Systematic Errors in South Asian Monsoon Simulation: Importance of Equatorial Indian Ocean Processes

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(Manuscript received 2 August 2016, in final form 17 July 2017)

ABSTRACT
Forecasting monsoon rainfall using dynamical climate models has met with little success, partly due to models’ inability to represent the monsoon climatological state accurately. In this article the nature and dynamical causes of their biases are investigated. The approach is to analyze errors in multimodel-mean climatological fields determined from CMIP5, and to carry out sensitivity experiments using a coupled model [the Coupled Model for the Earth Simulator (CFES)] that does represent the monsoon realistically. Precipitation errors in the CMIP5 models persist throughout the annual cycle, with positive (negative) errors occurring over the near-equatorial western Indian Ocean (South Asia). Model errors indicate that an easterly wind stress bias \(D_t\) along the equator begins during April–May and peaks during November; the severity of the \(D_t\) is that the Wyrtki jets, eastward-flowing equatorial currents during the intermonsoon seasons (April–May and October–November), are almost eliminated. An erroneous east–west SST gradient (warm west and cold east) develops in June. The structure of the model errors indicates that they arise from Bjerknes feedback in the equatorial Indian Ocean (EIO). Vertically integrated moisture and moist static energy budgets confirm that warm SST bias in the western EIO anchors moist processes that cause the positive precipitation bias there. In CFES sensitivity experiments in which \(D_t\) or warm SST bias over the western EIO is artificially introduced, errors in the EIO are similar to those in the CMIP5 models; moreover, precipitation over South Asia is reduced. An overall implication of these results is that South Asian rainfall errors in CMIP5 models are linked to errors of coupled processes in the western EIO, and in coupled models correct representation of EIO coupled processes (Bjerknes feedback) is a necessary condition for realistic monsoon simulation.

1. Introduction

a. Background

About two-thirds of the South Asian work force participate in agriculture. As such, the amount of precipitation during the summer (June–September) monsoon has huge socioeconomic impacts in the region, and accurate rainfall forecasts on time scales of days to seasons are of critical importance. Despite this societal need, skill in monsoon prediction by dynamical climate models remains low (DelSole and Shukla 2002; Turner and Annamalai 2012). One reason for the low skill is the existence of large, systematic model errors in the simulation of the mean annual cycle (climatology) of the monsoon (Sperber et al. 2013). During the summer monsoon, for example, positive rainfall errors \[-(3–4)\text{ mm day}^{-1}\] cover a large area of the tropical Indian Ocean (Fig. 1a), while a dry...
Fig. 1. Seasonal (June–September) mean climatology difference between the CMIP5 multimodel mean (MMM) and observations: (a) precipitation (color shaded; mm day$^{-1}$) and wind (vectors, m s$^{-1}$) and (b) SST ($^\circ$C). (c) Equatorial Indian Ocean (EIO; $3^\circ$S–$3^\circ$N; $40^\circ$–$100^\circ$E) monthly-mean wind stress climatology difference between CMIP5 MMM and ERA-Interim. (d) Bimonthly bias in CMIP5 models in precipitation (red; mm day$^{-1}$) averaged over $8^\circ$S–$8^\circ$N, $50^\circ$–$70^\circ$E; depth of the thermocline (brown; m) averaged over $10^\circ$S–$5^\circ$N, $45^\circ$–$65^\circ$E; wind stress (black; N m$^{-2}$) averaged over $3^\circ$S–$3^\circ$N, $40^\circ$–$100^\circ$E and SST gradient (blue; $^\circ$C) between western ($8^\circ$S–$8^\circ$N, $45^\circ$–$65^\circ$E) and eastern ($8^\circ$S–$8^\circ$N, $80^\circ$–$100^\circ$E) EIO.
bias exists along the monsoon trough (a low pressure area extending from central India to the plains of Indo-China). Their cause, however, is difficult to assess because the monsoon arises from complex interactions among ocean, atmosphere, and land components; as a result, misrepresentation of a process in one component can lead to errors in other components. Further, errors generated in one season can persist throughout the annual cycle (section 2). An indicator of the difficulty of the problem is that such model errors have persisted for the last decade, despite considerable efforts to eliminate them.

In models from phases 3 and 5 of the Coupled Model Intercomparison Project (CMIP3 and CMIP5), misrepresentation of a number of physical processes has been proposed to account for the dry bias over South Asia (Fig. 1a). These include fast atmospheric processes (Martin et al. 2010; Ma et al. 2014), orography (Boos and Martin 2010; McCreary et al. 1993), and cold SST bias in the northern Indian Ocean (Levine et al. 2013).

In tropical oceans, diagnostics based on satellite-derived and in situ observations show that climatological precipitation is controlled primarily by the mean column water vapor (CWV) in the troposphere (Raymond 2000; Bretherton et al. 2004), and CWV sources include surface evaporation, low-level moisture convergence, and moisture–convection and cloud–radiation feedbacks (Bretherton et al. 2004). In moist convective regions, high-mean SST (28°C) provides a necessary condition for the abundance of CWV (Neelin et al. 2009). In coupled climate models, therefore, one expects errors in SST and/or errors in the representation of processes that influence CWV to be responsible for precipitation errors over the tropical Indian Ocean (Fig. 1a).

The equatorial Indian Ocean (EIO) differs from the other equatorial oceans in that it lacks trade winds, owing to the strong atmospheric convection over the eastern EIO and Maritime Continent (Gill 1980). As a consequence, the EIO experiences semianual westerly winds at the times when atmospheric convection is located near the equator (the intermonsoon seasons). The zonal wind stress has a magnitude of about 0.4 dyn cm⁻² (1 dyn = 10⁻⁵ N; e.g., Clarke and Liu 1993) and forces the eastward-flowing Wyrtki jets (WJs; Wyrtki 1973), which attain velocities of the order of 1 m s⁻¹ in the upper 50 m (Reverdin 1987; McCreary et al. 1993). O’Brien and Hurlburt (1974) employed a two-layer model to demonstrate theoretically that a strong eastward jet develops as a “direct” response to switched on westerlies. Clarke and Liu (1993) confirmed Wyrtki’s results that observed sea level (thermocline) fluctuations over the eastern EIO are generated by the semianual equatorial winds. Rao and Sivakumar (2000) showed that thermocline deepening in the eastern EIO is due to “convergence of waters caused by WJs” (p. 995). The westerlies also force downwelling (upwelling) oceanic Kelvin (Rossby) waves, which deepen (shoal) the thermocline in the eastern (western) EIO (Han et al. 1999). Regarding equatorial dynamics, WJs are considered as an example of Yoshida jets (Yoshida 1959) in the real world and the sea level rise in the eastern EIO is partly due to the arrival of a downwelling-favorable Kelvin wave, but that wave is part of the wind-forced, bounded Yoshida jet response generated in the interior ocean [see McCreary (1985) for more details on the dynamics]. In summary, WJs are swift currents that carry mass and heat from the western to the eastern EIO, and thus play an important role in seasonal SST and heat content in the EIO (Schott and McCreary 2001). In CMIP5 models, errors in the representation of the WJs during the intermonsoon seasons (April–May and October–November), then, could have a major impact on air–sea coupled processes in the equatorial EIO, a hypothesis tested here. In the present study, we interpret WJs as fast oceanic processes that could lead to errors in the EIO coupled processes rather quickly (section 2d).

An important coupled process in the EIO is Bjerknes positive feedback (Bjerknes 1969), which links ocean and atmospheric variables (Fig. 1d). Consider a scenario as follows. In CMIP5 models, during the annual cycle an easterly wind stress bias Δτ develops along the EIO during April–May (Fig. 1c). As a consequence, the simulated spring WJ is weaker than observations, resulting in a smaller west–east SST gradient (warm west and cold east) along the EIO. In response to this gradient, Δτ amplifies as a consequence of the SST gradient imprinting on the temperature of the atmospheric boundary layer, resulting in pressure gradients (Lindzen and Nigam 1987; Back and Bretherton 2009). The warm SST bias in the western EIO generates positive rainfall bias there that in turn amplifies Δτ. The ocean responds to Δτ by tilting the thermocline, leading to enhance the warm (cool) SST in the west (east) intensifying the gradient (Fig. 1d), and so on. In this paper, we explore the possibility that South Asian rainfall errors stem from coupled feedback errors in the EIO, via misrepresentation of processes during the intermonsoon seasons (e.g., April–May).

b. Present research

In this paper, we continue the effort to understand the causes of error in dynamical climate models. For this purpose, we analyze the errors in the state-of-the-art CMIP5 models (Taylor et al. 2012) as measured by differences between climatologies of their multimodel-mean (MMM) fields and observations. In addition, we obtain sensitivity solutions to the Coupled Model for the Earth Simulator (CFES), a climate model that represents the monsoon climatological state and the WJs...
realistically; in these experiments, guided by $\Delta \tau$ (Fig. 1c), CFES is degraded by imposing equatorial easterlies along the EIO, essentially weakening the WJs and promoting coupled feedback errors along the EIO. To strengthen our claim that Bjerknes feedback is misrepresented in CMIP5 models and that there is no starting point in the feedback loop, we performed an additional run in which warm SST bias over the western EIO (Figs. 1b and 2e) is imposed in CFES. To identify causes of precipitation errors, we analyze the atmospheric moisture and moist static energy (MSE) budgets.

Key results are the following. Precipitation errors in the CMIP5 models persist throughout the annual cycle, with positive (negative) errors occurring over the near-equatorial western Indian Ocean (South Asian monsoon trough). Atmospheric budget diagnostics suggest that SST errors over western EIO initiate precipitation errors there. In the EIO, model errors indicate that $\Delta \tau$ begins in April–May and persists till December, leading to almost elimination of the WJs. The structure of the errors suggests that air–sea interactions are strong, particularly over the near-equatorial western Indian Ocean. In CFES sensitivity experiments in which WJs are artificially weakened or SST bias over the western EIO is imposed, errors in the EIO are similar to those in the CMIP5 models and precipitation over South Asia is reduced. An overall implication of these results is that the South Asian rainfall errors in the CMIP5 models are causally linked to errors in the EIO coupled processes.

The paper is organized as follows. In section 2, CMIP5 model errors are identified. A brief discussion of the models, observations, and budget diagnostics is also presented there. In section 3, after describing CFES model and its ability to simulate the monsoon–Indian Ocean climate, the design of the sensitivity experiments is outlined. Then, solutions to the sensitivity experiments

**Fig. 2.** Seasonal mean precipitation (mm day$^{-1}$) climatology difference between CMIP5 MMM and observations for (a) September–November, (b) December–February, and (c) March–May. Annual-mean differences between CMIP5 MMM and observations: (d) precipitation (mm day$^{-1}$), (e) SST (°C), and (f) depth of the 20°C isotherm (m).
are diagnosed and compared with CMIP5 model errors. In section 4, a succinct summary of the paper and implications of the present results on monsoon simulation are presented.

2. Systematic errors in the CMIP5 models

We begin this section with a summary of the observational data and CMIP5 models that we use, and define how we measure model–data error (section 2a). Next, we discuss the systematic biases in the CMIP5 MMM fields, reporting model–data differences in climatically important variables (section 2b). We then utilize vertically integrated moisture and MSE budgets to identify the leading processes that promote precipitation errors (section 2c) and discuss causes of errors in the WJs (section 2d). Finally, we summarize how all of these biases impact coupled processes in the EIO (section 2e).

a. Data, models, and error analysis

The observed atmospheric fields used here include rainfall from the Global Precipitation Climatology Project (GPCP; Huffman et al. 1997) and the Tropical Rainfall Measuring Mission (TRMM; Huffman et al. 2007) and other variables from the European Centre for Medium-Range Weather Forecasts (ECMWF) interim reanalysis (ERA-Interim; Berrisford et al. 2009). Observed oceanographic variables are SST from the TRMM Microwave Imager (TMI; Wentz et al. 2000) and the NOAA Extended Reconstructed SST (ERSST) version 3 (Smith et al. 2008); depth-integrated currents measured by the acoustic Doppler current profilers (ADCPs) that are part of the Research Moored Array for African–Asian–Australian Monsoon Analysis and Prediction (RAMA) project (McPhaden et al. 2009); surface currents from the Ocean Surface Currents Analyses–Real Time (OSCAR) product (Bonjean and Lagerloef 2002); and thermocline depth, as measured by the depth of the 20°C isotherm, from Argo floats (Roemmich and Gilson 2009) and the World Ocean Atlas 2002 (WOA; Conkright et al. 2002). The horizontal resolutions and period of various observations diagnosed are as follows: GPCP (2.5° × 2.5°, 1979–2015), TRMM/TMI (1° × 1°, 1998–2014), ERSST (2° × 2°, 1979–2015), ECMWF wind stress (1.5° × 1.5°, 1979–2015), Argo floats (1° × 1°, 2004–16), and WOA (1° × 1°).

Our measure of the observed WJ transport is based on a climatology of ADCP observations of upper-ocean (between ~25 and 175 m) zonal velocity taken from October 2004 to August 2008 along the equator at 80.5°E, a longitude near the location of maximum WJ strength (McPhaden et al. 2009; Nagura and McPhaden 2010). The climatology has an estimated error of 10%–15% and gives essentially the same seasonal cycle as that obtained from an 18-yr time series of OSCAR surface velocities (Nagura and McPhaden 2010). To illustrate the zonal extent of the WJ along the EIO, we use OSCAR surface zonal currents averaged over 1°S–1°N (or 3°S–3°N).

The basic information on the CMIP5 solutions analyzed here is discussed in detail in Taylor et al. (2012). The 25 CMIP5 models selected here are the same as those in Sperber et al. (2013) in their analysis of Asian summer monsoon characteristics. As part of the model datasets, each model provides its best estimates of natural (e.g., solar irradiance and volcanic aerosols) and anthropogenic (e.g., greenhouse gases, sulfate aerosols and ozone) climate forcing. In comparison to the earlier version (CMIP3), the CMIP5 models typically have higher horizontal and vertical resolution in the atmosphere and ocean, and a more detailed treatment of direct and indirect aerosol forcings. See Sperber et al. (2013, their Table 1) for further details on certain features of the CMIP5 models used here.

To measure model–data error, we first prepared monthly climatologies for both the observational and CMIP5 data. For the observations, the climatologies are determined for the available data period, whereas for the CMIP5 models they are obtained for the period 1961–99 using solutions of only one realization from “historical simulations” of each model. The climatological annual cycle of monthly rainfall among individual realizations of the same model is very robust (Colman et al. 2011), justifying our use of solutions from one realization from each model. Next, we prepared MMM composites of the CMIP5 climatologies, regridding variables onto a common grid, usually that of the particular observed variable. Finally, model–data errors are defined by the differences between MMM and observed climatological fields. Almost all error fields are labeled by a prime, the sole exception being wind stress error, which is labeled Δτ rather than τ. We used both conventional (ERSST and WOA) and satellite-derived (TRMM, TMI-SST, and OSCAR) observations to estimate the error. While the bias structures remain the same in both estimates, there are subtle differences in the magnitude. For brevity, for all variables we show the biases estimated with satellite-derived products.

b. Precipitation, SST, and wind biases

During boreal summer, modeled rainfall (Fig. 1a) is weaker than observed over South Asia, the central–northern Bay of Bengal, and the central–eastern EIO, and is stronger over the near-equatorial, western-central Indian Ocean (WCIO; 10°S–15°N, 40°–85°E) and along the Burmese and Himalayan orography. Indeed, almost all the CMIP5 models, irrespective of their overall monsoon performance, depict a wet bias over the WCIO

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(not shown). Along the EIO, distinct SST and precipitation biases are roughly collocated, with warm/wet (cold/dry) in the western (eastern) EIO (Fig. 1b). This relationship continues throughout the year, as evidenced by their annual-mean values (Figs. 2d,e), with errors peaking during fall and winter seasons (Figs. 2a,b). During the annual cycle, although the zonally extended wet bias during winter and spring seasons (Figs. 2b,c) roughly coincides with the longitudinal position of the climatological ITCZ, the wet bias in summer and fall seasons (as well as in the annual mean) occurs in regions (e.g., western EIO) that are climatologically dry. By contrast, summertime SST and precipitation errors in the Arabian Sea are not collocated: a warm SST bias occurs along the coasts of Oman and Somalia in response to the weakened southwestlies (Fig. 1b), whereas a positive precipitation bias occurs farther offshore (Fig. 1a).

In the EIO, the precipitation and SST errors occur together with biases in the simulated atmospheric circulation, with easterly bias in the equatorial wind stress $\Delta \tau$ throughout much of the year (Fig. 1c) and weakened cross-equatorial (southwesterly) flow during the summer monsoon (Fig. 1b). Note that $\Delta \tau$ begins in April–May, amplifies in June–July, weakens for a short period, and then revives and peaks during November (Fig. 1c). Thus, wind stress errors encompass the summer monsoon and both intermonsoon periods. Indeed, almost all of the CMIP5 models individually fail to simulate the amplitude of the intermonsoon westerlies (Nagura et al. 2013).

Note that the easterly bias $\Delta \tau$ is confined to the equatorial central and western Indian Ocean (west of 80°E) during both summer and fall seasons (Figs. 1a,c), and it becomes weaker and reverses sign (anomalous westerlies) during late winter and early spring (Fig. 1c). A plausible interpretation is that positive precipitation errors over the western EIO force an atmospheric Kelvin wave, resulting in easterly bias $\Delta \tau$, particularly when the local precipitation maximum is centered around the equator (e.g., summer and fall).

c. Biases in moist processes

In the previous subsection, we note that precipitation and SST biases are roughly collocated in the EIO but not in the Arabian Sea, suggesting that they result from different processes. To identify the processes that account for these differences, we analyze the atmospheric moisture and MSE budgets in two regions: REG1 (10°S–5°N, 40°–60°E) and REG2 (5°–15°N, 60°–85°E), corresponding to the western EIO and Arabian Sea, respectively.

The moisture budget relates precipitation to moisture convergence and heating. However, one limitation of moisture budget is that convergence-related variables are largely a result of the convection itself rather than a cause (e.g., Raymond et al. 2009), particularly over the Indo-Pacific warm pool where SST gradients are nearly absent. The MSE budget involves moisture and temperature processes that are critical to the interaction between tropical cumulus convection and the large-scale circulation (Back and Bretherton 2006); moreover, it is useful for determining the thermodynamic processes that anchor moisture divergence (Su and Neelin 2002).

1) EQUATIONS

The vertically integrated moisture budget is

$$P = -\left\langle \omega \left( \frac{\partial q}{\partial p} \right) \right\rangle + LH - \left\langle (V \cdot \nabla q) \right\rangle,$$

(1)

where $P$ is precipitation, $(V \cdot \nabla q)$ and $\left\langle \omega q_p \right\rangle$ are horizontal and vertical advection (or horizontal divergence) of moisture, respectively, and LH is the latent heat flux at the surface. In these quantities, $V$ is the horizontal velocity vector, $V$ is the gradient operator, $\omega$ is vertical pressure velocity, $q$ is specific humidity, and angle brackets designate vertical integration. Using (1), we obtain moisture-budget terms for both ERA-Interim and MMM fields; their difference, denoted by a prime, measures the model error of each term. Here, all the terms are expressed in energy units ($\text{W m}^{-2}$).

MSE ($h$) is defined by

$$h = C_p T + gz + L q,$$

(2)

where $C_p$ is the specific heat of constant pressure, $T$ is temperature, $g$ is the gravitational acceleration, $z$ is geopotential height, $L$ is latent heat of vaporization at 0°C, and $q$ is specific humidity. The vertically integrated MSE budget is then given by

$$\left\langle \frac{\partial h}{\partial t} \right\rangle = -\left\langle (V \cdot \nabla h) \right\rangle - \left\langle \omega \frac{\partial h}{\partial p} \right\rangle + LH + SH$$

$$+ \left\langle LW \right\rangle + \left\langle SW \right\rangle + R.$$

(3)

In (3), SH is sensible heat flux at the surface, $(\langle LW \rangle)$ and $(\langle SW \rangle)$ are net column longwave and shortwave heating rates, and $R$ is a residual. The terms $\langle V \cdot \nabla h \rangle$ and $\langle \omega q_p \rangle$ represent horizontal and vertical advection of MSE, respectively, and the former can be split into horizontal advection of moisture $L \langle V \cdot \nabla q \rangle$ and temperature $C_p \langle V \cdot \nabla T \rangle$. The sum, $\langle F_{rad} \rangle = \langle LW \rangle + \langle SW \rangle$, is the net radiative flux. As for the moisture budget terms, we evaluate the terms in (3) using both observed and MMM fields, and indicate their differences by a prime.

In our analysis, we assume that (3) is quasi-steady; that is, $\langle h_i \rangle = 0$, an approximation that is valid at seasonal time scales. In that case, (3) represents a
balance between the net flux of $h$ into the column and moist processes that determine convective instability (Annamalai 2010). Rearranging the terms in (3) leads to

$$\frac{2}{C^2} \frac{\partial h}{\partial p} = \frac{C^2}{\partial h} + \frac{C^2}{\partial h} + \frac{F_{rad}}{C^2} + R.$$

In the deep tropics, the “weak temperature gradient” (WTG) approximation is valid, and hence the contribution from $\frac{C^2}{\partial h}$ in (4) is small (Sobel et al. 2001). In tropical moist convective regions, $q$ determines $h$ and precipitation is directly proportional to $\frac{C^2}{\partial h}$. As such, the MSE budget provides insights into how processes such as $\frac{C^2}{\partial h}$, LH, SH, LW, and SW force convection (Raymond et al. 2009). In estimating the budgets, note that the vertical integrals through the depth of the troposphere are mass integrals (Neelin and Su 2005) and therefore all the terms are expressed in energy (W m$^{-2}$). More details on the derivation of moisture and MSE budgets are available in Yanai et al. (1973) and Neelin and Held (1987).

2) ERRORS

Figure 3 shows errors in specific humidity for the planetary boundary layer (PBL; Fig. 3a) and free troposphere (Fig. 3b), as well as the leading processes in the moisture and MSE budgets (Fig. 4). Vertical integrations of specific humidity for the PBL extend from surface to 850 hPa and for the free troposphere from 700 to 400 hPa. Here, PBL (free troposphere) moisture is associated with triggering of convection (intensity of convection). For the budget terms, vertical integrations are from 1000 to 100 hPa, and the terms averaged over REG1 (REG2) are shown in the top (bottom) panels in Fig. 4. Note that in the moisture (MSE) budget, all the terms are scaled by precipitation ($\langle \omega h_p \rangle$).

A specific humidity bias plot for the PBL (Fig. 3a) shows that over REG1 (REG2) a wet (dry) bias prevails. In contrast, in the free troposphere a prominent wet bias is seen over REG2 (Fig. 3b). In both regions, the availability of more water vapor in the free troposphere is expected to support deep convection, leading to a stronger wet bias. Throughout the troposphere, a dry bias exists poleward of 10$^\circ$N with a local maximum along the monsoon trough.

Over REG1, the moisture budget terms (Fig. 4a) indicate that the precipitation error $P_0$ is largely determined by moisture convergence, $-\langle \mathbf{V} \cdot \nabla q \rangle = \langle \omega q_p \rangle$, with a lesser contribution from evaporation $LH_0$. Both factors point toward SST errors as determining $P_0$ (Fig. 1a), the moisture convergence error caused by the error in the equatorial SST gradient (Lindzen and Nigam 1987; Back and Bretherton 2009) and evaporation error due to local warm SST bias. The MSE terms

\[\text{(a) Specific humidity 1000 – 850 hPa} \quad \text{(b) Specific humidity 700 – 400 hPa}\]
(Fig. 4b) indicate that errors in convective forcing, measured by $\left< \omega h_p \right>^\prime$, are opposed by errors in the horizontal advection of cold/dry air $(\mathbf{V} \cdot \nabla h)^\prime$, with most of the positive contributions from diabatic terms ($\left< F_{\text{rad}} \right>^\prime$ and $LH^\prime$) that favor convective instability. The errors in $F_{\text{rad}}$ arise from enhanced cloud cover trapping more LW. This cloud–radiation feedback process enhances radiative heating, which in turn increases $\left< \omega h_p \right>^\prime$. We conclude that in REG1 SST biases cause errors in atmospheric moist processes, which in turn lead to errors in PBL bias in specific humidity (Fig. 3a).

In REG2, rainfall errors are not collocated with SST errors and, consistent with this property, contributions to $P^\prime$ from errors in moisture convergence, $-\left< \omega q_p \right>^\prime$, and evaporation $LH^\prime$ are either weak or opposite in sign (Fig. 4c). The reduced evaporation is attributable to the cold SST bias (Fig. 1b) and to the weakened low-level monsoon westerlies (Fig. 1a). Instead, the moisture budget indicates that positive rainfall errors are primarily due to the horizontal advection term $-\left< \mathbf{V} \cdot \nabla q \right>^\prime$, a conclusion supported by the dominance of this term to favor convective instability in the MSE budget there (Fig. 4d). Sobel et al. (2001) suggest that free troposphere humidity is largely affected by horizontal advection. Similar to REG1, in REG2 errors in $\left< F_{\text{rad}} \right>^\prime$ favor convective instability and contribute to precipitation errors. Further, because of increased cloud cover in REG2, cold SST bias is attributable to reduced SW reaching the surface.

Given the excess rainfall in REG1, the moisture flux from REG1 into REG2 is reduced. In REG2, what are the moist processes that promote the positive precipitation error or how does $\left< \mathbf{V} \cdot \nabla q \right>^\prime$ dominate as the principal source of convective forcing? It happens because of the decreased precipitation over South Asia (Fig. 1a). In response to this forcing, an atmospheric Rossby wave is generated that radiates westward into the Arabian Sea. It is associated with northeasterly winds (Fig. 1a), which advect climatological moisture out of South Asia into REG2, causing precipitation there. An examination of various components of the term $-\left< \mathbf{V} \cdot \nabla q \right>^\prime$ confirms the dominance of anomalous wind advecting climatological moisture (not shown).
The estimated MSE divergence \( \langle \omega h_p \rangle \) depends on the model’s ability to represent vertical velocity accurately, which in turn depends on the cumulus parameterization employed (Raymond et al. 2009). We also note that the computation of the MSE budget from reanalysis data has substantial errors and uncertainties (Back and Bretherton 2006) because vertical velocity is not observed but rather inferred from a data-assimilation process. Therefore, a residual component arises in MSE budget diagnostics. On the other hand, the leading processes identified are expected to be robust and reproducible (e.g., Neelin and Su 2005; Annamalai et al. 2014).

d. WJ and thermocline-depth biases

WJs transport mass and heat from the western to eastern EIO. Basic aspects of WJ dynamics are captured by the upper-ocean, zonal momentum balance along the equator. For a linear 1.5-layer (reduced gravity) model, it is

\[
\frac{\partial u}{\partial t} + \frac{\partial}{\partial x} \left( \frac{\partial}{\partial z} \right) \frac{\rho_o}{\rho_o} = \frac{\tau}{\rho_o} H, \tag{5}
\]

where \( u \) is the zonal velocity, \( p_x \) is horizontal pressure gradient, \( f = 0 \) at the equator, \( H \) is the layer thickness, and \( \rho_o = 1 \, \text{g cm}^{-3} \) is a background density value. Consider the response of (5) to a wind patch of amplitude \( \Delta \tau \) and zonal extent \( L \). Initially, there are no pressure gradients and, owing to the lack of Coriolis force at the equator, \( u \) accelerates according to \( u = \frac{\Delta \tau}{\rho_o} H \). It continues to accelerate until an equatorial Kelvin wave crosses the region of the wind patch, that is, until time \( t_k = L/c \), where \( c \) is the Kelvin wave speed. An estimate of the speed attained by the zonal jet is then

\[
\tilde{u} = \frac{\Delta \tau}{\rho_o} H t_k. \tag{5}
\]

Given that \( t_k \) is only a few days, we can expect that errors in \( \Delta \tau \) in climate models will quickly imprint on the simulated WJs. In the CMIP5 models, a direct consequence of the \( \Delta \tau \) bias (Fig. 1c) is that both the spring and fall WJs, as measured by the depth-integrated (0–100 m) zonal current at \( 0^\circ, 80.5^\circ \) E, are weaker by 50%–60% compared to observations (red and black curves in Fig. 5, respectively). This weakness is apparent everywhere along the equator (cf. Figs. 6b and 6a), with biases in the amplitude, phasing, and duration of the WJs; moreover, the summertime westward flow is erroneously strong. The weak WJs and stronger westward flow result in shallow (deep) thermocline biases in the eastern (western) EIO, features that persist for most of the annual cycle (Fig. 2).

SST errors could also result from errors in surface heat flux, particularly those associated with models’ errors in surface shortwave radiation. To test this, we examined MMM’s shortwave radiation bias with satellite-derived CERES (Clouds and the Earth’s Radiant Energy System) observations for the period 2000–16. Over REG1 where warm SST errors are collocated with wet precipitation errors, a reduction in shortwave radiation is found (figure not shown). This is consistent with the view that in regions of wet bias shortwave radiation
reaching the surface will be reduced as a result of scattering and absorption by cumulus clouds.

**e. Impacts on the coupled system**

The model and data biases discussed above point toward the existence of air–sea feedbacks in the EIO (e.g., Fig. 1d), and their structure suggests they are generated by Bjerknes positive feedback (Bjerknes 1969). In the annual cycle, an equatorial easterly bias $\Delta \tau$ develops in May (Fig. 1c) that in turn weakens the spring WJ as well as its duration (Fig. 6b). During June, observations suggest that between 50°E and 70°E eastward transport still exists (Fig. 6a) but a westward flow dominates in CMIP5 models (Fig. 6b). As a consequence, warm (cold) SST errors in the western (eastern) EIO generate an erroneous equatorial SST gradient (e.g., Fig. 1b). MSE increases in the western EIO support precipitation there (Fig. 4b). These errors in precipitation and SST gradient drive a stronger $\Delta \tau$ during fall (Fig. 1c) that subsequently eliminates the fall WJ (Fig. 6b). As a consequence, a deeper (shallower) thermocline in the western (eastern) EIO is created (Fig. 2f); this thermocline gradient in turn helps to maintain the equatorial SST gradient, although it is weak over the eastern EIO (Fig. 2e). Given the persistence and spatial scale associated with the wet bias, the feedbacks over the near-equatorial western Indian Ocean (Figs. 2a–c) dominate model errors. It is notable that, despite positive rainfall errors over the Maritime Continent throughout the annual cycle, there is still an easterly bias in the EIO, a response to the much stronger positive rainfall bias over the western EIO. In the eastern EIO, despite a shallow bias in thermocline (Fig. 2f), the lack of cold (Fig. 2e) and dry (Figs. 2a–d) biases there indicates weak coupled feedbacks, perhaps due to lack of upwelling favorable winds along Java and Sumatra (e.g., Figs. 1a and 2a).

The low-level convergence driven by the positive precipitation error in the western EIO weakens the cross-equatorial moisture transport, thereby weakening the monsoon precipitation and subsequently the low-level cross-equatorial flow into the Arabian Sea (the Findlater jet), decreasing coastal upwelling and

![Fig. 6. Monthly evolution (ordinate) of the equatorial (3°S-3°N) zonal current (cm s⁻¹) from (a) observations, (b) CMIP5 MMM, (c) CFES_CTL, and (d) CFES_EXP2. The observations used here come from the OSCAR product.](http://journals.ametsoc.org/jcli/article-pdf/30/20/8159/4676488/jcli-d-16-0573_1.pdf)
increasing SST near Somalia and Oman. Precipitation in the interior of the Arabian Sea is linked to negative precipitation error over South Asia (section 2c). As discussed in section 3c, our CFES sensitivity experiments suggest that the weak South Asian monsoon may also be linked to western EIO precipitation.

3. CFES solutions

In this section, we first provide an overview of CFES (section 3a). Next, we demonstrate that our CFES control (CFES_CTL) run simulates the monsoon and WJs realistically and, by comparing the solution to its atmosphere-only counterpart, that the low error results from coupling (section 3b). We then report CFES sensitivity experiments with an artificially weakened WJs or strengthened Bjerknes feedback (section 3c), finding that they have similar biases to those in the CMIP5 MMM fields.

a. Model overview

CFES was developed at the Japan Agency for Marine-Earth Science and Technology. Its atmospheric component is the AGCM for the Earth Simulator (AFES), a spectral, Eulerian, primitive equation model (Numaguti et al. 1997). The dynamical framework of AFES is adapted from Hoskins and Simmons (1975). The cumulus convection scheme is that of Emanuel (1991), which is found to be efficient at very high spatial resolution and to improve the model’s climate (Enomoto et al. 2008). The radiation scheme is that of Sekiguchi et al. (2003), which helps to reduce cold bias in the lower stratosphere. The oceanographic component of CFES is the OGCM for the Earth Simulator including representation of ice (OIFES), which is based on version 3 of the Modular Ocean Model (Pacanowski and Griffies 2000). OIFES covers the global domain and solves the primitive equation system in spherical coordinates under the Boussinesq and hydrostatic approximations (Komori et al. 2008). The mixing parameterization of Noh and Kim (1999) is adopted for vertical mixing.

AFES is highly vertically resolved with 48-σ levels, allowing it to develop realistic vertical distribution of moisture and temperature (Enomoto et al. 2008). OIFES has 54 vertical levels, with a resolution varying from 5 m near the surface to 330 m near the bottom. The high vertical resolution in the upper ocean (13 levels in the top 100 m) is adequate to capture the stratification and the mixed-layer and barrier-layer processes (Sasaki et al. 2008), which appear to be important for realistic simulation of monsoon rainfall (Seo et al. 2009).

We analyze preexisting solutions to two versions of CFES that differ primarily in horizontal resolution, with the standard (mini) version having a horizontal spectral resolution of T239 (T119) for its atmospheric component, roughly equivalent to a 50-km (100 km) grid, and 0.25° (0.5°) for its oceanic component (Taguchi et al. 2012). In section 3b, however, we only discuss the CFES mini run (our control run), as the relevant properties of the CFES standard run are almost unchanged.

Because CFES realistically simulates the Asian monsoon and tropical Indian Ocean basic state, it provides a useful “laboratory” for testing hypotheses about coupled ocean–atmosphere processes in the EIO. In section 3c, we report sensitivity solutions to the mini version of CFES. They are integrated for 15 yr, and seasonal climatologies are determined from the last 10 yr of their respective integrations.

b. Control run

Figure 7 plots biases in summer precipitation and wind stress (Fig. 7a) and SST (Fig. 7b) for the CFES_CTL solution. They are all weaker than in the CMIP5 models (cf. with Figs. 1a and 1b, respectively). The CFES precipitation biases are weakly positive over the southeastern Arabian Sea; there is negative (positive) bias over the northern (southern) Bay of Bengal and positive bias over the plains of Indo-China, but their amplitudes are much less than in CMIP5. The magnitude of the SST bias is less than 0.5°C in most of the tropical Indian Ocean, except along the latitude strip 2°–10°N where it is about 1°C colder.

More important than the magnitude of the SST errors, however, the bias in the equatorial SST gradient is nearly absent in CFES. As a result, the low-level moisture convergence (not shown) and precipitation errors in the western Indian Ocean are smaller than in the CMIP5 models (Fig. 7a). Note further that in CFES the SST and rainfall errors over REG1 are not collocated, indicating that they do not arise from the coupling errors discussed in section 2 for the CMIP5 models. The improved precipitation fosters realistic simulations of the equatorial wind stress, including the intermonsoon westerlies (Nagura et al. 2013) and hence the WJs. In CFES (blue line in Fig. 5), the fall WJ is slightly weaker than the spring jet, whereas the opposite is true in the observations (black line in Fig. 5); nevertheless, the seasonal cycle of the equatorial currents, including weak westward flows during February and August and their zonal extent and duration, are well represented (Fig. 6c). Overall then, in CFES coupled ocean–atmosphere processes in the EIO are simulated more realistically than they are in the CMIP5 models.

Precipitation errors in the CMIP5 models have been hypothesized to arise from errors due to fast atmospheric, rather than coupled, processes, a view supported...
by simulations performed with atmosphere-only models (Ma et al. 2014). To check this idea, Fig. 8 compares precipitation and SST climatologies in the AFES (Fig. 8a) and CFES (Fig. 8b) control simulations. In both runs the atmospheric model is the same, the two solutions differing in that AFES is forced with daily-varying observed SST for the period 1979–2010. The simulated precipitation in AFES is biased with higher precipitation [>(4–8) mm day$^{-1}$] over REG1 (approximately west of 65$^\circ$E), a bias similar to that in the CMIP5 models and in other atmosphere-only models (Ma et al. 2014). In contrast, this erroneous feature is clearly rectified by the

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**Fig. 7.** Seasonal (June–September) mean climatology difference between CFES_CTL simulation and observations: (a) precipitation (color shading, mm day$^{-1}$) and wind stress (vectors, N m$^{-2}$) and (b) SST (color shading, °C).

**Fig. 8.** The seasonal (June–September) mean precipitation (color shading, mm day$^{-1}$) and SST (contours, °C) climatology from control solutions for (a) AFES and (b) CFES. Note that AFES is forced with daily observed SST for the period 1979–2010.
coupling in the CFES solution: While the structure of precipitation along the EIO is present in the AFES and CFES solutions, its amplitude distribution is more realistic in CFES, implying the need for the correct representation of EIO coupled processes. Similar results are noticeable in MIROC5 coupled (Sperber et al. 2013) versus uncoupled solutions (Ma et al. 2014).

c. Sensitivity experiments

Guided by the fact that EIO coupled processes are misrepresented in CMIP5 models, we report sensitivity experiments designed to degrade EIO feedback processes. We do so by externally imposing an easterly wind stress $\Delta \tau$ in the ocean component of CFES, essentially artificially weakening the WJs. The primary reason for using $\Delta \tau$ is that WJs set up in about 10 days (section 2d), highlighting the role of fast oceanic processes in generating model errors. It also supports our idea that misrepresentation of the WJs is a key coupled error in the EIO. On the other hand, since there is no starting point in the air–sea coupled feedback loop, we also perform another CFES sensitivity run by inserting warm SST anomalies in the western EIO.

We note that there are other significant biases in other aspects of the wind (e.g., in its meridional component and off the equator; Fig. 1a). It is nevertheless sensible to focus our study on $\Delta \tau$ because it is well known to be the strongest driver of equatorial zonal currents, a consequence of the lack of Coriolis force in the zonal momentum equation. For example, regarding forcing by other components of the equatorial winds, Miyama et al. (2003) investigated the impact of various idealized forcings (patches of meridional and zonal winds that are symmetric and antisymmetric about the equator), finding that only the symmetric zonal wind generates a significant equatorial jet. Regarding off-equatorial forcing, Rossby waves carry signals generated by Ekman pumping to the western boundary, where they propagate to the equator via coastal waves, and then along the equator via the equatorial Kelvin wave; however, the equatorial impact of such remote signals is weak, essentially because their mass transport is proportional to the slow, off-equatorial, Rossby wave speed (Kessler 1991).

In one experimental run (CFES_EXP1), we apply a time-independent $\Delta \tau$ throughout the coupled integration. The anomaly (Fig. 9) is imposed only over the equatorial band (5°S–5°N), and its structure and amplitude are given by the negative of the annual-mean $\tau$ from the first 10 yr of the CFES mini integration. As such, it “mimics” the intensity and spatial distribution of the $\Delta \tau$ error present throughout the annual cycle in the CMIP5 composites (Fig. 1c). In the second experiment (CFES_EXP2), we impose $\Delta \tau$ only during the intermonsoon seasons, by allowing it vary in time according to $T(t) = 1/2[1 + \sin(2\pi t/P)] + 1$, where $P = 0.5\text{yr}$. With this choice for $T(t)$, $\Delta \tau$ is at a maximum on 1 May and 1 November, reducing to climatological values on 1 August and 1 February. Except for amplitude, errors in both solutions are similar, and we therefore discuss only results from CFES_EXP2.

In response to $\Delta \tau$, the sensitivity runs develop westward equatorial currents throughout the year (cyan and magenta lines in Fig. 5a), suppressing the WJs in comparison to the control run (Figs. 6c,d). The anomalous forcing also excites Rossby and Kelvin waves that tend to deepen (shallow) the thermocline depth (Fig. 10a) in the western EIO (eastern EIO). In response, warm (cool) SST and wet (dry) conditions develop in each region (Figs. 10b,c). Additionally, the simulated cold SST bias along the equatorial central Indian Ocean closely resembles errors in the CMIP5 models (Fig. 1b). An analysis of moisture and MSE budgets in these solutions (Fig. 11) demonstrates that the precipitation bias over REG1 results from evaporation and moisture convergence, pointing to SST errors as being their cause. In summary, the imposed forcing results in SST and precipitation gradients along the EIO through its impact on the thermocline depth, as in the CMIP5 models. Our experiments, however, do not capture the positive rainfall bias over the Maritime Continent present in the CMIP5 models (Fig. 1a).

Along the Somali and Omani coasts, the narrow band of warm bias (Fig. 10b) is a consequence of reduced
upwelling of cold subsurface waters due to the weakened monsoon circulation. The solutions also have a positive rainfall bias in the Arabian Sea (REG2) and budget analysis (not shown) suggests the role of moist advection in anchoring the wet bias.

In both sensitivity runs, a striking result is the rainfall reduction over South Asia (Fig. 10c), a bias that closely resembles the CMIP5 error (Fig. 1a). (The precipitation bias from CFES_EXP1 bears close is very similar to Fig. 10c, and hence not shown.) Since errors in the sensitivity experiment are driven only from the equator, it follows that the South Asian precipitation errors are as well. What processes account for this causal linkage? We conjecture that it
results from a feedback loop between rainfall over South Asia and REG2. Because of the positive rainfall errors over REG1, moisture transport into South Asia is decreased thereby reducing rainfall there (Annamalai et al. 2005). As noted in section 2c(2), this South Asian forcing generates northeasterly wind errors that extend to the Arabian Sea (REG2) as a Rossby wave response (Fig. 1a). There, they weaken the moisture flux out of REG2 and, hence, enhance local precipitation. Once organized, positive rainfall errors in REG2 further reduce moisture transport to South Asia, which in turn weakens South Asian rainfall even more, and the cycle continues.

Based on the diagnostics presented in section 2c, we concluded that the precipitation bias over REG1 (10°S–5°N, 40°–60°E) is due to a warm, local SST bias. Therefore, in CFES_EXP3, we imposed an annual-mean warm SST bias over REG1 (Fig. 2e), retaining it throughout the annual cycle. The model was integrated for 10 yr, and the precipitation and near-surface (10 m) wind responses during boreal summer (June–September) are shown in Fig. 10d. In the experiment, precipitation is enhanced over the western equatorial Indian Ocean and also over parts of the southern Arabian Sea and southern Bay of Bengal; it is reduced over the equatorial central and eastern Indian Ocean and over the northern Bay of Bengal. More importantly, rainfall is reduced along the monsoon trough, and the cross-equatorial low-level flow is weakened. Anticyclonic vorticity over the northern Indian Ocean can be interpreted as a Rossby wave response to reduced precipitation (and hence reduced heating) along the monsoon trough. Along the EIO, easterly wind anomalies prevail. Finally, the equatorial WYrtki jets are weaker than in the control experiment (not shown). Note that the version of the CFES used in this is an updated version with modifications to convective entrainment, among other changes.

Yet, the response is encouraging. We conclude that the results of this experiment strengthen our hypothesis.

4. Summary and discussion

a. Summary

In the CMIP3 and CMIP5 models, misrepresentation of a number of physical processes has been proposed to account for the dry bias over South Asia (section 1). The present study shows that misrepresentation of equatorial Indian Ocean (EIO) coupled processes in the CMIP5 models can also cause the weak South Asian rainfall. Further, these coupled errors lead to biases throughout the monsoon–Indian Ocean climate system, causing errors in SST, thermocline depth, and precipitation over most of the tropical Indian Ocean and for most of the annual cycle (Fig. 2). To reach this conclusion, we analyze errors in CMIP5 MMM climatological fields and analyze solution to CFES, a coupled model that realistically represents the EIO and monsoon systems.

In CMIP5 models, the easterly wind bias $\Delta v$ along the EIO begins during April–May (the intermonsoon season) and weakens during August–September but revives and peaks in November (Fig. 1c). As a consequence, the eastward, equatorial currents, the WYrtki jets (WJs), during the intermonsoon seasons (April–May and October–November) are much weaker. The severity of these errors leads to errors in the coupled processes (Bjerknes feedback), particularly during June–November. We argued that the WJ errors are particularly important to the feedback: they are a fast oceanic process that can lead to errors in the coupled system in only about 10 days. It is concluded that warm SST bias over REG1 results from model errors in representing EIO coupled processes. Over the near-equatorial western Indian Ocean, model errors in precipitation
are too strong and they drive errors in $\Delta T$. The weaken-
ing in $\Delta T$ during winter and early spring is due to southward displacement of precipitation errors in the western Indian Ocean (Fig. 2).

In the CMIP5 models, the initiator of South Asian rainfall error is the warm SST bias over the western EIO ($10^\circS$–$5^\circN$, $40^\circ–60^\circE$; REG1). Analysis of moisture bud-
get demonstrates that the warm SST there leads to local precipitation excess, through its impact on evaporation and moisture convergence. An examination of MSE budget shows that positive contributions from diabatic terms ($LH'$ and $<F_{\text{rad}}>$) favor convective instability. This excess precipitation in turn weakens the cross-equatorial moisture transport in the northern Indian Ocean, resulting in decreased precipitation over South Asia. An additional feedback appears to be involved in this con-
nection: the South Asian rainfall deficit generates northeasterly wind anomalies that extend into the Ara-
bian Sea ($5^\circ–15^\circN$, $60^\circ–85^\circE$; REG2) via Rossby wave response to the reduced South Asian rainfall and these wind anomalies advect moisture into REG2; as a result, positive precipitation errors occur over REG2, further weakening South Asian rainfall.

Our analyses of CFES solutions also point toward the importance of EIO coupled processes.

In a solution to AFES, the atmospheric component of CFES, driven by observed climatological SST forcing, errors develop that are similar to those in the CMIP5 models and other atmosphere-only models (Fig. 8). Guided by equatorial, easterly wind stress $\Delta T$ (Fig. 1c), we also carried out CFES sensitivity experiments in which an externally prescribed $\Delta T$ was applied to the ocean component, in effect artificially weakening WJs. In addition, we carried out an experiment in which an externally imposed warm SST bias over the western EIO in order to strengthen the Bjerknes feedback. The sen-
sitivity experiments also developed errors similar to those in the CMIP5 models.

b. Discussion

In conclusion, we argue here that the use of coupled models, together with the correct representation of coupled processes along the EIO, is the only viable option for obtaining realistic monsoon simulations. Despite dedicated efforts by the modeling community, the progress in monsoon modeling is rather slow. This leads us to wonder if there are limits to re-
alistically simulate the monsoon, or if concerted ob-
servational and modeling efforts are needed to improve our understanding and enhance the fidelity of models in simulating the monsoon.

The fact that model errors are persisting suggests that they arise from multiple processes and their interactions. Why are the model errors in precipitation large and persistent over the western EIO? Let us consider the following scenario. Climatologically the western EIO receives much less rainfall (dotted line in Fig. 12a) compared to the eastern EIO throughout the annual cycle (thick line in Fig. 12a). An examination of vertical velocity profile (not shown) suggests weak descent (strong ascent) over the western (eastern) EIO for most of the annual cycle. Therefore, a higher amount of MSE is required to trigger and maintain the precipitation bias over the western EIO. During May, observed SST peaks around $30^\circC$ (Fig. 12b) and a weak cross-equatorial flow develops (Fig. 12c) that transports moisture from the southern Indian Ocean. Because of high-mean SST, local evaporation increases (not shown). These processes lead to the accumulation of CWV in the western EIO. As a result, a local maximum in precipitation ($\sim4$ mm day$^{-1}$) is observed (Fig. 12a). Immediately thereafter in June, SST drops to $\sim26^\circC$ and rainfall decreases subsequently. It is during this “time window” of the annual cycle that the model errors begin to emerge, say warm SST and easterly $\Delta T$ biases (Fig. 1). An examination of SST tendency errors (June minus May) in CMIP5 MMM clearly shows a warming (cooling) tendency over western (eastern) EIO and the emergence of SST gra-
dient along the EIO (Fig. 12d) that subsequently pro-
motes Bjerknes feedback. In CMIP5 models, a reversed gradient in precipitation along the EIO and its persistence result from errors in the coupled processes.

The implications from the present research are worth pursuing, particularly for better observing systems, process-based diagnostics, and sensitivity experiments. Note that MSE budget estimated biases are with respect to reanalysis products that are “model-based” them-

selfs. In data-sparse regions such as the Indian Ocean, model prejudices in reanalysis largely determine the nature of thermodynamic variables. The adiabatic terms (e.g., horizontal advection) depend on the dynamical core employed in models, and the term $<\omega'$) depends on the vertical profile of the vertical velocity, which in turn depends on cumulus parameterization schemes employed. Therefore, to constrain model physics and for realistic representation of processes in models, field and in situ observations over the monsoon/Indian Ocean region are needed.

In a recent study, Li et al. (2015) demonstrate the existence of model errors in Bjerknes-like feedbacks in the EIO, and discuss their impact on Indian Ocean di-
pole (IOD)-like variability at interannual time scales. The model errors in the seasonal cycle shown here (Figs. 1 and 2) bear some similarities to the interannual variability discussed in their study. One significant
difference between this study and ours, however, lies in the working hypothesis. Li et al. (2015) conclude that a weakened South Asian monsoon “led to a warm SST bias” over the western EIO during boreal summer, which Bjerknes-like feedback amplified during boreal fall resulting in IOD-like signals. Our work is based on the idea that EIO processes prior to the monsoon season lead to errors in monsoon simulation.

Other notable differences are that in a positive IOD year precipitation along the South Asian monsoon trough increases (e.g., Annamalai 2010), and even during boreal fall precipitation anomalies are much too strong over the eastern rather than over the western EIO (e.g., Li et al. 2015). In the seasonal errors discussed here, we note an opposite pattern (too much precipitation over the western EIO). Ignoring the amplitude, there is similarity in the “pattern” and our speculation is that this apparent similarity arises from the initial emergence of warm SST bias over the western EIO during May–June, which then leads to errors in the coupled feedbacks in the seasonal errors as well as during IOD years; our earlier research pointed out that triggering of the IOD occurs during late spring and early summer (Annamalai et al. 2003).

Another point of interest here is the evolution of the easterly wind stress error is associated with the mean seasonal cycle (Fig. 1c). The seasonality of the error development may very well be associated with the precipitation seasonal cycle itself. The ITCZ lies around the EIO during boreal spring resulting in the first peak in rainfall along the EIO, both over the eastern and western EIO (Fig. 12a). The initial error in the zonal wind stress develops during spring. Then the zonally integrated precipitation along the EIO increases in late summer and peaks during boreal fall season (e.g., Fig. 12a). In other words, during the

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**Fig. 12.** (a) Observed monthly precipitation (mm day$^{-1}$) climatology averaged over the eastern EIO ($5^\circ$S–$5^\circ$N, 90$^\circ$–105$^\circ$E, solid line) and western EIO ($5^\circ$S–$5^\circ$N, 50$^\circ$–60$^\circ$E, dashed line); (b) observed monthly SST ($^\circ$C) climatology averaged over western EIO; (c) observed wind stress (vectors, N m$^{-2}$) climatology during May, and (d) June – May SST ($^\circ$C) tendency bias in CMIP5 MMM.
seasonal cycle, the ITCZ is close to the equator during intermonsoon seasons and any perturbations to precipitation are thus expected to amplify due to moisture–convection–circulation feedbacks. This would result in the amplification of the zonal wind response (Fig. 1c). Note that when the ITCZ moves poleward in the Southern Hemisphere during boreal winter, the region of maximum wet bias also moves poleward (Fig. 2; note that maximum precipitation bias lies around 12°S), and the equatorial Kelvin wave response and associated easterly bias also weaken considerably.

Another potential issue not considered here is the impact of warm SST bias over the western EIO (Fig. 2) on the eastern African monsoon rainfall [both during the long (March–May) and short (October–November) rainfall seasons]. It is fair to mention that the poor skill on the eastern African monsoon rainfall [both during intermonsoon seasons and any perturbations improved the manuscript. This study is also supported by the Arctic Challenge for Sustainability (ArCS) Program and by the Japanese Ministry of Environment through the Environment Research and Technology Department Fund 2-1503. This work was also supported by JSPS through KAKENHI Grants 124540476 and 15K05284 and by the Japan Science and Technology Agency through Belmont Forum CRA “InterDec”. The Earth Simulator was utilized in support of JAMSTEC.

Acknowledgments. The authors acknowledge the financial support provided by JAMSTEC. Annamalai and McCreary are partially funded by the National Science Foundation (NSF) under Grant 1460742. We thank Jan Hafner for his assistance with diagnostics. The authors thank all the reviewers, whose comments and suggestions improved the manuscript. This study is also supported in part by the Arctic Challenge for Sustainability (ArCS) Program and by the Japanese Ministry of Environment through the Environment Research and Technology Department Fund 2-1503. This work was also supported by JSPS through KAKENHI Grants 124540476 and 15K05284 and by the Japan Science and Technology Agency through Belmont Forum CRA “InterDec”. The Earth Simulator was utilized in support of JAMSTEC.

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