Quantifying contributions of model processes to the surface temperature bias in FGOALS-g2

Bo Liu1,2, Tianjun Zhou1,3, and Jianhua Lu1,4

1State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China, 2University of Chinese Academy of Sciences, Beijing, China, 3Climate Change Research Center, Chinese Academy of Sciences, Beijing, China, 4Center for Ocean-Atmospheric Prediction Studies, Florida State University, Tallahassee, Florida, USA

Abstract To quantify the annual mean surface temperature bias due to various processes in Flexible Global Ocean-Atmosphere-Land-System model, Grid point version 2 (FGOALS-g2), the climate feedback-response analysis method (CFRAM) is used to isolate contributions from both radiative and nonradiative processes in the model by comparing the model simulation with ERA-Interim reanalysis. The observed surface temperature bias is decomposed into seven partial temperature biases associated with surface albedo, water vapor, cloud, both surface sensible and latent heat fluxes, land/ocean heat transport processes, and atmospheric transport processes. The global mean cold bias (−1.39 K) is mostly attributed to surface albedo and land/ocean heat transport processes while surface latent heat fluxes tend to weaken this bias. Cloud-induced bias is dominated by shortwave cloud radiative effect (SWCRE) over low-latitudes and longwave cloud radiative effect (LWCRE) over high latitudes. The mixed layer depth (MLD) bias is consistent with the bias due to ocean heat transport over North Pacific, North Atlantic, and the Southern Ocean. On global scale, contributions of radiative processes and nonradiative processes to the total observed cold bias are comparable, but tend to compensate each other over most regions except for the northern high latitudes. We suggest that the improvements in tropical clouds in the model may significantly decrease the global temperature bias through the interaction between clouds and circulation.

1. Introduction

Climate models are sophisticated tools designed to understand present climate and project future climate as well as to understand the mechanisms responsible for the past and projected climate change and variability. Surface temperature is one of the essential variables and perhaps the most routinely examined quantity when evaluating the performance of climate models. Over the past decades, the state-of-the-art climate models, though tremendous effort has been made to improve their performance, still have apparent surface temperature biases in many regions [Flato et al., 2013]. Therefore, identification and reduction of these biases are of vital importance for the development of the next-generation climate models.

Recently, Lu and Cai [2009] developed the coupled surface-atmosphere climate feedback-response analysis method (CFRAM) to quantify the contributions of individual model processes to the total temperature changes. In the framework of CFRAM, radiative and nonradiative processes can be resolved so that we can gain better understanding of the sources of temperature anomalies. Given the advantage of process resolving, the CFRAM has been adopted to quantify the contributions of various radiative and dynamical feedbacks in determining the polar warming amplification [Lu and Cai, 2010], the surface and atmospheric temperature anomalies associated with the El Niño-Southern Oscillation (ENSO), and the Northern Annular Mode (NAM) [Deng et al., 2012; Park et al., 2012; Deng et al., 2013]. Meanwhile, this framework has also been applied to assess the surface temperature biases of Community Earth System Model version 1 (CESM1) [Park et al., 2014] and Flexible Global Ocean-Atmosphere-Land-System model, spectral version 2 (FGOALS-s2) [Yang et al., 2015], and their results show that the process-decomposition analysis can explicitly quantify the contributions of individual processes to the observed surface temperature bias.

The evaluation of FGOALS-g2 (Flexible Global Ocean-Atmosphere-Land-System model, Grid point version 2) has shown that, compared with FGOALS-g1, there are many important improvements, including the better
simulation of the annual cycle of sea surface temperature (SST) along the equator in the Pacific and the improvement in the amplitude and period of ENSO [Li et al., 2013a; Bellenger et al., 2014]. Though FGOALS-g2 [Li et al., 2013a] and FGOALS-s2 [Bao et al., 2013] are both coupled climate models developed at the State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics (LASG, IAP), they have employed two different Atmospheric General Circulation Models (AGCMs)—Grid point Atmospheric Model of IAP LASG version 2 (GAMIL2) [Li et al., 2013b] and Spectral Atmospheric Model of IAP LASG version 2 (SAMIL2) [Bao et al., 2013], respectively. Indeed, their performances differ in many aspects such as the polar amplification of the warming trend as well as the related water vapor feedback mechanism and sea-ice albedo feedback mechanism [Zhou et al., 2013], and the climate sensitivities [Chen et al., 2014]. Accordingly, the model bias in surface temperature reported in present study also differs from the FGOALS-s2 reported by Yang et al. [2015].

The purpose of this study is to evaluate the simulation of surface temperature in FGOALS-g2 and decompose the bias into several radiative and dynamical processes utilizing the CFRAM method. Here we apply the CFRAM to quantify the contributions of seven processes, including surface albedo, cloud, water vapor, surface sensible/latent heat flux, land/ocean transport processes, and atmospheric transport processes, to the annual mean surface temperature bias simulated by FGOALS-g2. Note that the surface temperature bias defined here is with respect to the surface temperature record in the European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis Interim (ERA-Interim) [Dee et al., 2011].

The organization of this study is as follows. Section 2 presents the mathematical formulation of the CFRAM and its application in this study. In section 3, we show the main results. Section 4 gives the concluding remarks and some discussions.

2. Model, Data, and Method

2.1. Model and Data

FGOALS-g2 is a member of models taking part in the Coupled Model Intercomparison Project Phase 5 (CMIP5) experiments. The four components of FGOALS-g2 are listed as: the atmospheric components (GAMIL2); the oceanic components (LASG IAP climate system ocean model version2, LICOM2) [Liu et al., 2012]; the sea ice component CICE4 (Community Ice CodE)-LASG, an improved version of CICE4.0 (Los Alamos sea ice model version 4.0, http://climate.lanl.gov/Models/CICE); the land components CLM3 (Community Land Model version 3.0) [Oleson et al., 2010]. The CMIP5 historical run of FGOALS-g2 covers the period from 1850 to 2005.

The ERA-Interim data set covers the period from 1979 to present with the horizontal resolution of 1.5 × 1.5 degree². Therefore, our analysis is focused on the differences between FGOALS-g2 and ERA-Interim during 1979–2005, which is covered by both model and reanalysis data. Variables required here as input data for CFRAM include 2-D fields such as incident solar radiation at the top of atmosphere, surface temperature (skin temperature over land and SST over ocean), and surface albedo and 3-D fields including atmospheric temperature, specific humidity, cloud fraction, and cloud liquid/ice content.

2.2. Method

The CFRAM, developed by Lu and Cai [2009] and Cai and Lu [2009], is based on the total energy balance within the multilayer atmosphere-surface column at a specific horizontal grid of a climate model with one, two, or three dimensions. The total energy balance can be written as

\[ \vec{R} = \vec{S} + \vec{Q}_{\text{nonradiative}} - \frac{\partial \vec{E}}{\partial t}, \]  

indicating that within each layer, the divergence of the longwave radiation flux (\(\vec{R}\), or longwave radiative cooling, W/m²) is always equal to the sum of the convergence of shortwave radiation flux (\(\vec{S}\), or shortwave radiative heating), total energy influx due to nonradiative processes (\(\vec{Q}_{\text{nonradiative}}\)), and the decrease of heat storage in the column (\(-\frac{\partial \vec{E}}{\partial t}\)). The model layers in the CFRAM include all of atmospheric layers plus the first land/ocean layer. Because of the small heat capacity of the air, the heat storage term in atmospheric layers is close to zero even at the seasonal time scale. Because the first model layer for land (usually on the order of a tenth of meter) or ocean (about 5 m) is shallow, the heat storage term of the first land/ocean layer may also be set to zero.
To quantify the contributions of these seven model processes to the annual mean surface temperature bias in FGOALS-g2, we employ the CFRAM-based process-decomposing calculation (equation (6)) considering the differences between FGOALS-g2 and ERA-Interim annual mean state. Note that the ERA-Interim data set is a reanalysis and has gaps with truly observed climate state [e.g., Simmons et al., 2010]. All the radiation calculations here are performed using the Fu-Liou radiative transfer model [Fu and Liou, 1992, 1993] for each model grid point based on the 26 year monthly mean outputs from ERA-Interim and FGOALS-g2. To reduce the errors due to the unresolved variability of cloud profiles, when calculating the cloud radiative effect, a variation of Monte Carlo Independent Column Approximation (MCICA) [Barker et al., 2002; Pincus et al., 2003] is applied here following Taylor et al. [2013] and Park et al. [2014]. Instead of directly using monthly mean cloud profiles such as cloud fraction and cloud liquid/ice mixing ratios, MCICA here is performed by dividing each model column into 100 subcolumns and, therefore, generating 100 cloud profiles. These subcolumn profiles are generated using a maximum-random overlap cloud generator [Räisänen et al., 2004]. The energy flux differences due to surface sensible/latent heat flux are directly derived from the surface heat flux of FGOALS-g2 and ERA-Interim. In addition, the energy perturbations due to atmospheric dynamics and L/OHT are estimated as residuals, meaning that the rest of energy perturbations are all explained by L/OHT or atmospheric dynamics terms.
3. Results

3.1. Surface Temperature Bias and Its Decomposition

The surface temperature bias between FGOALS-g2 and ERA-Interim (FGOALS-g2 minus ERA-Interim, Figure 1) is similar to the results in Li et al. [2013a], in which FGOALS-g2 has been evaluated. From a global perspective, cold biases dominate over most regions and the simulated global mean surface temperature is 1.39 K lower than ERA-Interim. However, the surface temperature bias is also characterized by salient regional features. Over the oceans, significant cold biases are found over Barents Sea, North Pacific, Gulf of Stream region, Brazil Current region, the Antarctic Ocean, and its adjacent seas, while warm biases can be seen over northern North Atlantic, eastern South Pacific, and eastern South Atlantic. Over the land, cold biases dominate over most land areas such as Eurasia, Africa, and North America while warm biases are found over Greenland, northern South America, and Indian Peninsula.

In the CFRAM, the partial temperature anomalies due to different model processes are additive and the sum should be approximately equal to the total temperature anomaly [Lu and Cai, 2009; Lu and Cai, 2010]. The total temperature bias and the seven partial components induced by various radiative and dynamical processes through CFRAM are shown in Figure 2. As can be seen, whether for spatial structure and magnitude, the sum of the seven partial temperature biases derived through equation (6) in CFRAM bears a high degree of similarity with the original bias (Figure 2a). This similarity demonstrates that the CFRAM-based decomposition is reasonable [Park et al., 2014; Yang et al., 2015].

The partial temperature bias due to surface albedo covers, not surprisingly, over land and polar regions with nearly no effect over the oceans in low and middle latitudes (Figure 2b). The albedo-induced temperature biases are also evident with the warm bias over Desert regions, the Sahara Desert over Africa and Great Victoria Desert over Australia, and the cold bias over high elevations, the Tibetan Plateau. Overall, the albedo-induced bias is $-0.53$ K for global averaged surface temperature. The water-vapor-induced temperature bias is relatively small compared to other processes and it mainly occurs near the central and southeastern Pacific, eastern Indian Ocean, northwestern Europe, and adjacent seas (Figure 2c). Contrast to the albedo-induced bias, the contribution of cloud-induced bias to the total bias is presented throughout the globe (Figure 2d). The spatial pattern of the cloud-induced bias is characterized mainly by cold bias over the tropics and warm bias over the Southern Ocean and northern high latitudes. Warm cloud-induced
Figure 2. The climatological annual mean (a) total temperature bias (K) and partial temperature biases (K) associated with (b) surface albedo, (c) water vapor, (d) cloud, (e) surface sensible heat flux, (f) surface latent heat flux, (g) land/ocean heat transport, and (h) atmospheric dynamics.
biases also occur over the subtropical stratocumulus regions (Figure 2d), suggesting a too weak solar reflection by low clouds in the model.

The spatial patterns of temperature biases induced by sensible heat flux and latent heat flux of FGOALS-g2 are similar to that of CESM [Park et al., 2014]. For low-latitude oceans, the sensible heat flux contributes little to the total temperature bias, while the effect of latent heat flux is seen all over most of the oceans. This is not surprising because the latent heat flux dominates the total surface turbulent heat flux over the oceans. Over land, the biases induced by the sensible heat and latent heat fluxes tend to compensate each other (Figures 2e and 2f). Figure 2g suggests, whether for land or ocean, L/OHT plays an important role in determining the spatial pattern of total temperature biases. For tropical regions, the L/OHT tends to compensate the effect of cloud-induced temperature bias and latent-heat-induced bias. Compared to L/OHT-induced temperature bias, surface temperature bias due to atmospheric dynamics is relatively small and is nearly consistently negative over global oceans (Figure 2h), but we should note that the atmospheric dynamics is very important to the bias in 3-D structure of atmospheric temperature biases which are not presented in this study.

To quantify the relative contributions of the seven processes to the amplitude of surface temperature bias over certain region, here we calculate pattern-amplitude projection (PAP) coefficients following Park et al. [2012, 2014] and Deng et al. [2013]. The PAP coefficient is defined as

$$ PAP_i = A^{-1} \int_a^A \frac{a^2 A^2 \Delta T \cos \phi d \phi}{\int_a^A a^2 A^2 \Delta T \cos \phi d \phi} $$

where $\phi$ and $\lambda$ are latitude and longitude, respectively; $a$ is the mean radius of the earth, and $A$ is the area of the region under consideration. $\Delta T$ and $\Delta T_i$ are the total temperature bias and partial temperature biases associated with individual processes for a certain grid point. By definition, PAP is the weighted area average of the total temperature bias multiplied by a “pattern projection coefficient.” Since the sum of pattern projection coefficients equals to 1, the sum of all the PAPs due to these processes for a certain region equals exactly to the area average of the observed temperature bias. In this sense, $PAP_i$ can provide a more reasonable measure when assessing the relative contributions of individual processes to the observed total temperature bias.

The PAP coefficients of these seven processes for globe, land, and ocean are shown in Table 1. The PAP results indicate that the global mean bias ($-1.39$ K) is dominated by the temperature biases due to albedo ($-0.53$ K) and L/OHT ($-1.27$ K). Surface latent heat flux bias ($0.53$ K) tends to compensate the cooling effect. The temperature biases due to LHT and surface albedo dominate the land mean bias. The global ocean mean bias is mostly attributed to cold bias due to OHT and surface albedo and warm bias due to surface latent heat flux. In addition, the PAP coefficients associated with water vapor, cloud, surface sensible heat flux, and atmospheric dynamics are relatively small compared with the other three processes.

### 3.2. Analysis of the Temperature Bias Decomposition

After quantifying the contributions from individual processes to the total surface temperature bias by using the CFRAM method, we further investigate in this section the underlying processes related to partial temperature biases.

#### 3.2.1. Radiative Processes

#### 3.2.1.1. Surface Albedo

The high-latitude albedo bias is associated with the biases in sea ice and snow (Figure 3a), in which we see that sea-ice cover over Barents Sea, Gulf of Alaska, and the Antarctic are overestimated while sea-ice...
cover over Labrador Sea, southern Sea of Okhotsk, Hudson Bay, and Amundsen Sea are underestimated in FGOALS-g2, consistent with the previous assessment [Li et al., 2013a; Xu et al., 2013].

Similar to sea-ice bias, snow bias is also examined through assessing the relationship between bias of snow cover and bias of surface albedo as well as the albedo-induced temperature bias. Since the ERA-Interim
data set does not provide the snow cover, following Park et al. [2014], snow cover here is transformed from snow depth, which is available from ERA-Interim, by an empirical relationship [Niu and Yang, 2007; Jeong et al., 2013]:

\[ f_{sno} = h_{sno}/(10 \times z_0 + h_{sno}), \] (8)

where \( f_{sno} \) is snow cover fraction, \( h_{sno} \) is snow depth (in meter), and \( z_0 = 0.01 \) m is the surface roughness length. The snow cover is overestimated in the high latitudes of Northern Hemisphere including northern Eurasia and northern North America, resulting in positive biases of surface albedo (Figure 3c) as well as the cold temperature bias, while the bias of snow cover in Southern Hemisphere is relatively small (Figure 3b).

### 3.2.1.2. Cloud and Water Vapor

The net global mean cloud radiative effect (CRE) is approximately \(-20\) W/m\(^2\) [Loeb et al., 2009]. Cloud-related processes in climate models are poorly represented [e.g., Nam et al., 2012] and cloud responses associated with climate change significantly diverge [Bony et al., 2006] making clouds an important source of uncertainty in climate models.

The bias of the total cloud fraction (Figure 4a) is not totally consistent with the cloud-induced temperature bias (Figure 2d), possibly because the high cloud and low cloud play different roles for surface temperature, and hence, the total cloud fraction may not be well correlated with surface temperature. We see, however, that the total CRE at surface (Figure 4b) is well consistent with the cloud-induced temperature bias. Note that in calculating the temperature bias in Figure 2d, the vertical structure of CRE, i.e., the radiative
difference between all-sky and clear-sky conditions, in atmospheric layers is also included and may play important role in the vertical structure of temperature response. Together with Figure 4b, the vertical structure of CRE may be seen in Figure 4c for the CRE at the top of the atmosphere (TOA) and in Figure 4d for the atmospheric CRE which equals to the difference between the CRE at the TOA and at the surface. By design of CFRAM, the CRE contributions to surface temperature biases mainly come from the surface and lower troposphere. Specifically, the total surface CRE is dominated by shortwave cloud radiative effect (SWCRE) over low and middle latitudes and longwave cloud radiative effect (LWCRE) over high latitudes (Figures 4e and 4f). For low and middle latitudes—except over western Pacific where deep convection and high clouds dominate—the total surface CRE bias have the opposite signs with the total cloud fraction bias (Figures 4a and 4b), because in these regions, the low clouds dominate and positive SWCRE is associated with negative low-cloud fraction and vice versa. On the other hand, for western Pacific and the polar region where the LWCRE dominates, positive (negative) bias of cloud fraction exerts a positive (negative) bias of LWCRE and results in a positive (negative) bias of surface temperature by contributing to the greenhouse-like effect.

The high values of tropospheric specific humidity bias and associated total surface heating rate bias at surface well match those of temperature biases associated with water vapor—positive (negative) surface heating rate bias corresponds to positive (negative) humidity (Figures 5a and 5b). Furthermore, the water-vapor-induced heating rate bias at surface mainly results from the longwave heating rate bias (e.g., greenhouse effect), and the shortwave heating rate bias tend to counteract the longwave effect (Figures 5c and 5d).

The temperature bias induced by water vapor (WV hereafter) is smaller than albedo and cloud effects. However, it should be noted that the WV (especially of the upper layers) could be important if the temperature bias is decomposed based on the radiation balance at the TOA, as in the traditional climate feedback analysis method \cite{Held2000}, but there the effects of nonradiative processes are not visible because they have been lumped into the radiative effect of lapse rate \cite{Lu2009}. In CFRAM, the effect of WV on the surface temperature comes mainly from the lower troposphere while WV in the upper troposphere influences the atmospheric temperature.

3.2.2. Nonradiative Processes

Rather than focusing separately on the details of individual nonradiative processes, here we will pay more attention to the physical linkage between these processes.

It is not surprising to see that the annual mean biases of surface sensible heat and surface latent heat fluxes (Figures 6a and 6b, both upward positive) in FGOALS-g2 have exactly the opposite signs with the partial
temperature bias (Figures 2e and 2f) associated with heat flux biases. Note, however, the high similarity between the pattern of OHT convergence (Figure 6c) and that of latent heat flux (Figure 6b) and also the sum of latent and sensible heat fluxes (not shown). We further note that the vertically integrated total

Figure 6. The annual mean biases of (a) surface sensible heat flux (W/m², positive means surface to atmosphere fluxes) (b) surface latent heat flux (W/m²), and (c) Land/Ocean heat transport (L/OHT, W/m²) of FGOALS-g2 with respect to ERA-Interim.
atmospheric heat transport due to turbulent, convective, and large-scale motions (Figures 7b and 7c) generally has opposite sign over the global oceans with that of OHT convergence (Figure 6c) and surface sensible and latent heat fluxes. Figure 7a shows that the bias in atmospheric transport is consistent with the weaker,
zonal-averaged three-cell meridional circulation in both hemispheres in FGOALS-g2. Because the atmospheric heat transports in Figures 7b and 7c are independently calculated by integrating the residual term of energy balance equation (equation (2)) and by the difference between radiative fluxes at the TOA and at the surface, their resemblance validates the calculation of radiative fluxes used for CFRAM diagnosis and also the residual terms. Figures 6 and 7 suggest that the biases in OHT, surface turbulent fluxes, and atmospheric heat transport are tightly coupled with each other to contribute the observed total temperature bias. The mechanistic coupling between OHT, surface fluxes, and atmospheric dynamics has been observed by Lu et al. [2014] in the interaction between forced climate change and internal climate variability [see Lu et al., 2014, Figures 3 and 4]. Although neither of the temperature biases induced by OHT, surface fluxes, and atmospheric dynamics (Figures 2e and 2h) resembles with the total temperature bias, we will show little later that the sum of these nonradiative processes does explain significant part of the total temperature bias.

We further analyze the underlying mechanism responsible for the role of OHT (ocean heat transport) in temperature bias. Although only the first layer of ocean model (usually with about 5 m depth) is used in the CFRAM analysis, the energy balance of this layer reflects the energy balance of oceanic mixed layer. The mixed layer is characterized by the vigorous turbulent mixing processes and displays vertically uniform temperature, salinity, and density in the upper ocean, and therefore, the mixed layer depth (MLD) is one of the most important quantities for it measures the mixing strength. Although OHT includes not only mixing processes but also advection and convection, we may look at the MLD as a first step. Following de Boyer Montégut et al. [2004], the MLD is defined as the depth at which the potential temperature changes by 0.2°C with respect to its near-surface value at 10 m depth. The observed MLD climatology used here is also from de Boyer Montégut et al. [2004]. Figure 8 shows the MLD bias between FGOALS-g2 relative to the observed climatology. We find that the positive bias of OHT convergence in Figure 6c is usually associated with positive bias of MLD over North Pacific, North Atlantic, and also the Southern Ocean, suggesting the role of ocean mixing in OHT bias and OHT-induced temperature bias. However, the MLD bias may also mismatch with the OHT-induced temperature bias over other oceans, including in the tropics, indicating that other dynamical processes like advection or convection might be more important.

3.2.3. Radiative Versus Nonradiative Contribution to the Bias

Because of the tight coupling between the atmospheric, oceanic dynamics, and surface turbulent heat fluxes, it is useful to group the nonradiative processes—surface sensible/latent heat flux, L/OHT, and atmospheric...
dynamics—together, and then compare its effect with the net effect of radiative processes—surface albedo, water vapor, and cloud—in the total temperature bias [see Lu and Cai, 2010; Park et al., 2014].

Overall, the radiative and nonradiative processes contribute to the annual-mean negative global surface temperature bias (−1.39 K) by −0.70 and −0.69 K, respectively (Table 1). The spatial pattern of radiative-processes-induced bias to the total bias is shown in Figure 9a. The large cold biases over Barents Sea and the Tibetan Plateau are mostly attributed to bias of surface albedo while strengthened by water vapor and cloud, respectively. The bias due to radiative processes in the low latitudes may mainly be attributed to cloud-induced bias (Figure 2d). Over the Southern Ocean, the net cold bias is mainly attributed to nonradiative processes whereas the radiative processes tend to weaken the cold bias there (Figure 9b).

The comparison of Figures 9a and 9b, with their pattern correlation being −0.68, shows that the biases due to radiative and nonradiative processes tend to compensate each other over the globe except for the Arctic region. Figure 9 (bottom) shows the observed temperature bias (i.e., in Figure 2a), but grouped, respectively, with the regions where the effect of radiative processes dominates (Figure 9c) and with the regions where the effect of nonradiative processes dominate (Figure 9d). Note that “(non)radiative processes dominate” is meant by the larger absolute value of temperature bias due to (non)radiative processes. The temperature bias due to radiative processes is dominant over Barents Sea, the land area of mid-latitudes in the Northern Hemisphere, the low-latitude oceans, the southern Africa, Antarctic Ocean, and its adjacent seas while the nonradiative processes is more important over the Arctic, northwestern Eurasia, North Pacific, North Atlantic, Sahara Desert, and the Southern Ocean.

Note that the biases in tropical cloud and in atmospheric heat transport may also be coupled. This is clearly shown in the high anticorrelation (−0.7) between the atmospheric CRE (Figure 4d) and the atmospheric dynamics—climate change and their interaction make the results more realistic and reliable.
heat transport bias (Figure 7c). Therefore, the major sources of temperature bias, i.e., the clouds in the tropics and the nonradiative, dynamical processes in high latitudes, may well depend on each other through the coupling of clouds and circulation.

4. Conclusions and Discussion

In this study, a new climate feedback analysis method (CFRAM) has been applied to decompose the annual mean surface temperature bias between FGOALS-g2 and ERA-Interim into partial temperature biases associated with radiative (surface albedo, water vapor, and cloud) and nonradiative (sensible and latent heat fluxes, land/ocean heat transport, and atmospheric dynamics) processes. Collectively, the radiative and nonradiative processes contribute comparable parts (−0.70 and −0.69 K) to the total cold bias (−1.39 K) in FGOALS-g2 historical run. Despite important spatial differences of both radiative and nonradiative processes, they tend to compensate each other over most part of global except for the high latitudes of the Northern Hemisphere.

We stress the importance of understanding the nature of model bias through the linkage of physical and dynamical processes. It is found that the L/OHT, the surface turbulent heat fluxes, and the atmospheric heat transport processes are tightly coupled. The OHT-induced temperature bias matches well with the MLD bias in mid-high latitudes of both hemispheres. The partial canceling out of the temperature biases due to these processes suggest the importance of explicitly representing them in the climate uncertainty/bias analysis, because the collective bias might be small due to wrong reasons, i.e., the canceling out of large individual biases. The net, collective effect of the nonradiative processes leads to cold bias in the oceans at mid-to-high latitudes of both hemispheres and to warm bias mainly over the tropics and land areas of both hemispheres. On the other hand, the net effect of radiative processes in FGOALS-g2 leads to cold bias over the globe expect for the oceans over the mid-latitudes of the Southern Hemisphere and subtropical low-cloud regions. The albedo and cloud radiative effects comprise two of the major processes to the radiative-process-induced temperature bias. Cloud-induced temperature bias is dominated by the SWCRE over low and middle latitudes while LWCRE dominates the cloud-induced bias in high latitudes.

It is also found that the cloud-related processes are tightly coupled with atmospheric dynamics. The difference in major sources of temperature bias in the tropics and in mid-high latitudes may well be linked with each other through the interaction between clouds and circulation. Because the clouds dominate the tropical temperature bias, it is very likely that the improvements in tropical clouds in FGOALS-g2 may significantly decrease the global temperature bias through the interaction between clouds and circulation as highlighted by Bony et al. (2015).

Cautions are needed when applying the result of decomposition to improve the model. First, the ERA-Interim reanalysis is not a perfect observation as the basis used for model bias diagnostics. The ERA-Interim reanalysis is obtained by assimilating the observations into numerical weather prediction (NWP) model, not an actual observation. While the temperature and WV fields may be very close to the real observations, the reanalysis does not guarantee the energy balance of the system, especially at the surface and at the TOA. Given this limitation, the independent checks of the atmospheric energy balance (Figures 7b and 7c) and surface energy balance (not shown) suggest the analysis method used in this paper is reasonable. Second, the radiative forcing in FGOALS-g2 and ERA-Interim are different. For example, the ERA-Interim does not include the time-varying volcano-induced aerosol forcing, but it is included in FGOALS-g2 simulation. However, we should note that forcings including volcano may have been, at least partly, implicitly included in the ERA-Interim through the observations assimilated into the reanalysis.

Given the aforementioned limitations, the CFRAM decomposition provides a method to translate the process-based energy flux biases into temperature biases. By both evaluating the individual processes and also grouping these biases based on the nature of physical processes, we may obtain useful information about the linkage of the processes and hence a better understanding of the possible sources of the model bias.

References


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