A Robust but Spurious Pattern of Climate Change in Model Projections over the Tropical Indian Ocean

GEN LI

*State Key Laboratory of Tropical Oceanography, South China Sea Institute of Oceanology,
Chinese Academy of Sciences, Guangzhou, Guangdong, China*

SHANG-PING XIE

*Scripps Institution of Oceanography, University of California, San Diego, La Jolla, California, and
Physical Oceanography Laboratory/Qingdao Collaborative Innovation Center of Marine Science and
Technology, Key Laboratory of Ocean–Atmosphere Interaction and Climate in Universities of Shandong,
Ocean University of China, Qingdao, Shandong, China*

YAN DU

*State Key Laboratory of Tropical Oceanography, South China Sea Institute of Oceanology,
Chinese Academy of Sciences, Guangzhou, Guangdong, China*

(Manuscript received 12 August 2015, in final form 16 March 2016)

ABSTRACT

Climate models consistently project reduced surface warming over the eastern equatorial Indian Ocean (IO) under increased greenhouse gas (GHG) forcing. This IO dipole (IOD)-like warming pattern, regarded as robust based on consistency among models by the new Intergovernmental Panel on Climate Change (IPCC) report, results in a large increase in the frequency of extreme positive IOD (pIOD) events, elevating the risk of climate and weather disasters in the future over IO rim countries. These projections, however, do not consider large model biases in both the mean state and interannual IOD variance. In particular, a “present–future relationship” is identified between the historical simulations and representative concentration pathway (RCP) 8.5 experiments from phase 5 of the Coupled Model Intercomparison Project (CMIP5) multimodel ensemble: models with an excessive IOD amplitude bias tend to project a strong IOD-like warming pattern in the mean and a large increase in extreme pIOD occurrences under increased GHG forcing. This relationship links the present simulation errors to future climate projections, and is also consistent with our understanding of Bjerknes ocean–atmosphere feedback. This study calibrates regional climate projections by using this present–future relationship and observed IOD amplitude. The results show that the projected IOD-like pattern of mean changes and frequency increase of extreme pIOD events are largely artifacts of model errors and unlikely to emerge in the future. These results illustrate that a robust projection may still be biased and it is important to consider the model bias effect.

Denotes Open Access content.

Supplemental information related to this paper is available at the Journals Online website: <http://dx.doi.org/10.1175/JCLI-D-15-0565.s1>.

Corresponding author address: Gen Li, State Key Laboratory of Tropical Oceanography, South China Sea Institute of Oceanology, Chinese Academy of Sciences, 164 West Xingang Road, Guangzhou 510301, China.
E-mail: ligen@scsio.ac.cn

DOI: 10.1175/JCLI-D-15-0565.1

1. Introduction

Tropical patterns of sea surface temperature (SST) change under global warming were taken up as an important topic in the latest Intergovernmental Panel on Climate Change (IPCC) report (Christensen et al. 2014) because they have potentially important effects on regional changes in precipitation (e.g., Xie et al. 2010; Huang et al. 2013; Ma and Xie 2013), atmospheric circulation (e.g., Ma and Xie 2013; Huang and Ying 2015), tropical cyclones (e.g., Sugi et al. 2002; Vecchi and Soden 2007a; Yokoi and Takayabu 2009; Du et al. 2011),

and coupled ocean–atmosphere modes (e.g., Yeh et al. 2009; Collins et al. 2010; Yeh et al. 2012).

In the tropical Indian Ocean (IO), most coupled general circulation models (CGCMs) project a stronger SST warming in the western equatorial IO than in the eastern equatorial IO, accompanied by positive precipitation change over enhanced SST warming in the northwest basin and negative precipitation change over reduced SST warming in the southeast basin, driving strong surface easterly wind anomalies in the equatorial IO under increased greenhouse gas (GHG) forcing (Vecchi and Soden 2007b; Xie et al. 2010; Zheng et al. 2010, 2013; Cai et al. 2014). This is reminiscent of the interannual IO dipole (IOD) mode (Saji et al. 1999; Webster et al. 1999; Murtugudde et al. 2000; Ashok et al. 2003; Du et al. 2013) and suggestive of Bjerknes ocean–atmosphere feedback (Bjerknes 1969; Chang et al. 2006; Schott et al. 2009). The new IPCC report has regarded this IOD-like climate projection as robust based on high consistency among models (Christensen et al. 2014).

A multimodel ensemble under a high-emission scenario of representative concentration pathway (RCP) 8.5 from phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012) suggests that such an IOD-like warming pattern in the mean would result in more frequent occurrences of extreme positive IOD (pIOD) events in the future, from one event every 17.3 years over the twentieth century to one event every 6.3 years over the twenty-first century (Cai et al. 2014). This implies increased risks of climate and weather disasters in regions associated with extreme pIOD events. They include catastrophic flooding in parts of East Africa and the India subcontinent (e.g., Black et al. 2003; Behera et al. 2005; Zubair et al. 2003); devastating droughts and bushfires in East Asia (e.g., Guan and Yamagata 2003), Indonesia (e.g., Saji et al. 1999), and Australia (e.g., Cai et al. 2009a; Ummenhofer et al. 2011); and severe coral reef death and human health problems associated with natural disasters (e.g., Emmanuel 2000; Abram et al. 2003; Frankenberg et al. 2005; Hashizume et al. 2012).

With observed records still too short and too sparse to detect reliably spatial patterns of tropical SST warming amid natural variability, we have to rely heavily on climate model projections at present. Climate models, however, suffer from long-standing and common biases (e.g., Mechoso et al. 1995; Davey et al. 2002; Lin 2007; Hwang and Frierson 2013; Li and Xie 2012, 2014; Wang et al. 2014; Li et al. 2015a,b,c), potentially limiting the reliability of future climate projections (Boé et al. 2009; Cox et al. 2013; Brown et al. 2014). Thus, it is important to evaluate and correct the effects of model errors on regional climate projections.

Statistical techniques have been proposed to modify regional climate projections by taking into account modeling uncertainties and historical simulation errors (Xie et al. 2015). For example, a Bayesian statistical method combines information from multimodel ensembles with perturbed parameters and observations to quantify the weight of each member on the basis of its ability to reproduce observations (e.g., Tebaldi et al. 2005; Rougier 2007; Buser et al. 2009; Collins et al. 2012; Sunyer et al. 2014). This allows us to go beyond simple ensemble mean in regional assessments by trusting “better” models more based on evaluation of model errors. But such a model weighting technique cannot resolve errors common to all climate models.

Another statistical strategy called “emergent constraints” has been suggested to deal with the effects of model errors on future climate projections by deriving relationships between observable quantities in the present climate and projected responses of the climate system to global warming in a multimodel ensemble to constrain future climate projections (e.g., Whetton et al. 2007; Boé et al. 2009; Räisänen et al. 2010; Abe et al. 2011; Shiogama et al. 2011; Bracegirdle and Stephenson 2012, 2013; Cox et al. 2013; Huang and Ying 2015; Li et al. 2016). In essence, emergent constraints are based on an assumption that projected future climate responses of one variable strongly depend on the model’s present-day state. For example, Boé et al. (2009) identified a strong linear relationship between simulated twentieth-century Arctic sea ice extent trends and projected Arctic sea ice extent in the twenty-first century among models. Using this intermodel relationship, the projected sea ice cover over the twenty-first century by climate models could be constrained (calibrated) with the observed twentieth-century Arctic sea ice extent trends. Similarly, Bracegirdle and Stephenson (2012, 2013) used the statistical relationships between future and historical runs in large model ensembles to calibrate the projections of regional polar warming based on the concept of emergent constraints. In the emergent constraints, since the simulated present-day states in climate models are constrained with observations, calibrations using “present–future” relationships can remove the effect of historical simulation errors (including the ones common to all climate models) on future climate projection in each model, and thus also be constrained to a tighter range, reducing the projection uncertainty (e.g., Boé et al. 2009; Bracegirdle and Stephenson 2013; Huang and Ying 2015; Li et al. 2016).

Along the equatorial IO, CGCMs commonly simulate too weak westerly winds (Lee et al. 2013; Cai and Cowan 2013; Li et al. 2015b,c). With the equatorial easterly wind bias, the mean thermocline unrealistically shoals in

the equatorial eastern IO, generating an overly strong Bjerknes feedback in CGCMs. As a result, CGCMs tend to feature excessively large amplitudes of interannual IOD variability relative to observations (Cai and Cowan 2013; Liu et al. 2014; Li et al. 2015c). Conceivably such a common “distortion” of Bjerknes feedback that produces the IOD-like warming pattern in the first place would bias future climate projections over the tropical IO in CGCMs.

The present study investigates the effects of model errors on the projected tropical IO warming pattern and change of extreme pIOD occurrences in 24 CMIP5 CGCMs. We find that models with larger IOD amplitude biases tend to project a stronger IOD-like warming pattern in the mean and a larger increase in extreme pIOD occurrences under increased GHG forcing. We then develop a method to calibrate the model error effects based on an “observational/emergent constraint” of the IOD amplitude. The results show that the IOD-like warming pattern in the mean and the tendency for more frequent extreme pIOD events are both greatly scaled down after the corrections with the observed IOD amplitude.

The rest of the paper is organized as follows. In section 2, we describe models, datasets, and methods used in this study. Section 3 briefly describes the IOD-like warming pattern before the corrections. Section 4 investigates the effect of model errors on the projection of tropical IO warming pattern and compares the corresponding uncorrected and corrected projections. Section 5 further calibrates the projected change in the occurrences of extreme pIOD events under increased GHG forcing. Section 6 is a summary with discussion.

2. Models, datasets, and methods

a. Models and datasets

In this study, the historical runs and RCP 8.5 experiments from 24 CMIP5 CGCMs are examined (Taylor et al. 2012). The model names, modeling groups (or centers), and their letter labels are shown in Table 1. More information on individual models is available online at <http://cmip-pcmdi.llnl.gov/cmip5/availability.html>. We use the 1900–99 mean in the historical simulation as the present climatology, and the 2000–99 mean in the RCP 8.5 experiment as the future climatology. Their difference indicates climate change in the context of global warming. The multimodel ensemble (MME) mean is simply represented by using the average of 24 CMIP5 CGCMs. The global analyses of SST (Rayner et al. 2003) for 1900–99 and Global Precipitation Climatology Project (GPCP) analysis (Adler et al. 2003)

TABLE 1. A list of 24 CMIP5 models used in this study and the letter labels to denote them in the figures and text. (Expansions of acronyms are available online at <http://www.ametsoc.org/PubsAcronymList>.)

Model name	Model group (or center)	Letter label
ACCESS1.0	CSIRO-BOM	M1
BCC-CSM1.1(m)	BCC	M2
CCSM4	NCAR	M3
CESM1(CAM5)	NSF-DOE-NCAR	M4
CMCC-CESM	CMCC	M5
CNRM-CM5	CNRM-CERFACS	M6
CSIRO-Mk3.6.0	CSIRO-QCCCE	M7
FGOALS-s2	LASG-IAP	M8
GFDL CM3	NOAA GFDL	M9
GFDL-ESM2G	NOAA GFDL	M10
GFDL-ESM2M	NOAA GFDL	M11
GISS-E2-R	NASA GISS	M12
HadGEM2-AO	MOHC	M13
HadGEM2-CC	MOHC	M14
INM-CM4	INM	M15
IPSL-CM5A-LR	IPSL	M16
IPSL-CM5A-MR	IPSL	M17
IPSL-CM5B-LR	IPSL	M18
MIROC5	MIROC	M19
MPI-ESM-LR	MPI-M	M20
MPI-ESM-MR	MPI-M	M21
MRI-CGCM3	MRI	M22
NorESM1-M	NCC	M23
NorESM1-ME	NCC	M24

for 1979–2010 are also used in this study. Unless otherwise specified, a common $2^\circ \times 2^\circ$ horizontal grid interpolation is applied to all model outputs and observational datasets.

b. Definitions of the IOD amplitude and extreme pIOD events

The annual amplitude of interannual IOD variability is measured as the standard deviation of the dipole mode index (DMI; Saji et al. 1999), which is defined as the difference in SST anomaly between the western (10°S – 10°N , 50° – 70°E) and eastern (0° – 10°S , 90° – 110°E) parts of the IO. We also use two other IOD indices, namely the Sumatra cooling index (Xie et al. 2002) and the leading principal component of SST anomalies over the equatorial Indian Ocean (Weller and Cai 2013). The results from the three IOD indices are very similar, and thus we only give the results from the DMI in this study, unless otherwise specified.

We apply empirical orthogonal function (EOF) analysis to precipitation anomalies in the equatorial IO (10°S – 10°N , 40° – 110°E) during September–November (SON) to identify extreme pIOD events (Cai et al. 2014). The first EOF pattern (EOF1) represents an east–west precipitation/SST anomaly dipole pattern with strong precipitation reduction and SST cooling over the eastern

FIG. 1. (a) The MME mean changes in SST [color contours, contour interval (CI) 0.1°C], precipitation (gray shade and white contours, CI = 0.5 mm day⁻¹), and surface wind stress (vector scale is shown in the lower right corner; N m⁻²) during SON projected by 24 CMIP5 models under RCP 8.5 scenario. Intermodel scatterplots of (b) the changes in west-minus-east difference between SST and precipitation (west box: 10°S–10°N, 50°–70°E; east box: 0°–10°S, 90°–110°E), and (c) the changes in west-minus-east SST difference vs surface zonal wind stress (TAUx) in the central equatorial Indian Ocean (CEIO; 70°–90°E).

pole and moderate precipitation increase and SST warming over the western equatorial IO accompanied by equatorial easterly wind anomalies [figure not shown; also see Figs. 1c and 2a of Cai et al. (2014)], characteristic of a moderate pIOD event depicted by the

DMI (Saji et al. 1999). The second EOF pattern (EOF2) features a westward extending of precipitation reduction and SST cooling anomalies along the equator from the east [figure not shown; see also Figs. 1d and 2b of Cai et al. (2014)], which characterizes an extreme pIOD

FIG. 2. (a) Comparison of monthly IOD amplitudes between observations (blue) and the historical simulations of the CMIP5 MME mean (red), sIODAB (green), and wIODAB models (purple). (b) Annual IOD amplitudes in observations vs 24 CMIP5 models. Here, the IOD amplitude is defined as the s.d. of DMI proposed by Saji et al. (1999). The red error bars for the MME mean indicate the s.d. spread among models.

event along with EOF1 (Cai et al. 2014). An extreme pIOD event is defined when EOF1 is greater than 1 (or 1.5) standard deviation (s.d.) and EOF2 greater than 0.5 s.d., following the work of Cai et al. (2014). By this definition, the 1994 and 1997 events are the most extreme pIOD events for the present satellite era (1979–2010). We examine the EOF patterns of precipitation anomalies from each model. The two models [GISS-E2-R (M12) and IPSL-CM5A-MR (M17)] do not show a nonlinear relationship between EOF1 and EOF2 patterns (figure not shown; Cai et al. 2014) and cannot generate extreme pIOD events. These two models (M12 and M17) are excluded for the analyses of extreme pIOD occurrences, unless otherwise specified. Note that this study uses similar data and a similar observational/emergent constraint approach to those in the work of Li et al. (2016), but applies them to the tropical IO rather than the tropical Pacific. The following description of the method parallels that of Li et al. (2016) with some modifications.

c. Correction method for regional climate projection

Given historical climatology, $H(s, m)$, and future climatology, $F(s, m)$, the future climate change can be defined as

$$C(s, m) = F(s, m) - H(s, m), \quad (1)$$

where s and m denote space (latitude–longitude) and model, respectively. The interannual IOD amplitudes

for observations, $\text{AmpDMI}(\text{obs})$, and for each model, $\text{AmpDMI}(m)$, are measured with the standard deviations of corresponding DMIs during 1900–99. Then, the IOD amplitude bias for model m is expressed as

$$\text{AmpDMI}'(m) = \text{AmpDMI}(m) - \text{AmpDMI}(\text{obs}). \quad (2)$$

CGCMs commonly have too large an IOD amplitude relative to observations (Cai and Cowan 2013; Liu et al. 2014; Li et al. 2015c). The present–future relationship among CGCMs between the simulated IOD amplitudes, $\text{AmpDMI}(m)$, and projected climate changes, $C(s, m)$, can be obtained by a linear regression analysis as

$$C(s, m) = a(s) \times \text{AmpDMI}(m) + b(s), \quad (3)$$

where a is the regression pattern and b is the regression constant. Where the relationship between the IOD amplitudes, $\text{AmpDMI}(m)$, and projected climate changes, $C(s, m)$, in the multimodel ensemble is statistically significant [Eq. (3)], the climate projection, $C(s, m)$, can be calibrated based on this intermodel relationship and observed IOD amplitude, $\text{AmpDMI}(\text{obs})$, in analogy to the concept called “emergent constraints” (e.g., Boé et al. 2009; Bracegirdle and Stephenson 2012, 2013; Huang and Ying 2015).

The simulated IOD amplitude bias is due to excessive Bjerknes feedback, which would also bias future climate projections over the tropical IO (Li et al. 2015c). We can

FIG. 3. Composed pIOD patterns of SST ($^{\circ}\text{C}$) anomalies over the tropical IO for 1900–99 from (a) observations (HadISST), (b) sIODAB models (M4, M7, M8, M11, and M21), and (c) wIODAB models (M12, M15, M16, M18, and M22). Here, a pIOD event is defined when the DMI > 1 s.d. for HadISST observations and each model.

estimate the errors of climate change projection, $C'(s, m)$, from the IOD amplitude bias for each model:

$$C'(s, m) = a(s) \times \text{AmpDMI}'(m). \quad (4)$$

Therefore, the corrected future climate changes for each model are given as

$$C^*(s, m) = C(s, m) - C'(s, m). \quad (5)$$

Finally, the MME mean of corrected future climate changes in individual models is calculated as

$$\overline{C^*(s, m)} = \frac{1}{N} \sum_{m=1}^N C^*(s, m), \quad (6)$$

where N is the total number of climate models. Alternatively, by directly substituting $\text{AmpDMI}(\text{obs})$ into Eq. (3), we obtain the corrected MME mean of future climate projections among models as follows:

$$\overline{C^*(s, m)} = a(s) \times \text{AmpDMI}(\text{obs}) + b(s). \quad (7)$$

Equations (6) and (7) are identical for the MME mean.

3. The robust IOD-like warming pattern

Figure 1a shows the uncorrected MME mean changes in SST, precipitation, and surface wind stress vectors under increased GHG forcing during SON, the peak season for both interannual IOD variability (Saji et al. 1999; Liu et al. 2014; Li et al. 2015a) and future IOD-like projection (Zheng et al. 2013; Christensen et al. 2014; Cai et al. 2014). Indeed, SST warming displays a sharp west–east gradient along the equator, reaching 1.9°C in the northwestern equatorial IO but dropping to just 1.2°C off the Sumatra–Java coast. This SST warming pattern induces precipitation increase (decrease) in the northwest (southeast) basin with equatorial easterly wind change, suggestive of Bjerknes feedback. Such IOD-like changes in the mean are common to CMIP5 model projections before the corrections, albeit with the large intermodel diversity in magnitudes of up to ~1.5°C of west–east SST gradient change, ~6 mm day^{−1} of west–east precipitation difference change, and ~0.02 N m^{−2} of equatorial easterly wind stress change (Figs. 1b,c).

4. Correction of the tropical IO warming pattern

Figure 2a compares the monthly IOD amplitudes between observations and the CMIP5 historical simulations. CGCMs well reproduce the phase locking of IOD with the maximum standard deviation of DMI during SON but feature a too large amplitude in the MME mean compared to observations. Almost all CGCMs have an excessively strong interannual IOD variance—the CMIP5 MME mean of IOD amplitudes in the historical simulation is nearly twice as large as observations (Fig. 2b). We select five models with the largest amplitudes of interannual IOD variability as strong IOD amplitude bias (sIODAB) models (M4, M7, M8, M11, and M21), and five models with the least amplitudes of interannual IOD variability as weak IOD amplitude bias (wIODAB) models (M12, M15, M16, M18, and M22). Both the sIODAB and wIODAB models have a common seasonality of IOD variance with the maximum anomalies during SON (Fig. 2a). Also, both the composited pIOD patterns from the sIODAB and wIODAB models resemble the observed, with the pattern correlation coefficients of 0.80 and 0.81, respectively (Fig. 3). However, in contrast to the observations and wIODAB models, the sIODAB models have too strong IOD anomalies, particularly in the eastern pole (Fig. 3b), indicative of the excessive Bjerknes feedback.

FIG. 4. Scatterplots of the simulated present-day IOD amplitudes vs projected changes for SON in the west-minus-east (a) SST (°C) and (b) precipitation (mm day^{−1}) differences between the dipole regions, and (c) the TAUx (N m^{−2}) in the CEIO among 24 CMIP5 models under RCP 8.5 scenario. The red line in each panel denotes the observed IOD amplitude. The intermodel correlation (r) is shown in each panel.

To isolate the effect of model errors, the relationships between the simulated interannual IOD amplitudes and projected IOD-like changes in west-minus-east SST gradient, the precipitation dipole, and equatorial easterly wind anomalies under increased GHG forcing among 24 CMIP5 CGCMs are examined. Models with a greater IOD amplitude bias tend to produce a stronger IOD-like pattern of mean changes in

FIG. 5. Comparisons of the uncorrected (blue) and corrected (red) mean changes in the west-minus-east difference in (a) SST and (b) precipitation, and (c) the TAUx in the CEIO during SON under RCP 8.5 scenario for 24 CMIP5 CGCMs and the MME mean. The error bars in the MME mean indicate the s.d. spread among CMIP5 CGCMs; the one on the blue bar is for the uncorrected mean and on the right for the corrected mean although the red bar is barely visible.

west-minus-east SST/precipitation gradient and surface zonal wind stress along the equator (Fig. 4; Cai et al. 2011; Li et al. 2015c). The 100 years of SST data during the historical period (1990–99) are divided into two subgroups (1900–49 and 1950–99). Both the results from the two subgroups are very similar to those based on the entire study period 1900–99 (figure not shown), supporting the robustness of the results. The strong intermodel correlations between the simulated IOD amplitude bias and projected tropical IO future climate changes in the mean are also present in the Special Report on Emissions Scenarios (SRES) A2 for CMIP3 [see Figs. 2a and 2b of Weller and Cai (2013)] and could offer an “observational constraint” of the IOD amplitude to calibrate future climate projections in the region (see section 2c). The

corrections are equivalent to scaling down the Bjerknes feedback to the observed strength.

a. Correction of the IOD-like warming pattern

Figure 5 represents the uncorrected and corrected changes in west-minus-east SST difference, the precipitation dipole, and zonal surface wind stress on the equator during SON under RCP 8.5 forcing for 24 CMIP5 CGCMs and the MME mean. The error bars in the MME mean indicate the standard deviation of the spread among CMIP5 models. Before the corrections, CGCMs robustly project SST warming stronger in the west basin than east basin with positive west-minus-east precipitation changes and equatorial easterly wind anomalies. After the corrections, the projected changes in west-minus-east SST/precipitation difference and

FIG. 6. (a) The MME mean errors in projected changes in SST (color contours, $\text{CI} = 0.1^\circ\text{C}$), precipitation (gray shade and white contours, $\text{CI} = 0.5 \text{ mm day}^{-1}$), and surface wind stress (vector scale is shown in the lower right corner, N m^{-2}) as evaluated from the simulated IOD amplitude biases from 24 CMIP5 models under RCP 8.5 scenario. (b) As in (a), but for corrected MME mean changes.

zonal surface wind stress on the equator would be nearly zero in the CMIP5 MME mean and highly variable among models. In other words, the projected IOD-like changes in the mean vanish when constrained by the observed IOD amplitude (red lines of Fig. 4).

Figure 6a shows the MME mean errors of projected changes in SST, precipitation, and surface wind stress vectors during SON as evaluated from the simulated IOD amplitude biases from 24 CMIP5 models under RCP 8.5 scenario over the tropical IO. In the MME mean, the SST warming is overestimated by $\sim 0.3^\circ\text{C}$ in the northwestern equatorial IO whereas it is underestimated by $\sim 0.4^\circ\text{C}$ off the Indonesian coast. Associated with this

SST error pattern is an east–west dipole of precipitation change with easterly wind anomalies on the equator, suggestive of physically consistent IOD-like offsetting error changes.

Figure 6b displays the corrected MME mean changes in SST, precipitation, and surface wind stress vectors during SON under RCP 8.5 scenario from 24 CMIP5 CGCMs. Indeed, the MME mean IOD-like warming pattern on the equator disappears after the corrections. We examine the relationship between the uncorrected and corrected MME mean patterns for SST warming. The corrected warming is independent of the uncorrected warming, with the pattern correlation of nearly zero

FIG. 7. (a) The mean changes in SST (color contours, °C), precipitation (gray shade and white contours, CI = 0.5 mm day⁻¹), and surface wind stress (N m⁻²) during SON projected by sIODAB models (M4, M7, M8, M11, and M21). (b) As in (a), but showing the projections from wIODAB models (M12, M15, M16, M18, and M22). (c), (d) As in (a), (b), but showing the corrected projections.

(0.01) over the equatorial IO (10°S–10°N, 40°–110°E). Actually, while sIODAB models project the strong IOD-like mean changes in SST, precipitation, and surface wind stress vectors under increased GHG forcing (Fig. 7a), wIODAB models show a consistent absence of the IOD-like warming responses among SST, precipitation, and surface wind stress vectors along the equator (Fig. 7b). After the corrections with the observed IOD amplitude, such an absence of the IOD-like warming pattern on the equator would be present in both sIODAB (Fig. 7c) and wIODAB (Fig. 7d) models.

Rather, the corrected MME mean projections during SON (Fig. 6b) are similar to the future projections from wIODAB models (Fig. 7b), displaying considerable spatial variation of SST changes off the equator, with a tendency for a stronger warming in the northwestern than northeastern IO and a weaker warming in the

southwestern than southeastern IO. The latter pattern is linked to weakened southeast trade winds in the southeastern IO (Fig. 6b), suggestive of wind–evaporation–SST (WES) feedback (Xie and Philander 1994). Figure 8 examines the relationship between the corrected changes in SST difference between the southwestern and southeastern IO and surface meridional wind stress in the southeastern IO during SON under RCP 8.5 scenario among 24 CMIP5 CGCMs. Indeed, models with weakened surface meridional wind stress in the southeastern IO tend to feature a weaker warming in the southwestern than southeastern IO after the corrections, with an intermodel correlation of 0.65.

b. Intermodel uncertainty

The intermodel standard deviations of future changes in SST, precipitation, and surface zonal wind stress over

the tropical IO under RCP 8.5 scenario from 24 CGCMs before and after the corrections are compared in Fig. 9. The Bjerknes feedback causes a large intermodel uncertainty as manifested in the simulated amplitude spread of interannual IOD variability in CMIP5 CGCMs (Fig. 2b; Cai and Cowan 2013). When the IOD amplitude is constrained with observations (red lines of Fig. 4), the corrected projection would largely remove the effect of intermodel diversity due to Bjerknes feedback. As a result, the corrected intermodel diversities of regional climate projections decline with largest decreases of 15%–25% in SST and 25%–35% in precipitation over the dipole regions, and 30%–40% in surface zonal wind stress over the central equatorial IO (CEIO), respectively. A tighter intermodel range in the corrected changes in west-minus-east SST/precipitation difference and zonal wind stress on the equator than uncorrected ones is also found in Fig. 5, suggestive of a reduced intermodel uncertainty in the corrected projections.

c. The robustness of corrected results

To avoid outlier models dominating the correction results, we also calculate the new uncorrected and corrected MME mean changes in the west-minus-east SST/precipitation difference and surface zonal wind stress on the equator during SON under RCP 8.5 scenario projected by other 23 CGCMs excluding one selected model (Fig. 10). Both the uncorrected and corrected MME mean changes in the west-minus-east SST/precipitation difference and surface zonal wind stress on the equator during SON excluding any one selected model are almost the same as those from all 24 CMIP5 models.

The corrected MME mean projections during SON under RCP 8.5 scenario from other 23 CMIP5 CGCMs excluding any one selected model (see Fig. S1 in the supplementary material), almost the same as that from all 24 CGCMs (Fig. 6b), largely remove the mean IOD-like warming pattern on the equator but exhibit considerable spatial variation of future SST changes off the equator with a stronger warming over the northwestern IO than northeastern IO and a weaker warming over the southwestern IO than southeastern IO, documenting the robustness of the corrected estimations in this study.

5. Correction of the change in extreme pIOD occurrences

We turn our attention to the projected change in the frequency of extreme pIOD events under global warming from CMIP5 CGCMs. Figures 11a and 11b show composited precipitation anomalies during SON over the tropical IO associated with moderate and extreme pIOD events during the present satellite era (1979–2010),

FIG. 8. Scatterplot of the corrected changes in SST ($^{\circ}\text{C}$) difference between the western (0° – 15°S , 40° – 110°E) and eastern (0° – 15°S , 90° – 110°E) parts of the southern IO vs surface meridional wind stress (TAUy; N m^{-2}) in the southeastern IO (SEIO; 0° – 15°S , 90° – 110°E) during SON under the RCP 8.5 scenario among 24 CMIP5 CGCMs. The intermodel correlation (r) is shown in the lower right corner.

respectively. Following the work of Cai et al. (2014), the 1994 and 1997 events are identified as two extreme pIOD events for 1979–2010; moderate pIOD events are defined when the detrended DMI (Saji et al. 1999) is greater than 0.75 s.d. except for the 1994 and 1997 extreme pIOD events, including the 1982, 1987, 2002, and 2006 events in the satellite era. Compared to moderate pIOD events, the drying in the eastern IO penetrates farther westward and equatorward and the precipitation increase over northeastern equatorial Africa (NEEA) is more intense in extreme pIOD events (Figs. 11a,b).

Without the corrections, CMIP5 CGCMs consistently project a large increase in the occurrence number of extreme pIOD events from the twentieth to twenty-first century under increased GHG forcing (Figs. 11c,d; see also Cai et al. 2014). This implies an increased risk of climate and weather disasters in the future over IO and rim countries.

Figure 12 examines the relationships between the projected changes in the number of extreme pIOD events and IOD-like mean changes between the twenty-first and twentieth centuries among 22 CMIP5 CGCMs. The projected increase in extreme pIOD occurrences is closely linked to the IOD-like pattern of mean changes. Models with a stronger IOD-like mean changes in the west-minus-east SST/precipitation difference and zonal wind stress on the equator tend to project a larger increase in the occurrences of extreme pIOD events under RCP 8.5

FIG. 9. Uncorrected intermodel standard deviations of projected changes in (a) SST ($^{\circ}\text{C}$), (b) precipitation (mm day^{-1}), and (c) TAUx (N m^{-2}) under RCP 8.5 scenario from 24 CMIP5 CGCMs. (d)–(f) As in (a)–(c), but for corrected intermodel standard deviations. The contours in (d)–(f) display the reduced percentages of corrected intermodel standard deviations than the uncorrected ones.

scenario with high intermodel corrections ($p < 0.001$). The IOD-like mean changes are in favor of more frequent reversals of wind and oceanic current along the equatorial IO, leading to more frequent occurrences of extreme pIOD events (Cai et al. 2014). Given that the IOD-like mean changes are largely artifacts of exaggerated Bjerknes feedback in CMIP5 CGCMs, strong doubt is casted on the projected increase in extreme pIOD occurrences under the RCP 8.5 scenario. In other words, The CGCM errors in mean changes contribute to the projected increased frequency of extreme pIOD events.

Similar to the correction of projected mean changes (Fig. 4), we identify a strong linear relationship between the IOD amplitudes and projected changes in number of

extreme pIOD events between the twenty-first and twentieth centuries among 24 CMIP4 CGCMs (Figs. 13a and 13b). Indeed, models with excessive IOD amplitudes tend to project a larger increase in occurrence number of extreme pIOD events under the RCP 8.5 scenario. By adjusting the IOD amplitude to the observed value, the corrected change in extreme pIOD occurrences in the twenty-first century is nearly zero in the MME mean and highly variable among models (Figs. 13c and 13d).

6. Summary and discussion

Under increased GHG forcing, CGCMs commonly project an IOD-like warming pattern with positive

FIG. 10. Comparisons of the uncorrected (blue) and corrected (red) MME mean changes projected by all 24 models vs the uncorrected and corrected MME mean changes projected by the other 23 models excluding one selected model in the west-minus-east difference in (a) SST and (b) precipitation, and (c) the TAUx in the CEIO during SON under the RCP 8.5 scenario. The error bars for the MME mean indicate the s.d. spread among CMIP5 models.

precipitation change over enhanced SST warming in the northwest IO and negative precipitation change over reduced SST warming in the southeast IO accompanied by strong surface easterly wind anomalies along the equatorial IO (Fig. 1; Vecchi and Soden 2007b; Xie et al. 2010; Zheng et al. 2010, 2013; Cai et al. 2014). Such IOD-like changes in the mean would facilitate to generate wind and oceanic current reversal, enhanced west-minus-east SST gradient, and the associated nonlinear zonal advection as seen during extreme pIOD events (Cai et al. 2014), resulting in a large increase in the frequency of extreme pIOD events in the future projected by CGCMs (Fig. 12; Cai et al. 2009b,c, 2014). This implies increased risks of climate and weather disasters in IO rim countries and regions affected by extreme pIOD events, including catastrophic flooding in East Africa and devastating droughts in Indonesia (e.g., Saji et al. 1999; Black et al. 2003; Behera et al. 2005; Cai et al.

2014). On the other hand, the increased frequency of extreme pIOD events might also enhance the future IOD-like warming pattern in the mean similar to the rectification effect of El Niño–Southern Oscillation (ENSO; Sun et al. 2014; Hua et al. 2015), which could in turn increase the extreme pIOD occurrences. These regional responses to increased GHG forcing have been widely regarded as robust and consistent among CGCMs (e.g., Christensen et al. 2014; Cai et al. 2014).

These projections, however, do not consider large model biases in both the mean state and interannual IOD variance. CGCMs suffer from common biases including too weak westerly winds and too steep an eastward shoaling of the mean thermocline in the equatorial IO (e.g., Lee et al. 2013; Cai and Cowan 2013; Li et al. 2015b,c). This leads to too strong a Bjerknes feedback as manifested in excessively large amplitudes of interannual IOD variability (Liu et al. 2014; Li et al.

FIG. 11. Composites precipitation anomalies (mm day^{-1}) during SON associated with (a) moderate (1982, 1987, 2002, and 2006) and (b) extreme (1994 and 1997) pIOD events. (c) Comparison of occurrence number of extreme pIOD events during the 20th vs 21st centuries among 22 CMIP5 models. The error bars for the MME mean indicate the s.d. spread among models. An extreme pIOD event in (c) is defined when EOF1 of precipitation anomalies > 1 s.d. and EOF2 > 0.5 s.d.. (d) As in (c), but for an extreme pIOD event that is defined when EOF1 and EOF 2 are > 1.5 and > 0.5 s.d. values, respectively.

2015c). By identifying the “present–future relationships” between the simulated IOD amplitude biases and projected IOD-like climate changes (Figs. 4 and 13a,b), our study casts strong doubt on the IOD-like mean state change and resultant increase in the frequency of extreme pIOD events. Further, we applied an observational constraint of the IOD amplitude to calibrate regional climate projections. The correction shows that the IOD-like pattern of mean changes and increased occurrences of extreme pIOD events, while common to CMIP5 model projections, are largely artifacts of model errors and unlikely to materialize in the future. After the corrections, both the projected mean state change and occurrence change of extreme pIOD events are not related with the simulated IOD

amplitude biases, removing the effect of excessive IOD amplitude and Bjerknes feedback biases. Rather, the corrected MME mean projection during SON displays a weaker warming in the southwestern IO than southeastern IO. The pattern is linked to weakened southeast trade wind change in the southeastern IO, suggestive of WES feedback. These results highlight the importance of evaluating and correcting model bias effects on regional climate projections.

Before the corrections, the MME mean projection shows the IOD-like warming pattern in the IO and El Niño-like warming pattern in the Pacific, accompanied by weakened mean Walker circulations in both basins (Fig. 14a; Vecchi and Soden 2007b; Xie et al. 2010; Tokinaga et al. 2012). However, we find that the

FIG. 12. Scatterplots of the projected changes in number of extreme pIOD events vs projected mean changes for SON in the west-minus-east difference in (a) SST and (c) precipitation, and (e) the TAUx in the CEIO under RCP 8.5 scenario among 22 CMIP5 CGCMs. An extreme pIOD event in (a),(c),(e) is defined when EOF1 of precipitation anomalies > 1 s.d. and EOF2 > 0.5 s.d.. (b),(d),(f) As in (a),(c),(e), but for an extreme pIOD event that is defined when EOF1 and EOF2 are >1.5 and >0.5 s.d., respectively. The intermodel correlation (r) is shown in each panel.

relationships between the projected IOD-like and El Niño-like warming responses in the mean among 24 CMIP5 models are not significant (Figs. 14b,c), although there is a moderate relationship ($r = 0.43$) between the simulated present ENSO amplitudes and IOD amplitudes among 24 CMIP5 CGCMs (figure not shown). This suggests that different mechanisms may dominate the projected regional warming responses in the tropical IO and Pacific. In other words, the effect of the weakened Pacific Walker circulation on the regional future climate projections in the tropical IO may not be important. Thus, it is unsurprising that the IOD-like warming pattern and equatorial

easterly wind trend in the tropical IO do not emerge in the corrected projection, albeit with an El Niño-like warming pattern and weakened Walker circulation in the tropical Pacific (Fig. 14d). The weakened Pacific Walker circulation does not necessarily lead to a significant influence on the tropical IO climate projections.

Our correction method is similar to the emergent constraints concept (e.g., Boé et al. 2009; Bracegirdle and Stephenson 2013). This approach requires a significant linear relationship between model's present-day state and projected future climate responses. For locations where the climate response is uncorrelated with the present-day state [e.g., $a(s) = 0$ in Eq. (3)], this

FIG. 13. (a) Relationship between the simulated IOD amplitudes and projected changes in number of extreme pIOD events under RCP 8.5 scenario among 22 CMIP5 CGCMs. The red line denotes the observed IOD amplitude. (c) Comparison of uncorrected and corrected changes in number of extreme pIOD events under RCP 8.5 scenario among 22 CMIP5 CGCMs. The error bars for the MME mean indicate the s.d. spread among models. An extreme pIOD event in (a) and (c) is defined when EOF1 of precipitation anomalies > 1 s.d. and EOF2 > 0.5 s.d.. (b),(d) As in (a),(c), but for an extreme pIOD event that is defined when EOF1 and EOF 2 are > 1.5 and > 0.5 s.d., respectively.

method effectively reverts to an ensemble mean approach. In our case, the linear present–future relationship among models is clear enough. So much changes in the mean characteristics (e.g., SST gradient, precipitation pattern, and equatorial zonal wind stress) and extreme IOD occurrences are linearly related to the simulated present IOD amplitudes among models (e.g., Figs. 4 and 13a,b), with the strong correlations at the 99.9% confidence level according to a two-tailed Student's t test. Moreover, it is generally important to evaluate the risk that the present–future relationship is an artifact of climate models. A previous study (Cai and Cowan 2013) has focused on the cause of the commonly overestimated IOD amplitudes in CMIP3 and CMIP5 climate models. The results show that the overestimated IOD amplitudes in CGCMs originate from too strong a positive Bjerknes

feedback, but rather than a weaker damping effect. Indeed, models with larger IOD amplitudes tend to have stronger positive Bjerknes feedbacks and negative damping feedbacks, and vice versa. On the other hand, it is well known that the projected IOD-like warming pattern is produced by Bjerknes feedback in the first place (Vecchi and Soden 2007b; Xie et al. 2010; Zheng et al. 2010; Christensen et al. 2014). As a result, models with a larger IOD amplitude tend to project stronger IOD-like warming responses among SST, precipitation, and surface wind stress vectors along the equatorial IO (Fig. 4; Li et al. 2015c), ascribed to an overly strong Bjerknes feedback (Cai et al. 2011; Weller and Cai 2013). In other words, the intermodel relationship between the IOD amplitude and IOD-like future projections is not only statistically significant but also

FIG. 14. (a) The MME mean changes in SST (color contours, $^{\circ}\text{C}$), precipitation (gray shade and white contours; $\text{CI} = 0.5 \text{ mm day}^{-1}$), and surface wind stress (N m^{-2}) over the tropical IO and Pacific during SON projected by 24 CMIP5 models under RCP 8.5 scenario. Intermodel scatterplots of (b) the changes between the west-minus-east SST difference in the IO (west box: 10°S – 10°N , 50° – 70°E ; east box: 0° – 10°S , 90° – 110°E) and east-minus-west SST difference in the Pacific (west box: 5°S – 5°N , 130° – 180°E ; east box: 5°S – 5°N , 130° – 80°W), and (c) the changes of TAUx between the central equatorial IO (2°S – 2°N , 70° – 90°E) and Pacific (2°S – 2°N , 150°E – 110°W). (d) As in (a), but for corrected MME mean changes.

consistent with our understanding of Bjerknes ocean–atmosphere feedback. Therefore, the projection corrections using the present–future relationship and an observational constraint of the IOD amplitude in this study are physically credible.

The excessive Bjerknes feedback bias of the IO originates from the equatorial easterly wind bias (Lee et al. 2013; Cai and Cowan 2013; Li et al. 2015b,c). In particular, this equatorial easterly wind error also forces a westward-propagating downwelling Rossby wave in the southern IO, inducing too deep a thermocline dome over the southwestern IO (SWIO) in CGCMs (Li et al. 2015b). The deepening SWIO thermocline reduces the simulated amplitude of interannual IO basin (Klein et al. 1999; Lau and Nath 2000; Schott et al. 2009) mode and limits the models' skill of regional climate prediction (Li et al. 2015b). Our recent study (Li et al. 2015c) has traced this easterly wind bias back to errors in the South Asian summer monsoon. Thus, improving the monsoon simulation is a priority and would lead to more reliable regional climate projections/predictions in the IO.

Acknowledgments. This work was supported by the National Basic Research Program of China (2012CB955603), the Natural Science Foundation of China (41406026), the Guangdong Natural Science Funds for Distinguished Young Scholar (2015A030306008), the Youth Innovation Promotion Association CAS, the Pearl River S&T Nova Program of Guangzhou (201506010094), the Strategic Priority Research Program of the CAS (XDA11010103 and XDA11010203), the U.S. National Science Foundation, and the CAS/SAFEA International Partnership Program for Creative Research Teams. We also wish to thank the climate modeling groups (Table 1) for producing and making available their model output, the WCRP's Working Group on Coupled Modeling (WGCM) for organizing the CMIP5 analysis activity, the Program for Climate Model Diagnostics and Intercomparison (PCMDI) for collecting and archiving the CMIP5 multimodel data, and the Office of Science, U.S. Department of Energy for supporting these datasets in partnership with the Global Organization for Earth System Science Portals.

REFERENCES

- Abe, M., H. Shiogama, T. Nozawa, and S. Emori, 2011: Estimation of future surface temperature changes constrained using the future–present correlated modes in inter-model variability of CMIP3 multimodel simulations. *J. Geophys. Res.*, **116**, D18104, doi:10.1029/2010JD015111.
- Abram, N. J., M. K. Gagan, M. T. McCulloch, J. Chappell, and W. S. Hantoro, 2003: Coral reef death during the 1997 Indian Ocean dipole linked to Indonesian wildfires. *Science*, **301**, 952–955, doi:10.1126/science.1083841.
- Adler, R. F., and Coauthors, 2003: The version 2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (1979–present). *J. Hydrometeor.*, **4**, 1147–1167, doi:10.1175/1525-7541(2003)004<1147:TVGPCP>2.0.CO;2.
- Ashok, K., Z. Guan, and T. Yamagata, 2003: Influence of the Indian Ocean dipole on the Australian winter rainfall. *Geophys. Res. Lett.*, **30**, 1821, doi:10.1029/2003GL017926.
- Behera, S. K., J.-J. Luo, S. Masson, P. Delecluse, S. Gualdi, A. Navarra, and T. Yamagata, 2005: Paramount impact of the Indian Ocean dipole on the East African short rains: A CGCM study. *J. Climate*, **18**, 4514–4530, doi:10.1175/JCLI3541.1.
- Bjerknes, J., 1969: Atmospheric teleconnections from the equatorial Pacific. *Mon. Wea. Rev.*, **97**, 163–172, doi:10.1175/1520-0493(1969)097<0163:ATFTEP>2.3.CO;2.
- Black, E., J. M. Slingo, and K. R. Sperber, 2003: An observational study of the relationship between excessively strong short rains in coastal East Africa and Indian Ocean SST. *Mon. Wea. Rev.*, **131**, 74–94, doi:10.1175/1520-0493(2003)131<0074:AOSOTR>2.0.CO;2.
- Boé, J., A. Hall, and X. Qu, 2009: September sea-ice cover in the Arctic ocean projected to vanish by 2100. *Nat. Geosci.*, **2**, 341–343, doi:10.1038/ngeo467.
- Bracegirdle, T. J., and D. B. Stephenson, 2012: Higher precision estimates of regional polar warming by ensemble regression of climate model projections. *Climate Dyn.*, **39**, 2805–2821, doi:10.1007/s00382-012-1330-3.
- , and —, 2013: On the robustness of emergent constraints used in multimodel climate change projections of Arctic warming. *J. Climate*, **26**, 669–678, doi:10.1175/JCLI-D-12-00537.1.
- Brown, S. J., J. M. Murphy, D. M. H. Sexton, and G. R. Harris, 2014: Climate projections of future extreme events accounting for modelling uncertainties and historical simulation biases. *Climate Dyn.*, **43**, 2681–2705, doi:10.1007/s00382-014-2080-1.
- Buser, C. M., H. R. Künsch, D. Lüthi, M. Wild, and C. Schär, 2009: Bayesian multi-model projection of climate: Bias assumptions and interannual variability. *Climate Dyn.*, **33**, 849–868, doi:10.1007/s00382-009-0588-6.
- Cai, W., and T. Cowan, 2013: Why is the amplitude of the Indian Ocean dipole overly large in CMIP3 and CMIP5 climate models? *Geophys. Res. Lett.*, **40**, 1200–1205, doi:10.1002/grl.50208.
- , —, and M. Raupach, 2009a: Positive Indian Ocean dipole events precondition southeast Australia bushfires. *Geophys. Res. Lett.*, **36**, L19710, doi:10.1029/2009GL039902.
- , —, and A. Sullivan, 2009b: Recent unprecedented skewness towards positive Indian Ocean dipole occurrences and its impact on Australian rainfall. *Geophys. Res. Lett.*, **36**, L11705, doi:10.1029/2009GL037604.
- , A. Sullivan, and T. Cowan, 2009c: Climate change contributes to more frequent consecutive positive Indian Ocean dipole events. *Geophys. Res. Lett.*, **36**, L23704, doi:10.1029/2009GL040163.
- , —, —, J. Ribbe, and G. Shi, 2011: Simulation of the Indian Ocean dipole: A relevant criterion for selecting models for climate projections. *Geophys. Res. Lett.*, **38**, L03704, doi:10.1029/2010GL046242.
- , A. Santoso, G. J. Wang, E. Weller, L. Wu, K. Ashok, Y. Masumoto, and T. Yamagata, 2014: Increased frequency of extreme Indian Ocean dipole events due to greenhouse warming. *Nature*, **510**, 254–258, doi:10.1038/nature13327.
- Chang, P., and Coauthors, 2006: Climate fluctuations of tropical coupled system—The role of ocean dynamics. *J. Climate*, **19**, 5122–5174, doi:10.1175/JCLI3903.1.

- Christensen, J. H., and Coauthors, 2014: Climate phenomena and their relevance for future regional climate change. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, 1217–1308.
- Collins, M., and Coauthors, 2010: The impact of global warming on the tropical Pacific Ocean and El Niño. *Nat. Geosci.*, **3**, 391–397, doi:[10.1038/ngeo868](https://doi.org/10.1038/ngeo868).
- , R. E. Chandler, P. M. Cox, J. M. Huthnance, J. Rougier, and D. B. Stephenson, 2012: Quantifying future climate change. *Nat. Climate Change*, **2**, 403–409, doi:[10.1038/nclimate1414](https://doi.org/10.1038/nclimate1414).
- Cox, P. M., D. Pearson, B. B. Booth, P. Friedlingstein, C. Huntingford, C. D. Jones, and C. M. Luke, 2013: Sensitivity of tropical carbon to climate change constrained by carbon dioxide variability. *Nature*, **494**, 341–344, doi:[10.1038/nature11882](https://doi.org/10.1038/nature11882).
- Davey, M. K., and Coauthors, 2002: STOIC: A study of coupled model climatology and variability in tropical ocean regions. *Climate Dyn.*, **18**, 403–420, doi:[10.1007/s00382-001-0188-6](https://doi.org/10.1007/s00382-001-0188-6).
- Du, Y., L. Yang, and S.-P. Xie, 2011: Tropical Indian Ocean influence on northwest Pacific tropical cyclones in summer following strong El Niño. *J. Climate*, **24**, 315–322, doi:[10.1175/2010JCLI3890.1](https://doi.org/10.1175/2010JCLI3890.1).
- , W. Cai, and Y. Wu, 2013: A new type of the Indian Ocean dipole since the mid-1970s. *J. Climate*, **26**, 959–972, doi:[10.1175/JCLI-D-12-00047.1](https://doi.org/10.1175/JCLI-D-12-00047.1).
- Emmanuel, S., 2000: Impact to lung health of haze from forest fires: The Singapore experience. *Respirology*, **5**, 175–182, doi:[10.1046/j.1440-1843.2000.00247.x](https://doi.org/10.1046/j.1440-1843.2000.00247.x).
- Frankenberg, E., D. McKee, and D. Thomas, 2005: Health consequences of forest fires in Indonesia. *Demography*, **42**, 109–129, doi:[10.1353/dem.2005.0004](https://doi.org/10.1353/dem.2005.0004).
- Guan, Z., and T. Yamagata, 2003: The unusual summer of 1994 in East Asia: IOD teleconnections. *Geophys. Res. Lett.*, **30**, 1544, doi:[10.1029/2002GL016831](https://doi.org/10.1029/2002GL016831).
- Hashizume, M., L. F. Chaves, and N. Minakawa, 2012: Indian Ocean dipole drives malaria resurgence in East African highlands. *Sci. Rep.*, **2**, 269, doi:[10.1038/srep00269](https://doi.org/10.1038/srep00269).
- Hua, L., Y. Yu, and D.-Z. Sun, 2015: A further study of ENSO rectification: Results from an OGCM with a seasonal cycle. *J. Climate*, **28**, 1362–1382, doi:[10.1175/JCLI-D-14-00404.1](https://doi.org/10.1175/JCLI-D-14-00404.1).
- Huang, P., and J. Ying, 2015: A multimodel ensemble pattern regression method to correct the tropical Pacific SST change patterns under global warming. *J. Climate*, **28**, 4706–4723, doi:[10.1175/JCLI-D-14-00833.1](https://doi.org/10.1175/JCLI-D-14-00833.1).
- , S.-P. Xie, K. Hu, G. Huang, and R. Huang, 2013: Patterns of the seasonal response of tropical rainfall to global warming. *Nat. Geosci.*, **6**, 357–361, doi:[10.1038/ngeo1792](https://doi.org/10.1038/ngeo1792).
- Hwang, Y.-T., and D. M. M. Frierson, 2013: Link between the double-Intertropical Convergence Zone problem and cloud biases over the Southern Ocean. *Proc. Natl. Acad. Sci. USA*, **110**, 4935–4940, doi:[10.1073/pnas.1213302110](https://doi.org/10.1073/pnas.1213302110).
- Klein, S. A., B. J. Soden, and N.-C. Lau, 1999: Remote sea surface temperature variations during ENSO: Evidence for a tropical atmospheric bridge. *J. Climate*, **12**, 917–932, doi:[10.1175/1520-0442\(1999\)012<0917:RSSTVD>2.0.CO;2](https://doi.org/10.1175/1520-0442(1999)012<0917:RSSTVD>2.0.CO;2).
- Lau, N.-C., and M. J. Nath, 2000: Impact of ENSO on the variability of the Asian-Australian monsoons as simulated in GCM experiments. *J. Climate*, **13**, 4287–4309, doi:[10.1175/1520-0442\(2000\)013<4287:IOEOTV>2.0.CO;2](https://doi.org/10.1175/1520-0442(2000)013<4287:IOEOTV>2.0.CO;2).
- Lee, T., D. E. Waliser, J.-L. F. Li, F. W. Landerer, and M. M. Gierach, 2013: Evaluation of CMIP3 and CMIP5 wind stress climatology using satellite measurements and atmospheric reanalysis products. *J. Climate*, **26**, 5810–5826, doi:[10.1175/JCLI-D-12-00591.1](https://doi.org/10.1175/JCLI-D-12-00591.1).
- Li, G., and S.-P. Xie, 2012: Origins of tropical-wide SST biases in CMIP multi-model ensembles. *Geophys. Res. Lett.*, **39**, L22703, doi:[10.1029/2012GL053777](https://doi.org/10.1029/2012GL053777).
- , and —, 2014: Tropical biases in CMIP5 multimodel ensemble: The excessive equatorial Pacific cold tongue and double ITCZ problems. *J. Climate*, **27**, 1765–1780, doi:[10.1175/JCLI-D-13-00337.1](https://doi.org/10.1175/JCLI-D-13-00337.1).
- , Y. Du, H. Xu, and B. Ren, 2015a: An intermodel approach to identify the source of excessive equatorial Pacific cold tongue in CMIP5 models and uncertainty in observational datasets. *J. Climate*, **28**, 7630–7640, doi:[10.1175/JCLI-D-15-0168.1](https://doi.org/10.1175/JCLI-D-15-0168.1).
- , S.-P. Xie, and Y. Du, 2015b: Climate model errors over the South Indian Ocean thermocline dome and their effect on the basin mode of interannual variability. *J. Climate*, **28**, 3093–3098, doi:[10.1175/JCLI-D-14-00810.1](https://doi.org/10.1175/JCLI-D-14-00810.1).
- , —, and —, 2015c: Monsoon-induced biases of climate models over the tropical Indian Ocean. *J. Climate*, **28**, 3058–3072, doi:[10.1175/JCLI-D-14-00740.1](https://doi.org/10.1175/JCLI-D-14-00740.1).
- , —, —, and Y. Luo, 2016: Effects of excessive equatorial cold tongue bias on the projections of tropical Pacific climate change. Part I: The warming pattern in CMIP5 multi-model ensemble. *Climate Dyn.*, doi:[10.1007/s00382-016-3043-5](https://doi.org/10.1007/s00382-016-3043-5), in press.
- Lin, J.-L., 2007: The double-ITCZ problem in IPCC AR4 coupled GCMs: Ocean-atmosphere feedback analysis. *J. Climate*, **20**, 4497–4525, doi:[10.1175/JCLI4272.1](https://doi.org/10.1175/JCLI4272.1).
- Liu, L., S.-P. Xie, X.-T. Zheng, T. Li, Y. Du, G. Huang, and W.-D. Yu, 2014: Indian Ocean variability in the CMIP5 multi-model ensemble: The zonal dipole mode. *Climate Dyn.*, **43**, 1715–1730, doi:[10.1007/s00382-013-2000-9](https://doi.org/10.1007/s00382-013-2000-9).
- Ma, J., and S.-P. Xie, 2013: Regional patterns of sea surface temperature change: A source of uncertainty in future projections of precipitation and atmospheric circulation. *J. Climate*, **26**, 2482–2501, doi:[10.1175/JCLI-D-12-00283.1](https://doi.org/10.1175/JCLI-D-12-00283.1).
- Mechoso, C. R., and Coauthors, 1995: The seasonal cycle over the tropical Pacific in coupled ocean-atmosphere general circulation models. *Mon. Wea. Rev.*, **123**, 2825–2838, doi:[10.1175/1520-0493\(1995\)123<2825:TSCOTT>2.0.CO;2](https://doi.org/10.1175/1520-0493(1995)123<2825:TSCOTT>2.0.CO;2).
- Murtugudde, R., J. P. McCreary, and A. J. Busalacchi, 2000: Oceanic processes associated with anomalous events in the Indian Ocean with relevance to 1997–1998. *J. Geophys. Res.*, **105**, 3295–3306, doi:[10.1029/1999JC900294](https://doi.org/10.1029/1999JC900294).
- Räsänen, J., L. Ruokolainen, and J. Ylhäisi, 2010: Weighting of model results for improving best estimates of climate change. *Climate Dyn.*, **35**, 407–422, doi:[10.1007/s00382-009-0659-8](https://doi.org/10.1007/s00382-009-0659-8).
- Rayner, N. A., and Coauthors, 2003: Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *J. Geophys. Res.*, **108**, 4407, doi:[10.1029/2002JD002670](https://doi.org/10.1029/2002JD002670).
- Rougier, J., 2007: Probabilistic inference for future climate using an ensemble of climate model evaluations. *Climatic Change*, **81**, 247–264, doi:[10.1007/s10584-006-9156-9](https://doi.org/10.1007/s10584-006-9156-9).
- Saji, N. H., B. N. Goswami, P. N. Vinayachandran, and T. Yamagata, 1999: A dipole mode in the tropical Indian Ocean. *Nature*, **401**, 360–363.
- Schott, F. A., S.-P. Xie, and J. P. McCreary, 2009: Indian Ocean circulation and climate variability. *Rev. Geophys.*, **47**, RG1002, doi:[10.1029/2007RG000245](https://doi.org/10.1029/2007RG000245).
- Shiogama, H., S. Emori, N. Hanasaki, M. Abe, Y. Masutomi, K. Takahashi, and T. Nozawa, 2011: Observational constraints indicate risk of drying in the Amazon basin. *Nat. Commun.*, **2**, 253, doi:[10.1038/ncomms1252](https://doi.org/10.1038/ncomms1252).
- Sugi, M., A. Noda, and N. Sato, 2002: Influence of the global warming on tropical cyclone climatology: An experiment with

- the JMA global model. *J. Meteor. Soc. Japan*, **80**, 249–272, doi:[10.2151/jmsj.80.249](https://doi.org/10.2151/jmsj.80.249).
- Sun, D.-Z., T. Zhang, Y. Sun, and Y. Yu, 2014: Rectification of El Niño–Southern Oscillation into climate anomalies of decadal and longer time scales: Results from forced ocean GCM experiments. *J. Climate*, **27**, 2545–2561, doi:[10.1175/JCLI-D-13-00390.1](https://doi.org/10.1175/JCLI-D-13-00390.1).
- Sunyer, M. A., H. Madsen, D. Rosbjerg, and K. Arnbjerg-Nielsen, 2014: A Bayesian approach for uncertainty quantification of extreme precipitation projections including climate model interdependency and nonstationary bias. *J. Climate*, **27**, 7113–7132, doi:[10.1175/JCLI-D-13-00589.1](https://doi.org/10.1175/JCLI-D-13-00589.1).
- Taylor, K. E., J. S. Ronald, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.*, **93**, 485–498, doi:[10.1175/BAMS-D-11-00094.1](https://doi.org/10.1175/BAMS-D-11-00094.1).
- Tebaldi, C., R. L. Smith, D. Nychka, and L. O. Mearns, 2005: Quantifying uncertainty in projections of regional climate change: A Bayesian approach to the analysis of multimodel ensembles. *J. Climate*, **18**, 1524–1540, doi:[10.1175/JCLI3363.1](https://doi.org/10.1175/JCLI3363.1).
- Tokinaga, H., S.-P. Xie, A. Timmermann, S. McGregor, T. Ogata, H. Kubota, and Y. M. Okumura, 2012: Regional patterns of tropical Indo-Pacific climate change: Evidence of the Walker circulation weakening. *J. Climate*, **25**, 1689–1710, doi:[10.1175/JCLI-D-11-00263.1](https://doi.org/10.1175/JCLI-D-11-00263.1).
- Ummenhofer, C. C., and Coauthors, 2011: Indian and Pacific Ocean influences on southeast Australian drought and soil moisture. *J. Climate*, **24**, 1313–1336, doi:[10.1175/2010JCLI3475.1](https://doi.org/10.1175/2010JCLI3475.1).
- Vecchi, G. A., and B. J. Soden, 2007a: Effect of remote sea surface temperature change on tropical cyclone potential intensity. *Nature*, **450**, 1066–1070, doi:[10.1038/nature06423](https://doi.org/10.1038/nature06423).
- , and —, 2007b: Global warming and the weakening of the tropical circulation. *J. Climate*, **20**, 4316–4340, doi:[10.1175/JCLI4258.1](https://doi.org/10.1175/JCLI4258.1).
- Wang, C. Z., L. P. Zhang, S. K. Lee, L. X. Wu, and C. R. Mechoso, 2014: A global perspective on CMIP5 climate model biases. *Nat. Climate Change*, **4**, 201–205, doi:[10.1038/nclimate2118](https://doi.org/10.1038/nclimate2118).
- Webster, P. J., A. M. Moore, J. P. Loschnigg, and R. R. Leben, 1999: Coupled ocean–atmosphere dynamics in the Indian Ocean during 1997–98. *Nature*, **401**, 356–360, doi:[10.1038/43848](https://doi.org/10.1038/43848).
- Weller, E., and W. Cai, 2013: Realism of the Indian Ocean dipole in CMIP5 models: The implications for climate projections. *J. Climate*, **26**, 6649–6659, doi:[10.1175/JCLI-D-12-00807.1](https://doi.org/10.1175/JCLI-D-12-00807.1).
- Whetton, P., I. Macadam, J. Bathols, and J. O’Grady, 2007: Assessment of the use of current climate patterns to evaluate regional enhanced greenhouse response patterns of climate models. *Geophys. Res. Lett.*, **34**, L14701, doi:[10.1029/2007GL030025](https://doi.org/10.1029/2007GL030025).
- Xie, S.-P., and S. G. H. Philander, 1994: A coupled ocean–atmosphere model of relevance to the ITCZ in the eastern Pacific. *Tellus*, **46A**, 340–350, doi:[10.1034/j.1600-0870.1994.t01-1-00001.x](https://doi.org/10.1034/j.1600-0870.1994.t01-1-00001.x).
- , H. Annamalai, F. A. Schott, and J. P. McCreary, 2002: Structure and mechanisms of South Indian Ocean climate variability. *J. Climate*, **15**, 864–878, doi:[10.1175/1520-0442\(2002\)015<0864:SAMOSI>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<0864:SAMOSI>2.0.CO;2).
- , C. Deser, G. A. Vecchi, J. Ma, H. Teng, and A. T. Wittenberg, 2010: Global warming pattern formation: Sea surface temperature and rainfall. *J. Climate*, **23**, 966–986, doi:[10.1175/2009JCLI3329.1](https://doi.org/10.1175/2009JCLI3329.1).
- , and Coauthors, 2015: Towards predictive understanding of regional climate change. *Nat. Climate Change*, **5**, 921–930, doi:[10.1038/nclimate2689](https://doi.org/10.1038/nclimate2689).
- Yeh, S.-W., J.-S. Kug, B. Dewitte, M.-H. Kwon, B. P. Kirtman, and F.-F. Jin, 2009: El Niño in a changing climate. *Nature*, **461**, 511–514, doi:[10.1038/nature08316](https://doi.org/10.1038/nature08316).
- , Y.-G. Ham, and J.-Y. Lee, 2012: Changes in the tropical Pacific SST trend from CMIP3 to CMIP5 and its implication of ENSO. *J. Climate*, **25**, 7764–7771, doi:[10.1175/JCLI-D-12-00304.1](https://doi.org/10.1175/JCLI-D-12-00304.1).
- Yokoi, S., and Y. N. Takayabu, 2009: Multi-model projection of global warming impact on tropical cyclone genesis frequency over the western North Pacific. *J. Meteor. Soc. Japan*, **87**, 525–538, doi:[10.2151/jmsj.87.525](https://doi.org/10.2151/jmsj.87.525).
- Zheng, X.-T., S.-P. Xie, G. A. Vecchi, Q. Liu, and J. Hafner, 2010: Indian Ocean dipole response to global warming: Analysis of ocean–atmospheric feedbacks in a coupled model. *J. Climate*, **23**, 1240–1253, doi:[10.1175/2009JCLI3326.1](https://doi.org/10.1175/2009JCLI3326.1).
- , —, Y. Du, L. Liu, G. Huang, and Q. Liu, 2013: Indian Ocean Dipole response to global warming in the CMIP5 multi-model ensemble. *J. Climate*, **26**, 6067–6080, doi:[10.1175/JCLI-D-12-00638.1](https://doi.org/10.1175/JCLI-D-12-00638.1).
- Zubair, L., S. A. Rao, and T. Yamagata, 2003: Modulation of Sri Lankan *Maha* rainfall by the Indian Ocean dipole. *Geophys. Res. Lett.*, **30**, 1063, doi:[10.1029/2002GL015639](https://doi.org/10.1029/2002GL015639).