are two pathways that aerosol biases influence the CF simulation in GCMs. The first way is that the aerosol amount (represented by AOD here) is simulated incorrectly so that the corresponding CF is predicted with errors (denoted here as “AOD error”). The second way is through the incorrect representation of the aerosol–CF relationship (denoted here as “aerosol–CF error”). While there were studies evaluating the performance of models in simulating aerosol amount and examining the representation of aerosol–CF relationship (Myhre et al., 2007; Quaas et al., 2009), few studies have focused on the correspondence of model performance in CF simulations regarding the model simulations in aerosol amount. Here we try to understand how significantly the biases in the simulated aerosol concentration contribute to the simulated CF biases. We separate the AOD error from the aerosol–CF error using the “conditional sampling approach” (Bony et al., 2004). Note that the aerosol–CF error also contains the CF errors due to deficiencies in the dynamical and thermodynamics representations in the model in addition to errors due to aerosol–cloud interaction (i.e., cloud microphysics). The bias due to dynamical errors has been studied extensively in Su et al. (2013). This study does not attempt to discuss the impacts of dynamical/thermodynamical errors on CF bias relative to aerosol error, but focuses on quantifying the contribution of aerosol error by separating it from other source of the CF bias. We will also demonstrate the aerosol–CF error in the models by showing the difference between model-simulated and satellite-observed AOD–CF relationship.

This article is constructed as follows. Section 2 describes the satellite data, the aerosol–CF schemes in GCMs, and the methodology to decompose the source of CF biases. Section 3 evaluates the total CF and AOD simulated by GCMs against moderate resolution imaging spectroradiometer (MODIS) observations and analyses the
contribution of AOD bias to the CF error. Section 4 discusses the AOD–CF relationship under different liquid water path conditions. Conclusions are given in section 5.

2 | DATA AND METHODOLOGY

2.1 | Satellite data
This study makes use of the monthly mean AOD and CF from MODIS Terra Collection 6 (MOD08_M3), which were obtained from National Aeronautics and Space Administration (NASA) Level 1 and Atmosphere Archive and Distribution System (LAADS, https://ladsweb.nascom.nasa.gov/). MODIS observations 2001–2008 are used for analysis. The MODIS data were regridded to 2.0 × 2.5° by using area-weighted averaging method to match the model resolutions. We use the MODIS combined AOD retrievals from Dark Target (Levy et al., 2010) and Deep Blue algorithm (Hsu et al., 2004). The Dark Target approach is applied to ocean region in Collection 6 and the Deep Blue algorithm covers the entire land including both dark and bright surfaces. Here we use the term “CF bias” to denote the difference of CF and “AOD bias” to refer to the AOD difference between model simulations and MODIS observations.

2.2 | CF schemes in CMIP5/AMIP GCMs
Although representing the impact of aerosol on the CF remains rudimentary in most GCMs, progress has been made in some GCMs by adding more flexibility for the cloud schemes to respond to physical processes, including the cloud lifetime effect of aerosols. For example, Wilson et al. (2008) introduced a prognostic scheme which links the CF changes with cloud microphysics and other physical processes (convection, boundary layer turbulence, radiation, etc.). The cloud lifetime effect of aerosols is mainly dependent on the autoconversion process whereby cloud droplets convert to rain droplets by collision and coalescence. More and more GCMs incorporated the “cloud lifetime effect” by using autoconversion parameterizations as a function of cloud droplet number concentration, which is related to aerosol number concentration in their cloud droplet nucleation schemes (Rotstayn and Liu, 2005; Lohmann et al., 2007; Morrison and Gettelman, 2008).

A sensitivity study shows that the modelled CF is sensitive to the choice of autoconversion parameterizations (Chuang et al., 2012). While “cloud lifetime effect” occurs in liquid stratiform clouds, physically based ice microphysical treatment can enhance simulation of the cirrus cloudiness (Liu et al., 2007; Xie et al., 2013). The impact of aerosols on convective clouds has just been incorporated into very limited number of GCMs (Song et al., 2012). Because the GCMs have been evolving to incorporate more aerosol impacts, we also evaluate the simulated relationship between CF and aerosol and the sensitivity of CF to aerosol changes in the current generation of GCMs in this study.

The simulations of the Coupled Model Inter-comparison Project Phase 5 (CMIP5) Atmosphere Model Intercomparison Project (AMIP) provide an experimental protocol for models to carry out atmospheric-only simulations and archive aerosol and cloud outputs (Gates, 1992; Taylor et al., 2012). The models in AMIP-type simulations employ the same constrained sea surface temperature, sea ice, solar constant, and atmospheric composition (including CO2 and aerosols) due to both anthropogenic and volcanic influences (Taylor et al., 2012). A total of 12 GCMs from CMIP5/AMIP with available outputs of AOD at 550 nm and total CF have been selected for this study. The data are downloaded from the Earth System Grid Federation (ESGF, http://esgf.llnl.gov/). We choose these CMIP5/AMIP GCMs because they include the simulations of aerosol–cloud interactions and feature a variety of types of CF schemes. Although aerosols may have different impacts on low, middle, and high clouds, the total CF is examined in this study because it is a very important climate variable to represent the cloud bulk properties. Actually, aerosols may have different impacts on clouds at different heights (Li et al., 2011; Zhao et al., 2018). However, this study only examines the AOD–CF relationship. The reason is that aerosols at different heights are not available for the CMIP5 model output. Moreover, cloud vertical profiles are only available for limited number of CMIP5 models. Instead, the total CF is available for most CMIP5 model outputs.

Table 1 lists the 12 models examined in this study along with the CF schemes and the aerosol indirect effects (AIEs) considered. CF in most current GCMs is a variable diagnosed by the critical relative humidity or cloud water (Sundqvist, 1978; Slingo, 1987; Sundqvist et al., 1989; Smith, 1990; Bony and Emanuel, 2001). The CFs simulated from diagnostic schemes have a strong dependence on water vapour or cloud water due to the underlying assumption that moisture variability follows a probability distribution and usually the fraction of the cloudy part in the model grid box is determined by the probability of moisture passing a certain threshold (Wilson et al., 2008). Water vapour is further influenced by the aerosol impacts on radiation and cloud microphysical properties simulated in the model. In other words, the CF is indirectly related to aerosol through water vapour in the model simulations with a diagnostic scheme. By contrast, the prognostic CF schemes do not suffer from this issue, and CF has been related to aerosols through processes of cloud droplet nucleation and autoconversion. They include the schemes used in ACCESS-1.3 proposed by Wilson et al. (2008), in MIROC proposed by Watanabe et al. (2009), in CSIRO-Mk3.6.0 proposed by Rotstayn (1997; 1998) and Rotstayn et al. (2000), and in MRI-CGCM3 proposed by Tiedtke (1993). All model results are regridded to 2.0 × 2.5° by using area-weighted averaging method to be consistent in the spatial
resolution. Because there are relatively large uncertainties in both model simulations and satellite observations over the Polar regions, this study considers the global evaluations in the region between 60°S and 60°N. Eight years of simulations from 2001 to 2008 are used for analysis. Considering that climate model outputs are usually given in monthly means, monthly mean AOD and CF results are evaluated both globally and regionally. How-

categorize the CF in each model grid box into the parameter space of AOD in lieu of geographical location, that is, CF as a function of AOD (denoted by α),

\[ \text{CF}=\text{CF}(\alpha). \]

The global or regional mean cloud fraction, \( \langle \text{CF} \rangle \), can be obtained by integrating \( \text{CF}(\alpha) \) multiplied by the probability density function (PDF) over all possibility values of AOD (0 to +∞),

\[ \langle \text{CF}^{o,m} \rangle = \int_{0}^{+\infty} \text{CF}^{o,m}(\alpha) P^{o,m}(\alpha) d\alpha, \quad (1) \]

where superscript \( o \) and \( m \) stand for observation and model, respectively, and \( P(\alpha) \) is the PDF of \( \alpha \). The difference between modelled and observed CFs is then

\[ \langle \text{CF}^{m} - \text{CF}^{o} \rangle = \langle \text{CF}^{m} \rangle - \langle -\text{CF}^{o} \rangle 
= \int_{0}^{+\infty} \text{CF}^{m}(\alpha) P^{m}(\alpha) d\alpha - \int_{0}^{+\infty} \text{CF}^{o}(\alpha) P^{o}(\alpha) d\alpha 
= \int_{0}^{+\infty} \delta(\text{CF}(\alpha) P(\alpha)) d\alpha, \quad (2) \]

in which

\[ \delta(\text{CF}(\alpha) P(\alpha)) = \text{CF}^{m}(\alpha) P^{m}(\alpha) - \text{CF}^{o}(\alpha) P^{o}(\alpha). \quad (3) \]

The integrand can be decomposed into

\[ \delta(\text{CF}(\alpha) P(\alpha)) = \text{CF}^{o}(\alpha) \delta P(\alpha) + P^{o}(\alpha) \delta \text{CF}(\alpha) + \delta P(\alpha) \delta \text{CF}(\alpha), \quad (4) \]

where

\[ \delta \text{CF}(\alpha) = \text{CF}^{m}(\alpha) - \text{CF}^{o}(\alpha), \]
\[ \delta P(\alpha) = P^{m}(\alpha) - P^{o}(\alpha). \]

The CF bias, \( \langle \text{CF}^{m} - \text{CF}^{o} \rangle \), is now separated into three parts:

\[ \langle \text{CF}^{m} - \text{CF}^{o} \rangle = \int_{0}^{+\infty} \text{CF}^{o}(\alpha) \delta P(\alpha) d\alpha 
+ \int_{0}^{+\infty} P^{o}(\alpha) \delta \text{CF}(\alpha) d\alpha 
+ \int_{0}^{+\infty} \delta \text{CF}(\alpha) \delta P(\alpha) d\alpha. \quad (5) \]

The first term on the right is the “AOD error,” which can cause CF bias by the incorrectly modelled aerosol loading represented by the bias of AOD probability (i.e., \( \delta P(\alpha) \)). With AOD–CF relationship (i.e., \( \text{CF}^{o}(\alpha) \)) being correctly represented, this term means that AOD bias alone can introduce CF bias in the models. The second term represents CF bias introduced by biased AOD–CF relationship (i.e., \( \delta \text{CF}^{o}(\alpha) \)).
CF, and aerosol error source because the relative significances of first two terms, the approach is not applicable to identify the major “(i.e., AOD–CF) relationship because the “covariation error.” If the “covariation error” term is larger than any of the first two terms, the approach is not applicable to identify the major error source because the relative significances of first two terms are not conclusive.

This approach assumes that the observed aerosol amount, CF, and aerosol–CF relationship are the “ground truth.” Many previous studies focus on the analysis of dependence of aerosol–cloud relationship on the meteorological conditions (e.g., covariation of AOD and CF to relative humidity or wind speed) (Quaas et al., 2009; 2010; Engström and Ekman, 2010; Jeong and Li, 2010; Koren et al., 2010; Grandey et al., 2013; Gryspeerdt et al., 2016) or retrieval techniques (e.g., 3D scattering of light near clouds, cloud contamination of aerosol retrievals) (Zhang et al., 2005a; 2005b; Twory et al., 2009; Vårnai and Marshak, 2009; Huang et al., 2011). Here we do not attempt to discuss the influential factors behind the observed AOD–CF relationship, which is still an open question, and simply assume that they are reliable. The “conditional sampling approach” applies even if there are meteorological influences on the AOD–CF relationship because the “AOD error” is calculated assuming that the GCMs reproduce the AOD–CF relationship under the influence of meteorological covariation. To minimize cloud contamination to AOD retrievals, we confine our analysis to data with AOD less than .5 for both observations and models because low AOD conditions are less likely contaminated by clouds.

2.4 Cloud simulator

We evaluate the model performance based on satellite-retrieved CF because they provide global coverage. However, our analysis does suffer from the different ways that the models and the satellites see clouds. Over the past 10 years, cloud simulators have been developed to evaluate the simulation of clouds in models (Zhang et al., 2005a; 2005b). Cloud simulators are software tools that enable models to mimic the observational process of satellite sensors. The Cloud Feedback Model Intercomparison Package (CFMIP) Observational Simulator Package (COSP) has been developed to enable the simulation of CF in models for several active satellite sensors, including CALIPSO, and passive satellite sensors (Bodas-Salcedo et al., 2011). To best compare the modeled CF with satellite observations, in addition to direct output of the calculated cloud property from the model, the cloud simulators were embedded in some GCMs to allow the models to mimic the satellite retrieval process (Zhang et al., 2005a; 2005b; Bodas-Salcedo et al., 2011). MODIS simulator results are not available from the AMIP data set. Hence, we examine the total CF from the CALIPSO simulator that are available in 6 out of the 12 CMIP5/AMIP models (CESM1-CAM5, HadGE2-A, the three IPSL models, and MIROC5). We downloaded the simulator outputs from Deutsches Klimarechenzentrum (DKRZ) world data center for climate (https://www.dkrz.de/daten-en/data-access). In order to include all 12 GCMs, here we present both the results calculated by the simulator and directly by the model scheme. We use the relationship of AOD and CF from the cloud simulator to justify the conclusions that we draw from the model direct calculation.

3 RESULTS

3.1 Evaluating the simulation of AOD and CF by the CMIP5/AMIP models

3.1.1 Global and zonal-averaged AOD and CF

We first evaluate how well the CMIP5/AMIP GCMs simulate the AOD and CF compared to the satellite observations. Global averages of AODs and total CFs simulated by 12 models are shown and compared with the MODIS retrievals in Figure 1. The differences of AODs and CFs between all individual model simulations and MODIS observations are statistically significant at 95% confidence level. The difference in globally averaged AOD between the MODIS retrieval and multi-model ensemble mean is .04 (.18 vs. .14). The multi-model ensemble mean AOD is 22.2% lower than the MODIS AOD. GISS-E2-R global average AOD is .26, which is much higher than MODIS retrieval and other models. By contrast, MRI-CGCM3 global average AOD is .07, which is much lower than others. Global-averaged total CFs from all the models are lower than MODIS retrieval. The multi-model ensemble mean CF is 56.5%, which is 15.2% lower than the MODIS mean value of 66.6%. For global-averaged CF, CSIRO-Mk3-6-0 is most comparable to MODIS with a value of 65.3%, and HadGEM2-A is worst comparable to MODIS with a value of 51.8%. Note that the ensemble mean of global-averaged CF from 12 CMIP5/AMIP model results is comparable with that from 28 CMIP5/AMIP models (56.5 vs. 57.6%) (Dolinar et al., 2015). We notice that both the global mean AOD and CF are underestimated by the models in the sense of ensemble mean, which makes us wondering if the AOD error contributes to the CF bias in the models.

To study the latitudinal variations, Figure 2 shows the zonally averaged multi-model ensemble mean AOD and CF from 60°S to 60°N, along with the standard deviations, minimums, and maximums from 12 CMIP5/AMIP models and MODIS observations. Compared to MODIS, the multi-model ensemble mean captures the zonal variations of observed AOD and CF reasonably well. However, the
multi-model ensemble mean and most individual GCMs-simulated AODs and CFs are underestimated at latitudes between 30°S and 60°N and at all latitudes, respectively. The multi-model ensemble mean AOD is comparable to the MODIS results between 60°S and 30°S where marine aerosols dominate. The observed AOD peaks between 10°N and 30°N where the anthropogenic activities predominate. The latitudinal averages of CF feature a maximum value in the stormy Southern Ocean where the mid-latitude cyclones prevail (Haynes et al., 2011). There are another two minor peaks, one in the intertropical convergence zone (ITCZ) where the convective clouds prevail (Waliser and Gautier, 1993), and the other in the mid-latitude extratropics of the Northern Hemisphere where persistent marine stratocumulus dominates in the eastern sides of the oceans (Klein and Hartmann, 1993). There is nearly no correlation between the latitudinal variations of AOD and CF in the Northern Hemisphere. This may imply that aerosols influence the CF in a regional scale while large-scale atmospheric dynamics and water vapour supply are more influential in the latitudinal-averaged cloudiness. For instance, the high AOD in East Asia near 30°N is associated with the high CF (as will be shown in Figure 3) but the latitudinally averaged CF appears to be a minimum. The low cloudiness near 30°N is due to large-scale downwards air motion in the descending branch of the Hadley circulation and lack of moisture in the African desert region. However, there is a weak correlation between the latitudinal dependence of AOD and CF in the Southern Hemisphere. A likely explanation is that both AOD and CF are related to the surface wind speed over the Southern Ocean (Engström and Ekman, 2010).
3.1.2 Global distribution of AOD and CF

Figure 3a–f shows the global distribution of 8-year mean AOD at 550 nm and total CF of the MODIS observations, the CMIP5/AMIP model ensemble mean, and their difference. The models generally capture the global distributions of AOD and CF reasonably well. The multi-model ensemble mean AOD tends to be underestimated in East Asia, India, Taklimakan/Gobi Desert, Central America, Amazon Basin, downwind of the Africa tropical rainforest, and tropical oceans, but overestimated in deserts of Africa (the Sahara Desert and Namib Desert), Middle East (the western rim of Arabian Desert and Iran Desert), Indian Desert, Turkistan Desert, Australia Desert, and Southern Ocean. The model underestimation in East Asia and India is likely due to anthropogenic aerosols. The CFs are generally underestimated, especially in the stratocumulus dominant regions in the eastern boundaries of the Atlantic and Pacific Oceans in the subtropics and the mid-latitude oceans. Figure 3e,f shows the geographical collocation of AOD and CF biases in the models, which are consistent in sign for some regions (East Asia, India, and tropical Africa) but inconsistent for other regions (e.g., ITCZ). Generally speaking, the biases of AOD and CF are consistent in sign over land but differ in sign over the ocean. This implies that the CF bias could be possibly linked to the aerosol bias for some specific regions or cloud types, however, with the caveat that covariation between AOD bias and CF bias does not imply causality.

Figure 3g,h shows the global distribution of standard deviations of AODs and CFs among the 12 CMIP5/AMIP models normalized by the multi-model mean (i.e., standard deviation over mean) of (g) AOD and (h) CF.
Figure 3h shows that the models are inconsistent with each other in CF simulations over the remote tropical Pacific Ocean, Sahara Desert, Afghanistan, and North Australia, where the CFs are low. For the CV values of AOD and CF, we barely find any similarity in their spatial patterns, which may imply that although the aerosol differences among models are relatively large in some regions, they may not attribute much to the differences in CFs.

3.2 Evaluating the relationship between AOD and CF

3.2.1 Global AOD–CF relationship

Figure 4 shows the relationships between AOD and CF in MODIS observations and CMIP5/AMIP model simulations between 60°S and 60°N. The difference of the relationship corresponds to the $\delta$CF($\alpha$) term in Equation (5). AOD values in all grid boxes are binned into 30 bins from .0 to .5 with equal bin widths. The corresponding CFs in each AOD bin are averaged and the standard deviations are shown as vertical bars. The resultant relationship reflects the averaged state across a wide range of cloud types over the globe. There are systematic underestimations for modelled CF compared with the observations, which have also been illustrated in Figures 1 and 2. Putting aside the differences in the magnitude of CF, we find similar slopes in the AOD–CF relationship between the AMIP simulations and MODIS observations over the whole AOD space. This implies that the “aerosol–CF error” term in Equation (5) could be mostly associated with the systematically low-biased CF, which should be caused by dynamic and thermodynamic reasons, instead of incorrect aerosol–cloud interaction. MODIS observations show that CF increases sharply with AOD in the small AOD regime ($\alpha < .1$), varies little for AOD between .1 and .2, and decreases for AOD larger than .2. The model results show similar relationship, but CF decreases for AOD less than .07. As indicated by Myhre et al. (2007), most AOD–CF relationships for AOD less than .20 are likely the result of aerosol–cloud interactions and cloud lifetime effects because in this AOD range the cloud contamination is very weak.

The sensitivity of CF to AOD, defined as $d\log$CF/$d\log\alpha$, is $-.08$ for MODIS and $-.11$ for CMIP5/AMIP models, which is opposite in sign with previous studies and lower in magnitude (1–3 in Quaas et al., 2010 and Grandey et al., 2013). One reason is that we use 8-year monthly mean results to investigate the long-term statistics of the AOD–CF relationships, while Quaas et al. (2009) analysed 1-year daily data to capture the short-term (daily) AOD–CF relationship. Monthly averaging could smooth out the short-term CF variation with AOD, making the sensitivity smaller or even opposite in sign.

Also shown in Figure 4 is the joint PDF of AOD and CF. The most frequent occurrence (>80%) of CF in MODIS observation occurs at AOD around .10 (.07–.20) and the corresponding mean CF increases with AOD from about 65 to 75%. The most frequent occurrence of CF in the CMIP5/AMIP models occurs at a lower and broader range of AOD (.05–.20).

Figure 5 further shows the relationship between AOD and CF for every CMIP5/AMIP model simulations. There is large variability for the AOD–CF relationships and joint PDFs among models as the result of different model representations of aerosol–cloud interaction, along with their differences in simulated circulation and radiation. For AOD values less than .2, some models feature strong negative relationships between AOD and CF (i.e., CESM1-CAM5, GISS-E2-R, HadGEM2-A, the three IPSL-CM5 models, and MRI-CGCM3), which are not seen in MODIS observations. In addition to the influence of aerosol–cloud interaction on AOD–CF relationship, meteorological factors could also play important roles (Myhre et al., 2007). For example, the high-pressure system over land is often associated with low CF and a build-up of high AOD, while storms over the ocean blow up sea salt and favour a cloudy sky. We find similar dependence of CF output from CALIPSO cloud simulator (Figure S2, Supporting information) with the direct CF model output on AOD in six models, which confirms that model-simulated AOD–CF relationships are different.
from the observed one. We also note that the multi-model mean AOD–CF relationship (Figure 4) agrees better with observations than each individual model.

The global distribution of the correlation coefficient (R) between AOD and CF is shown for both MODIS observations and CMIP5/AMIP model simulations in Figure 6. Note that 8-year monthly averages are used to obtain the R values in each model grid box and observation grid. The global pattern of R for both MODIS observations and CMIP5/AMIP model simulations is consistent with the previous studies using daily data (Engström and Ekman, 2010), but the magnitude is higher. The AOD–CF relationships over oceans are dominated by the positive correlations while negative correlations are more commonly seen over lands. The negative correlations between AOD and CF are much stronger for the models than MODIS over lands, which leads to the globally averaged negative relationships between AOD and CF as seen in Figure 4. The MODIS AOD–CF correlation coefficients are high in the tropical Atlantic Ocean (20°S–20°N) downwind of Sahara Desert dust and smoke, where the shallow cloud covers increase from clean to dusty or smoky conditions associated with aerosol change (Kaufman et al., 2005). The multi-model ensemble mean reproduces the AOD–CF correlation quite well. The models also reproduce the high AOD–CF correlation over the tropical Indian Ocean (0°–20°N) east and west to the Indian Peninsula. The AOD–CF correlation over the Southern Ocean is small because the CFS are large regardless of the AOD conditions. The positive correlations over the remote Pacific Ocean in the Southern Hemisphere observed by MODIS are simulated as negative correlations in the models. In other words, the AMIP models do not capture the increase of CF with AOD in this region. Note that this region is clean remote ocean where the trade-wind

![Figure 5](wileyonlinelibrary.com)  
**FIGURE 5** Same as Figure 4, except for the 12 individual CMIP5/AMIP models. Compared to MODIS retrieved AOD and CF, some GCMs simulated too many low AOD cases, such as ACCESS1-0, ACCESS1-3, CESM-CAM5, HadGEM2-A, MIROC5, and MRI-CGCM3, and too high CFS, such as GISS-E2-R, IPSL-CM5A-LR, IPSL-CM5A-MR, and IPSL-CM5B-LR. Most of the GCMs had negative correlations between CF and AOD, opposite to the MODIS results. ACCESS1-3 did have positive correlations but with slightly different slopes as the MODIS-observed one [Colour figure can be viewed at wileyonlinelibrary.com]

![Figure 6](wileyonlinelibrary.com)  
**FIGURE 6** (a) Global (60°N–60°S) distribution of MODIS correlation coefficient between AOD and CF. (b) Same as (a) but for CMIP5/AMIP model ensemble mean. Dotted areas correspond to regions where MODIS AOD–CF correlation that passes the 5% significant level [Colour figure can be viewed at wileyonlinelibrary.com]
cumulus dominates with low CF between 30 and 50%. There are about 58.3% of the grids for MODIS observations and 75.1% of the grids for AMIP simulations with the correlation passing the 95% significance test.

### 3.2.2 Regional AOD–CF relationship

The relationships between AOD and CF vary with regions where different cloud types prevail. To demonstrate the regional difference, Figure 7 illustrates the AOD–CF relationships in 14 regions over the globe (see Figure S1 for region definition). To demonstrate the details for small AOD regimes, we use logarithmic scale for AOD. The northern Pacific Ocean (NPO) and northern Atlantic Ocean (NAO) are characterized by low stratiform clouds due to the large-scale subsidence in the descending branch of the Hadley cell. The CFs in these regions are high. MODIS CFs increase with AOD at high AOD, which is consistent with aerosol prolonging cloud lifetime by inhibiting precipitation. As for the whole AOD range, the AOD and CF are positively correlated in NPO ($R = .23$ for MODIS and $.16$ for the models) but negatively correlated in NAO ($R = -.27$ for MODIS and $-.12$ for the models). The tropical regions, such as tropical Pacific Ocean (TPO), tropical Atlantic Ocean (TAO), and tropical Indian Ocean (TIO), are typically characterized by deep convective clouds and high cirrus clouds. The MODIS observations show moderate to weak positive correlations ($R = .28$, $.22$, and $+.10$ for TPO, TAO, and TIO, respectively) while the multi-model ensemble mean shows a weak negative dependence of CF on AOD. The discrepancies imply that models cannot simulate the increase of convective CF with very low AODs over the pristine remote oceans. Most ocean regions in the Southern Hemisphere, including South Atlantic Ocean (SAO) and south Indian Ocean (SIO), are covered by vast areas of stratocumulus. It is likely that the CFs are so large that the aerosol impact on CF is weak for both MODIS and the models.

Over most continental areas, we find weak positive relationships in North America (NAM), Asia (ASI), and South America (SAM), even negative one in Europe (EUR) between AOD and CF. Usually, there are less water supply over land so that the water competition among aerosol could be more severe, for which the cloud formation is likely more difficult. The modelled AOD–CF correlation is consistent with the MODIS observations. Two exception areas are Africa (AFR, $R = .46$) and Oceania (OCE, $R = .62$) where AOD and CF are highly positively correlated for MODIS observations, but weakly ($R = .07$ for AFR) to moderately ($R = .22$ for OCE) correlated for the model simulations.

The MODIS AOD–CF correlation coefficients in seven regions (NPO, NAO, TPO, TAO, SAO, AFR, and OCE)
The largest error source term is the aerosol error. We analyse the contributions of the error variation is attributed to AOD variation on global average. The CF biases (total error) are decomposed into "aerosol error," "aerosol–CF error," and "covariation error" according to the "conditional sampling approach." Model names are labelled by numbers 1–12 as listed on the right. The numbers marked with diamonds are GCMs with prognostic CF schemes [Colour figure can be viewed at wileyonlinelibrary.com].

are larger than .20 with mean value of .33 (.20–.62). In the univariate regression model, the square of the correlation coefficient (i.e., $R^2$) depicts the variation of CF explained by AOD. This suggests 10.9% (4.0–38.4%) of the observed variation in CF could be explained by the AOD variation in these regions. The critical $R$ value of .20 is used here because it is a minimum value when AOD–CF correlation is significant at 95% level. The global mean AOD–CF correlation coefficient for the model simulations is .10 ($-.01-.22$), which is generally smaller than the MODIS retrievals. This indicates that only 1.0% of the modelled CF variation is attributed to AOD variation on global average.

### 3.3 Contributions of “AOD error” and “aerosol–CF error” to CF bias

We analyse the contributions of the “AOD error” and the “aerosol–CF error” to the simulated CF bias using the “conditional sampling approach” described in section 2.3. Figure 8 and Table 2 show the magnitude of the CF error due to “AOD error,” “aerosol–CF error,” and “covariation error” in 12 CMIP5/AMIP models. Generally speaking, the largest error source term is the aerosol–CF error, which is $-11.11\% (-24.35\text{ to } .55\%)$ in the CF bias. This could be expected because the CF in the models are low-biased for the whole AOD range as illustrated in Figure 4. The AOD biases are generally small in all models, contributing to the model mean CF bias of $-0.48\% (-3.71\text{ to } 1.03\%)$. The mean covariation error term is larger than the aerosol error term with a value of $1.93\% (-.27\text{ to } 14.75\%)$. The percentage contributions are calculated by dividing the absolute values of each error source by the total of the absolute values and are listed in the brackets in Table 2. The aerosol–CF errors play the dominant contribution to the CF bias with model mean of 82.17%, followed by the covariation error (14.28%) and the aerosol error (3.55%). These results indicate that improving the aerosol representation in most CMIP5/AMIP models barely help to reduce the CF bias, while improving the CF schemes will reduce the CF bias dramatically. Therefore, generally speaking, aerosol simulation bias is not a major contribution to the CF bias in the models.

There is one model with relatively high AOD error contribution term, that is, CSIRO-Mk3.6.0. The CF bias due to AOD error ($-75\%$) in CSIRO-Mk3.6.0 is higher than that due to the aerosol–CF error ($55\%$) in terms of the magnitude and both terms are much larger than the covariation term. The CF bias in CSIRO-Mk3.6.0 is among the smallest in the 12 models. It means that when models simulate reasonable CF values, the aerosol–CF error term will be reduced and the AOD error becomes comparable to it. At this time, reducing the aerosol bias will further improve the CF simulation. The GISS-E2-R, MIROC5, and MRI-CGCM3 have larger CF bias associated with aerosol error than other models but the CF bias associated with aerosol–CF error are larger than that associated with aerosol error, which indicates that the improvement of aerosol will help to improve the CF simulations in these models, although not as significantly as the improvement of CF schemes. The aerosol bias in ACCESS1-3 contributes to $-92\%$ of CF error, which exceeds the CF biased due to aerosol–CF error ($81\%$). However, the covariation error ($-1.60\%$) is the

**Table 2** The error terms that contribute to the CF bias (in CF unit of %) in 12 CMIP5/AMIP models and their percentage in the absolute bias

<table>
<thead>
<tr>
<th>No.</th>
<th>Model</th>
<th>Aerosol error (%)</th>
<th>Aerosol–CF error (%)</th>
<th>Covariation error (%)</th>
<th>Total error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ACCESS1-0</td>
<td>.35 (2.46%)</td>
<td>-13.70 (96.34%)</td>
<td>-.17 (1.20%)</td>
<td>-13.52</td>
</tr>
<tr>
<td>2</td>
<td>ACCESS1-3</td>
<td>.21 (4.90%)</td>
<td>-.22 (5.13%)</td>
<td>-3.86 (89.98%)</td>
<td>-3.87</td>
</tr>
<tr>
<td>3</td>
<td>CESM1-CAM5</td>
<td>-.65 (4.72%)</td>
<td>-8.94 (64.92%)</td>
<td>4.18 (30.36%)</td>
<td>-5.42</td>
</tr>
<tr>
<td>4</td>
<td>CSIRO-Mk3.6.0</td>
<td>-.76 (55.88%)</td>
<td>.55 (40.44%)</td>
<td>.05 (3.68%)</td>
<td>-1.26</td>
</tr>
<tr>
<td>5</td>
<td>GISS-E2-R</td>
<td>-2.07 (22%)</td>
<td>-7.07 (75.13%)</td>
<td>-.27 (2.87%)</td>
<td>-9.41</td>
</tr>
<tr>
<td>6</td>
<td>HadGEM2-A</td>
<td>.37 (2.36%)</td>
<td>-14.86 (94.71%)</td>
<td>.46 (2.93%)</td>
<td>-14.03</td>
</tr>
<tr>
<td>7</td>
<td>IPSL-CM5A-LR</td>
<td>1.03 (5.66%)</td>
<td>-15.36 (84.35%)</td>
<td>1.82 (9.99%)</td>
<td>-12.51</td>
</tr>
<tr>
<td>8</td>
<td>IPSL-CM5A-MR</td>
<td>1.01 (5.98%)</td>
<td>-14.18 (84.00%)</td>
<td>1.69 (10.01%)</td>
<td>-11.49</td>
</tr>
<tr>
<td>9</td>
<td>IPSL-CM5B-LR</td>
<td>.99 (8.02%)</td>
<td>-9.50 (76.92%)</td>
<td>1.86 (15.06%)</td>
<td>-6.65</td>
</tr>
<tr>
<td>10</td>
<td>MIROC5</td>
<td>-2.68 (16.93%)</td>
<td>-10.85 (68.54%)</td>
<td>2.30 (14.53%)</td>
<td>-11.22</td>
</tr>
<tr>
<td>11</td>
<td>MRI-CGCM3</td>
<td>-3.71 (8.67%)</td>
<td>-24.35 (56.88%)</td>
<td>14.75 (34.45%)</td>
<td>-13.31</td>
</tr>
<tr>
<td>12</td>
<td>NorESM1-M</td>
<td>.11 (.77%)</td>
<td>-13.78 (96.43%)</td>
<td>.40 (2.80%)</td>
<td>-13.27</td>
</tr>
</tbody>
</table>

Model mean - .48 (3.55%) -11.11 (82.17%) 1.93 (14.28%) -9.66
largest among the three terms, implying that the approach is unable to separate the contribution of AOD error and aerosol–CF error. In contrast, the rest eight models feature much smaller AOD errors compared to their aerosol–CF errors, implying limited improvement of CF simulation by reducing the aerosol bias.

Four models that incorporate prognostic CF scheme and the second AIE (ACCESS1-3, CSIRO-Mk3.6.0, MIROC5, and MRI-CGCM3, refer to Table 1) show lower aerosol–CF errors compared to their aerosol–CF errors (ACCESS1-0, HadGEM2-A, the IPSL-CM5 models, and NorESM1-M). This implies that the prognostic CF schemes may help reduce the relative error contribution in CF biases due to CF schemes. Actually, the prognostic CF scheme links the simulation of CF with aerosols more directly, making its CF simulations more sensitive to aerosol properties.

We further analyse the contributions of the AOD error and aerosol–CF error to total CF biases for different AOD regimes, that is, the integrands of the first and second terms in the right side of Equation (5), $\delta P(\alpha) P(\alpha) d\alpha$ and $P(\alpha) \delta CF(\alpha) d\alpha$. Figure 9 shows the AOD dependence of the error terms for the 12 CMIP5/AMIP models. The aerosol error term is sensitive to the AOD. All the models, except GISS-E2-R, overestimate the probability of AOD less than some critical value and underestimate the probability of AOD larger than that critical value. The critical AOD values range from .1 to .3 in different models. As a result, $\delta \alpha$ CF is positively biased below the critical AOD value and negatively biased above the critical AOD value. Compared to the aerosol error, the aerosol–CF error is mostly negative over all AOD regimes. The shape of the total error is consistent with the shape of the AOD error term in most models.

From the mathematical view, the probability difference $\delta P(\alpha)$ is added up to zero, but when multiplied by the CF values that vary with AOD (the $P(\alpha)$ term), the integral (the aerosol error term) is not zero. In the extreme case that CF is not related to aerosol burden at all (CF$^a(\alpha)=$Constant), the integral is zero which indicates that the error in the aerosol prediction does not influence the modelling of CF at all. This suggests that only in the condition with a strong dependence of AOD–CF relationship, the contribution of aerosol error term depends on the degree of the misinterpretation of the AOD probability, $\delta P(\alpha)$. As we showed in section 3.2, the dependence of CF on AOD is not very evident in both MODIS and the CMIP5/AMIP models. Therefore, although the AOD is not well represented in most CMIP5/AMIP models, the aerosol error does not contribute too much to the total CF error as seen in Figure 8.

Figure 10 shows the aerosol and aerosol–CF error terms modelled by the 12 CMIP5/AMIP models in 14 regions (see Figure S1 for the region definitions). There are regions where positive CF simulation biases are mainly associated with aerosol error by many models, such as SIO, SAO, SAM, ASI, and EUR. The aerosol biases are relatively larger in SIO, EUR, ASI, NAO, and NPO than others. The aerosol–CF errors in most regions are negative in many models. The overestimation of CF in the TPO as shown in Figure 3f is identified as the combined result of aerosol and aerosol–CF errors. The aerosol–CF error leads to negative CF bias as predicted by all models in SAM; therefore, the

**FIGURE 9** The AOD dependences of the total CF error (green lines) and aerosol (pink lines), CF scheme (blue lines), and covariation (purple lines) error terms in the 12 CMIPS/AMIP models [Colour figure can be viewed at wileyonlinelibrary.com]
overestimation of CF in the western part of SAM is most likely due to the aerosol error. The magnitude of the positive aerosol error is generally smaller than the negative aerosol–CF error, which makes the multi-model ensemble mean CF underestimated in most part of the land and ocean.

4 | DISCUSSION

Figure 11 demonstrates that MODIS AOD–CF relationship shows different characteristics for high and low cloud water path (CWP) conditions. Based on MODIS observations, clouds with high CWPs are generally associated with high CFs (Figure 11a). The CFs barely increase with AOD for low CWPs (0–20 g/m²) and increase with AOD for larger CWPs (>20 g/m²). The sensitivities of CFs to AOD increase with increasing CWP. In the dry cases, increased AOD does not increase the CF because there is not enough water vapour to condense and form clouds. By contrast, in water abundant clouds there is ample water vapour for the aerosol particles to activate as cloud droplets, and as AOD increases, either due to the increase of aerosol number concentration or the hygroscopic growth of aerosols, or both, adequate supply of water vapour fuels up the growing clouds. Interestingly, at the same AOD level, the CF does not decrease as CWP increases as predicted by the “cloud lifetime effects” that precipitation starts to dissipate clouds at certain point. However, we do find CF levels off as AOD reaches a certain threshold value. The larger the CWPs are, the smaller the AOD thresholds are, which are consistent with the “cloud lifetime effects.” Based on model results, clouds with high CWPs tend to be characterized by large CFs, which agrees with the MODIS observations. However, the simulated CFs do not become more sensitive to AOD as CWPs increase. For example, CFs in MIROC are insensitive to AOD changes for all CWPs ranges (Figure 11b). In the dry cases with CWPs less than 40 g/m², MIROC5 CFs even decrease with AOD. This indicates that the MIROC model may not handle the physical aerosol–cloud interaction well enough.

5 | CONCLUSIONS

CF is one of the key parameters in cloud radiative forcing calculation in GCMs. Here we evaluate the total CFs and AODs in 12 CMIP5/AMIP GCMs against 8-year monthly mean MODIS Collection 6 retrievals. The global-averaged multi-model ensemble mean AOD (.14) is 22.2% lower than the MODIS retrieval (.18) and the CF (56.5%) is 15.2% lower than MODIS retrieved CF (66.6%). Because the
GCMs now incorporate mechanisms that aerosols influence CF by activation and autoconversion, we raise a key question in this study: How significantly do the biases in the simulated aerosol concentration contribute to the simulated CF bias?

We investigate the discrepancies in AOD–CF relationships between MODIS observations and AMIP simulations. Overall, the global (60°S–60°N) multi-model ensemble mean results show similar AOD–CF relationship with that from the MODIS observations. CFs are generally underestimated in the models for all AOD regimes. The sensitivity of the monthly mean CF to AOD is −.08 and −.11 for MODIS observations and models, respectively. The sensitivity found here is lower in magnitude and even opposite in sign with those found by previous studies using daily data (Quaas et al., 2009) probably due to different temporal resolutions. However, large discrepancies in the AOD–CF relationships exist among the 12 individual models, while most models show strong negative relationships.

Over the mid-latitude oceans where stratiform clouds dominate (e.g., NPO and NAO), the CMIP5/AMIP models do not capture the decreasing CF trend for low AOD and the increasing trend for high AOD in MODIS. For deep convection zone over the pristine oceans, MODIS AOD–CF relationship shows a positive relationship while the CMIP5/AMIP multi-model ensemble mean shows a weak negative dependence. Over land, the air is dry so that CF weakly increases with AOD due to moisture competition, which is consistent between MODIS and the models. We also investigated the AOD–CF dependence in MODIS and MIROC5 under different CWPs. The MIROC5 CF is not sensitive to AOD under all these conditions as the MODIS observations do.

We analysed the relative contribution of errors introduced by aerosol and CF schemes to the CF bias using the “conditional sampling approach” (Bony et al., 2004). By decomposing the CF bias into AOD error and aerosol–CF error, we demonstrated that CF bias introduced by CF schemes in GCMs is the largest source of CF error. Generally, the AOD error itself barely contributes to the global mean CF bias in most GCMs. According to our analysis, the AOD error contributes −.48% (−3.71 to 1.03%) to the CF bias, while the aerosol–CF error contributes −11.11% (−24.35 to .55%) to the CF bias for global means of different models. The aerosol–CF error dominates the contribution to the CF bias with model mean of 82.17% of the absolute CF total error, followed by the covariation error (14.28%) and the aerosol error (3.55%). Even so, improving the AOD simulations in some CMIP5/AMIP models, such as CSIRO-Mk3.6.0, GISS-E2-R, MIROC5, and MRI-CGCM3, could improve the CF prediction better than the other models.

The sensitivity of CF to AOD is not strong in most models, so that the improvement of AOD PDF is not likely to affect the global-averaged monthly mean CF too much.

The aerosol error terms are positive in many regions as predicted by CMIP5/AMIP GCMs, while the aerosol–CF errors are mostly negative. There are some regions where the CF errors due to AOD biases are larger than the other regions, such as SIO, ASIA, EUR, NAO, and NPO.

This study suggests that CF schemes in GCMs are the most problematic factor in CF simulation, which is consistent with the findings of previous studies (Su et al., 2013; Yoo et al., 2013). Using a prognostic CF scheme instead of a diagnostic scheme such as in the model CSIRO-Mk3-6-0, more consistent CF simulations have been found compared with MODIS observations. We recommend prognostic CF scheme for climate model simulations and suggest future efforts to incorporate sub-grid-scale aerosol effects on the cloud microphysical and macrophysical properties such as those performed in the cloud-resolving models (Fan et al., 2013).

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Conflict of interests

The authors declare no potential conflict of interests.

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