Evaluation of the surface heat budget over the tropical Indian Ocean in two versions of FGOALS

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ABSTRACT
Changes of the net ocean surface heat flux (Qnet) into the tropical Indian Ocean (TIO) may be an indicator of the climate changes in the Asia and Indian–Pacific Ocean regions with the steadily warming trend in the TIO since the 1950s. Using two observational ocean surface flux products, this letter evaluates the historical simulations of Qnet over the TIO during 1984–2005 in two versions of FGOALS, from CMIP5. The results show that both models present a basin-wide underestimation of net surface heat flux, possibly resulting from the positive latent heat flux biases extending over almost the entire TIO basin. Both models share an Indian Ocean dipole-like bias in the net surface heat flux, consistent with precipitation, SST, and subsurface ocean temperature biases, which can be traced to errors in the South Asian summer monsoon. Area-averaged annual time series analyses of the surface heat budget imply that the FGOALS-s2 bias lies more in radiative imbalance, illustrating the need to improve cloud simulation; while the FGOALS-g2 bias presents ocean surface turbulence flux as the key process, requiring improvement in the simulation of oceanic processes. Neither FGOALS-g2 nor FGOALS-s2 can capture the decreasing tendency of Qnet well. All observed and simulated datasets imply surface latent heat flux as the primary contributing component, indicating the simulation biases of models may derive mainly from the biases in simulating latent heat flux. A small latent heat flux increase in models can be considered to be slowed by relaxed wind, increased stability, and surface relative humidity.

KEYWORDS
Indian Ocean; heat budget analysis; climatology; trend; FGOALS

1. Introduction

Earth’s energy balance is controlled by the incoming solar radiation and the outgoing thermal radiation. Climate changes may derive from an imbalance in global energy. Oceans play a key role in the climate system, partly because of their large heat-holding capacity. Deser et al. (2010) indicated that only 3.5 m of water can hold as much energy as the total column air. Energy in the oceans not only drives ocean circulation, but also—after moving from ocean to atmosphere via evaporation cooling, sensible heat flux, and longwave radiation—then drives atmospheric circulation (Trenberth, Fasullo, and Kiehl 2009; Trenberth and Fasullo 2010). The Indian Ocean (IO) is the third largest of the world’s oceans, covering about 20% of Earth’s water surface. The differential heating between the land mass and adjacent ocean results in the strongest tropical monsoon system; namely, the South Asia monsoon, or Indian monsoon. Studying the IO’s heat budget changes can provide us with a better understanding of the changes in the Asian monsoon systems. The tropical Indian Ocean (TIO) has been showing a significant basin-scale warming trend since the 1950s (Giannini, Saravanan, and Chang 2003; Hoerling and Kumar 2003; Hoerling et al. 2004), and this warming trend has been detected and discussed using climate models (Du and Xie 2008; Dong, Zhou, and Wu 2014; Dong and Zhou 2014; Li, Xie, and Du forthcoming; Zheng et al. 2016).
Alory and Meyers (2009) ascribed the IO’s surface warming mainly to a decrease in upwelling related to the slowing of wind-driven Ekman pumping.

Climate models face a number of challenges, but one of the more prominent issues is their large underestimation of surface flux imbalance (IPCC 2007). Two versions of once such model—the grid-point and spectral versions of FGOALS, developed with considerable ongoing effort at the LASG, IAP, Chinese Academy of Sciences—are no exception in this respect. Dong and Zhou (2014) investigated the IO’s warming mechanisms in version 2 of the grid-point and spectral versions of FGOALS and stated that in both models it is mainly caused by atmospheric forcing via radiative and turbulent fluxes. Net ocean–surface heat flux ($Q_{net}$), as a result of the radiation and turbulence heat budget, can reflect the level of surface heat imbalance. Rahul and Gnanaseelan (2013) investigated the decreasing trend of $Q_{net}$ in the TIO, and suggested that radiation imbalance plays a secondary role relative to changing oceanic processes, which are mainly responsible for the IO’s warming trend.

However, the performance of FGOALS in simulating the ocean surface heat budget over the TIO, as well as the related bias sources, remains unclear. Version 2 of the grid-point and spectral versions of FGOALS were chosen for this study because of their continuous improvements in many aspects of model performance. The models have been involved in various model intercomparison projects and subjected to numerous evaluations and analyses, especially in the joining areas of Asia and the Indian–Pacific Ocean (see Zhou et al. (2014) for a summary). On the other hand, the FGOALS models have also been widely used for climate predictions and projections over East Asia. It is therefore important to study the model biases in representing the ocean surface heat budget and related physical processes over the TIO, for improving regional climate predictions and projections.

This study aims to detect the changes and trends of $Q_{net}$ and evaluate (against observation) the historical simulations with regard to the ocean surface heat budget over the TIO in the two models of FGOALS version 2. Section 2 presents the models, data, and method. In Section 3, the results are evaluated and the related bias sources discussed with respect to the climatology, annual variability, and trend of $Q_{net}$. Section 4 provides a brief summary of the key findings.

## 2. Model, data, and method

The grid-point and spectral versions of FGOALS (both version 2; FGOALS-g2 and FGOALS-s2, respectively) are the latest versions of the model developed by researchers mainly working at LASG, IAP, and have participated in CMIP5. They both include four individual components: atmosphere, ocean, land, and sea-ice components, using LICOM2.0 as the oceanic component; the atmospheric components are GAMIL2.0 for FGOALS-g2 and SAMIL2.0 for FGOALS-s2 (more details available in Li et al. (2013) and Bao et al. (2013)).

The OAFlux data-set (Yu and Weller 2007) is provided by the Woods Hole Oceanographic Institution OAFlux project (http://oaflux.whoi.edu). The turbulence heat flux data in this data-set are combined with numerical weather prediction reanalysis and satellite observations using an objective analysis method. The ocean surface radiation products (including shortwave radiation and longwave radiation) are directly adapted from the ISCCP data-set (Zhang et al. 2004). Yu, Jin, and Weller (2007) compared several heat flux products and concluded that OAFlux+ISCCP matches better with observations from ships and buoys over the IO. The National Oceanography Centre Southampton (NOCS) Version 2.0 Surface Flux Data-set, constructed using optimal interpolation by the in situ ship observations from ICQADS (Berry and Kent 2011), is used as another observational data-set. These two datasets have independent data sources and quite different analysis methods.

In general, the $Q_{net}$ into oceans can be computed from radiation heat fluxes and turbulence heat fluxes by the following equation:

$$Q_{net} = SW - LW - LH - SH,$$

where $SW$ and $LW$ are net downward shortwave radiation and upward longwave radiation, respectively, and $LH$ and $SH$ are upward latent heat flux and sensible heat flux, respectively.

## 3. Results

### 3.1. Climatology

Figure 1 presents the climatological mean $Q_{net}$ into the TIO ($30^\circS$–$25^\circN$, $35$–$115^\circE$) using the two observational data-sets of OAFlux+ISCCP and NOCS-V2, and the two model-simulated datasets of FGOALS-g2 and FGOALS-s2, for the present study period of 1984–2005. It is evident that both the observed and model-simulated datasets characterize the pattern of heat gain in the northern tropical IO and heat loss in the southern tropical IO. However, the amplitude of heat gain according to the observational datasets is much larger than that according to the model-simulated datasets. The overall amplitude bias (underestimation) of the models is approximately 30 W m$^{-2}$, resulting in the zero line of $Q_{net}$ in the two models being about 10° north of that observed. The largest heat loss occurs in the southeastern tropical IO, off the west coast of Australia, which is captured by all the observed and
model-simulated datasets. However, the largest observed heat gain, occurring over the northwestern tropical IO, off the east coast of Africa and the Middle East coast, is not reproduced by the two models. Relatively, the large heat gain observed in the South China Sea and Indonesian regions can be fairly well reproduced by the models. Pattern correlation coefficients between the observed and simulated datasets in presenting the climatology of $Q_{\text{net}}$ over the TIO are computed using the centered pattern correlation method (Santer, Wigley, and Jones 1993). The results show that the two observed datasets correlate with a coefficient of 0.76, and the model simulation of FGOALS-g2 (FGOALS-s2) correlates to the observations of OAFlux+ISCCP and NOCS-V2 with coefficients of 0.60 and 0.55 (0.63 and 0.63), respectively. Therefore, the two versions of FGOALS2 capture the basic characteristics of climatological mean $Q_{\text{net}}$ over the TIO during 1984–2005 reasonably well.

In particular, both versions of FGOALS share an IOD-like (IOD: Indian Ocean dipole) bias in the net surface heat flux. Actually, physically consistent biases in precipitation, SST, and subsurface ocean temperature, with a strong easterly wind bias along the equatorial IO, which resemble the IOD mode of interannual variability in nature, are common in these two versions of FGOALS (figure not shown), and most CMIP5 climate models (Li, Xie, and Du 2015a). Li, Xie, and Du (2015a, 2015b) traced such IOD-like biases back to errors in the South Asian summer monsoon. Thus, improving the monsoon simulation is a priority and would lead to better regional climate simulations in the ocean surface heat budget and related physical processes over the TIO.

Figure 2 presents the models biases of relevant components including SW, LW, LH, and SH, against the results of OAFlux+ISCCP data. It is evident that the basin-wide underestimation of $Q_{\text{net}}$ may come from the positive LH biases extending over almost the entire TIO region, especially in FGOALS-s2, whose sensitivity to greenhouse gas forcing is greater than in most CMIP5 models (Chen, Zhou, and Guo 2014). This is very different from most CMIP5 models. Actually, Li and Xie (2012, 2014) identified the tropical-wide biases in SST and surface heat fluxes, and traced them back to a common overestimation of tropical cloud in coupled models that can reflect incoming solar shortwave radiation and thus result in negative surface SW bias.

### 3.2. Interannual variability

The time series of $Q_{\text{net}}$ averaged over the TIO during 1984–2005 from the observed and simulated datasets are shown
in Figure 3, together with time series of related surface heat flux components including SW, LW, LH, and SH. On an annual average basis, over the TIO, both observational datasets show an approximate 30 W m$^{-2}$ yr$^{-1}$ heat gain, but the simulated heat gain is almost zero, with values mostly below 5 W m$^{-2}$. Analysis of the annual cycle shows that, in observations, two (June and July) out of twelve months in a complete year lose heat; whereas in simulations, four (May, June, July and August) out of twelve months in a complete year lose heat. These differences may partly explain the underestimation of simulated $Q_{\text{net}}$ on the interannual scale. The OAFlux+ISCCP $Q_{\text{net}}$ presents a relatively steady series with interdecadal variability from 1984 to 2001; however, there is an abrupt decline after 2001, which has been suggested to be a nonphysical change—affected by satellite cloud viewing geometry artifacts, as well as errors in ancillary datasets (Evan, Heidinger, and Vimont 2007; Raschke, Bakan, and Kinne 2006). Despite these uncertainties, the $Q_{\text{net}}$ variability undoubtedly results from variabilities of turbulent and radiative heat flux components. The two observational datasets and FGOALS-g2 show good agreement in terms of SW estimates, but FGOALS-s2 shows an overestimation of about 6 W m$^{-2}$ relative to ISCCP. Previous assessments of FGOALS-s2 show that overestimated SW along the eastern coast of the Pacific and Atlantic oceans, which is related to the warm biases in these regions, is due to the underestimation of low-level cloud (Lin, Yu, and Liu 2013). The ISCCP data-set gives a decadal-scale variability in LW, which seems akin to nonphysical changes, while NOCS-V2 and the two models show steady states; although, there are overestimations of approximately 15 W m$^{-2}$ in both models relative to NOCS-V2. For LH, both OAFlux and NOCS-V2 show an increasing trend during 1984–1999 and a weak decreasing trend during 1999–2005. The simulations of FGOALS-g2 and FGOALS-s2, however, produce overestimations of about 13 W m$^{-2}$ and 30 W m$^{-2}$ relative to OAFlux. NOCS-V2 is 10 W m$^{-2}$ larger than OAFlux in estimating LH. For SH, FGOALS-s2 agrees well with both observational datasets, except small underestimations and the non-reproduction of an observed increasing trend, but FGOALS-s2 shows large overestimations of about 7 W m$^{-2}$ relative to OAFlux. These biases of the two models in simulating the surface heat flux components ultimately result

Figure 2. The simulated biases of SW, LW, LH, and SH in (a–d) FGOALS-g2 and (e–h) FGOALS-s2. Note: The observational data are from OAFlux+ISCCP. Positive values of SW are downward, and others are upward. Units: W m$^{-2}$. 

![Figure 2](image-url)
Other components make relatively small contributions to the variability of $Q_{\text{net}}$, with either weak correlations or small variance contributions. Nevertheless, it is the LH trend that primarily determines the trend of $Q_{\text{net}}$ for both observations and model simulations.

### 3.3. Trend

Using time series of net surface heat flux averaged over the TIO during 1984–2005 from the observational and simulated datasets shown in Figure 3, the trends of $Q_{\text{net}}$ and related heat flux components are computed by linear least-squares fitting and presented in Table 1. In the observational datasets, the net surface heat flux change during 1984–2005 shows a significant decreasing tendency over the TIO, and there is a significant increase in LH and SH that contributes primarily to the decreased $Q_{\text{net}}$. In the simulated results of the FGOALS models, however, there is no significant trend, and the computed trend amplitudes are far below the detection limit of observations (Yu, Jin, and Weller 2007), consistent with results of previous studies performed using CMIP3 climate models (Du and Xie 2008).

In terms of spatial patterns, the trends of $Q_{\text{net}}$ over the TIO during 1984–2005 determined using the two observational and two simulated datasets are shown in Figure 4. The OAFlux+ISCCP data-set shows a distinct negative trend in the central TIO and very weak trends in surrounding regions, while the NOCS-V2 data-set presents a basin-wide negative trend. Given the fact that the OAFlux+ISCCP data-set may feature a non-physical abrupt decline in 2001, the 1984–2000 $Q_{\text{net}}$ trend for the OAFlux+ISCCP data-set is also computed (not shown), and the pattern is similar to the 1984–2005 trend, except with smaller amplitude. A robust feature of the observations is the maximum decrease in the equatorial central TIO. These results mean that the net heat into the TIO is generally decreasing from the 1980s through to the early 2000s, consistent with previous studies (Schott, Xie, and McCreary 2009; Rahul and Gnanaseelan 2013). The trend patterns of net heat flux produced by the FGOALS models do not show an identifiable trend, which is consistent with the TIO field mean trends.

To investigate the contributions of surface heat flux components to the $Q_{\text{net}}$ trends in different datasets, a Taylor diagram (Figure 5) is produced to show how these

![Figure 3](image-url). Time series of $Q_{\text{net}}$ and related heat flux component (SW, LW, LH, and SH) averaged over the TIO from the observational and simulated datasets.

|                   | OAFlux+ISCCP | NOCS−V2 | FGOALS−g2 | FGOALS−s2 |
|-------------------|--------------|---------|-----------|-----------|
| $Q_{\text{net}}$  | $-0.42 \pm 0.17$ | $-0.80 \pm 0.14$ | $0.03 \pm 0.06$ | $0.03 \pm 0.04$ |
| SW                | $0.07 \pm 0.07$ | $-0.17 \pm 0.04$ | $0.03 \pm 0.05$ | $-0.08 \pm 0.05$ |
| LW                | $0.02 \pm 0.20$ | $-0.07 \pm 0.01$ | $-0.04 \pm 0.02$ | $-0.15 \pm 0.03$ |
| LH                | $0.37 \pm 0.06$ | $0.56 \pm 0.11$ | $0.05 \pm 0.04$ | $0.04 \pm 0.06$ |
| SH                | $0.10 \pm 0.01$ | $0.14 \pm 0.02$ | $-0.02 \pm 0.01$ | $-0.01 \pm 0.01$ |

**Table 1.** The linear trends and 95% confidence levels of net surface heat flux ($Q_{\text{net}}$) and related heat flux components.

Notes: (SW: net surface downward short-wave radiation; LW: net surface upward long-wave radiation; LH: surface latent heat flux; SH: surface sensible heat flux) averaged over the TIO for the period 1984–2005 using the two observational and two FGOALS-simulated datasets. Boldface indicates the linear trend exceeds the 95% confidence level, according to a two-tailed t-test.
component trends match the $Q_{net}$ trends with pattern statistics. Significantly, all the observational and simulated datasets present LH as the primary contributing component. The NOCS-V2 data-set is the most obvious, and the LHs in OAFlux+ISCCP and FGOALS-s2 have the same correlation coefficient with their respective $Q_{net}$ trends, but FGOALS-s2 simulates a larger variance contribution to $Q_{net}$. Meanwhile, the LHs in OAFlux+ISCCP and FGOALS-g2 show the same variance contribution to $Q_{net}$, but FGOALS-g2 has a weaker correlation. Other components show either too

Figure 4. Trends of $Q_{net}$ over the TIO during 1984–2005 determined observationally by (a) OAFlux+ISCCP and (b) NOCS-V2, and simulated by (c) FGOALS-g2 and (d) FGOALS-s2.
Note: Positive values are downward. Units: W m$^{-2}$.

Figure 5. Taylor diagram showing how the trends of ocean surface heat flux components (SW, LW, LH, and SH) contribute to the trend of $Q_{net}$ over the TIO during 1984–2005, determined by the two observational datasets (OAFlux+ISCCP and NOCS-V2) and two simulated datasets (FGOALS-g2 and FGOALS-s2).
weak a correlation or too small a variance contribution to $Q_{\text{net}}$ in both the observational and simulated datasets. These results show that the biases of FGOALS-g2 and FGOALS-s2 in simulating the $Q_{\text{net}}$ trends may derive mainly from the biases in simulating LH trends. Further evaluations of LH trend biases in models may be helpful in understanding the model–observation inconsistency. Li et al. (2011) investigated the ocean surface LH trend and suggested that the LH increase is closely associated with both the SST warming forces as direct causes, and surface wind circulation changes as indirect factors. A recent study by Cao, Ren, and Zheng (2015) shows that trends of LH-related SST (i.e. ocean surface warming) and air specific humidity are grossly overestimated over the Pacific. Du and Xie (2008) suggested that relaxed wind, increased stability, and relative humidity slow the rate of latent heat flux increase.

4. Summary

Using two independent observational ocean surface heat flux products (OAFlux+ISCCP and NOCS-V2), the characteristics of the climatology, annual variability and trend of $Q_{\text{net}}$ simulated by two versions of FGOALS over the TIO during 1984–2005 are assessed in this paper, and the related possible causes of model biases discussed.

For the mean state, despite the uncertainties of observations, both models present a basin-wide underestimation of approximately 30 W m$^{-2}$, resulting in the zero line of $Q_{\text{net}}$ in the models being about 10° north of that observed. Surface latent heat flux, which is largely overestimated over almost the entire TIO region, is considered to be the most likely source of this basin-scale underestimation of $Q_{\text{net}}$ especially in FGOALS-s2, whose sensitivity to greenhouse gas forcing is greater than that in most CMIP5 models. Besides, both models share an IOD-like bias in net surface heat flux. Physically consistent biases in precipitation, SST, and subsurface ocean temperature with a strong easterly wind bias along the equatorial IO, which resemble the IOD mode of interannual variability in nature, are common in these two versions of FGOALS, and most CMIP5 climate models. Li, Xie, and Du (2015a, 2015b) traced such IOD-like biases back to errors in the South Asian summer monsoon. Thus, improving the monsoon simulation is a priority and would lead to better regional climate simulation in the ocean surface heat budget and related physical processes over the TIO.

In the annual time series of net surface heat flux averaged over the TIO, both FGOALS models indicate relatively balanced surface heat, with an approximate 0 W m$^{-2}$ heat flux into the ocean, which is far below the approximate 30 W m$^{-2}$ flux in both observational datasets. Notable features are that the FGOALS-s2 bias mainly lies in the overestimations of SW and LH, while the FGOALS-g2 bias mainly lies in the overestimation of turbulence heat flux, including latent and sensible heat fluxes. As FGOALS-s2 has a greater sensitivity to greenhouse gas forcing, the key process of the surface heat budget over the TIO is more likely the radiative imbalance, illustrating the need to improve cloud simulation. Meanwhile, FGOALS-g2 presents surface turbulence flux as the key process, though it seems to need further improvement in representing oceanic processes. A maximum decreasing tendency exists in the equatorial central TIO in both observational datasets, meaning that the net heat into the TIO shows a generally decreasing trend from the 1980s through to the early 2000s. Neither FGOALS-g2 nor FGOALS-s2 can capture this feature well. All the observational and simulated datasets imply surface latent heat flux as the primary contributing component, indicating the simulated biases of FGOALS-g2 and FGOALS-s2 may derive mainly from the biases in simulating LH. A small LH increase in models can be considered to be slowed by relaxed wind, increased stability, and surface relative humidity.

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