Can CMIP5 Earth System Models Reproduce the Interannual Variability of Air–Sea CO₂ Fluxes over the Tropical Pacific Ocean?

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ABSTRACT

Interannual variability of air–sea CO₂ exchange is an important metric that represents the interaction between the carbon cycle and climate change. Although previous studies report a large bias in the CO₂ flux interannual variability in many Earth system models (ESMs), the reason for this bias remains unclear. In this study, the performance of ESMs in phase 5 of the Coupled Model Intercomparison Project (CMIP5) is assessed in the context of the variability of air–sea CO₂ flux over the tropical Pacific related to El Niño–Southern Oscillation (ENSO) using an emission-driven historical experiment. Using empirical orthogonal function (EOF) analysis, the first principal component of air–sea CO₂ flux shows a significant relationship with the Niño-3.4 index in both the observation-based product and models. In the observation-based product, the spatial pattern of EOF1 shows negative anomalies in the central Pacific, which is, however, in contrast to those in several ESMs, and even opposite in sign to those in HadGEM2-ES and MPI-ESM-LR. The unrealistic response of the air–sea CO₂ flux to ENSO mainly originates from the biases in the anomalous surface-water CO₂ partial pressure ($p\text{CO}_2^{\text{sea}}$). A linear Taylor expansion by decomposing the anomalous $p\text{CO}_2^{\text{sea}}$ into contributions from salinity, sea surface temperature, dissolved inorganic carbon (DIC), and alkalinity is applied to diagnose the $p\text{CO}_2^{\text{sea}}$ biases. The results show that decreased $p\text{CO}_2^{\text{sea}}$ during El Niño results from reduced upwelling of high-concentration DIC from deeper layers that overwhelms the increasing $p\text{CO}_2^{\text{sea}}$ caused by warmer sea surface temperature. Overly weak reduction of vertical motion during El Niño and weak vertical gradients of climatological DIC concentration are the main reasons for biases in the negative surface DIC anomalies and eventually the $p\text{CO}_2^{\text{sea}}$ anomalies. This study highlights the importance of both physical ocean responses to El Niño and climatological distributions of carbon-related tracers in the simulation of the interannual variability of air–sea CO₂ fluxes.

1. Introduction

The concentration of atmospheric CO₂ increased by about 45% from 277 ppm in 1750 (Joos and Spahni 2008) to 402.8 ± 0.1 ppm in 2016 (Dlugokencky and Tans 2018). Meanwhile, the ocean has absorbed 160 ± 20 Pg C ($1 \text{ Pg} = 10^{15} \text{ g}$), which is about one-third of the anthropogenic CO₂ emissions (Le Quéré et al. 2016), from the atmosphere via air–sea CO₂ exchanges. Based on about

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3 million measurements of surface-water CO_2 partial pressure ($p\text{CO}_2^{\text{sea}}$) obtained from 1970 to 2007, [Takahashi et al. \(2009\)](#) estimated that the total ocean uptake CO_2 flux was $2.0 \pm 1.0 \text{ Pg C yr}^{-1}$ in the reference year 2000. However, the tropical Pacific Ocean (14°S – 14°N) releases $0.48 \text{ Pg C yr}^{-1}$ to the atmosphere, which accounts for 70% of the carbon released by the global tropical ocean ([Le Quéré et al. 2000](#)). The interannual variability of CO_2 outgassing over the tropical Pacific Ocean is affected by El Niño–Southern Oscillation (ENSO), which exhibits large variability ([Feely et al. 1999, 2002, 2006](#); [Ishii et al. 2004](#); [Wanninkhof et al. 2013](#)). The peak-to-peak amplitude of CO_2 flux during the cold and warm phases of ENSO is $0.40 \pm 0.09 \text{ Pg C yr}^{-1}$ according to the ocean general circulation models embedded with biogeochemistry models (OBGCMs), and $0.27 \pm 0.07 \text{ Pg C yr}^{-1}$ according to the diagnostic models ([Ishii et al. 2014](#)).

The mechanism of interannual variability of the air–sea CO_2 flux over the tropical Pacific Ocean associated with ENSO has been well established through previous research on both observations and models. In the El Niño phase, the warmer sea surface temperature (SST) helps increase the air–sea CO_2 flux, whereas the reduction in dissolved inorganic carbon (DIC) due to weakened upwelling acts to suppress the flux ([Feely et al. 2006](#); [Wang et al. 2006, 2015](#); [Long et al. 2013](#)). Among these two competing processes, the reduction in DIC is a dominant factor in controlling the interannual variability of air–sea CO_2 flux related to ENSO ([McKinley et al. 2004](#); [Li and Xu 2013](#); [Jin et al. 2017](#)).

Earth system models (ESMs) are the latest generation of the state-of-the-art climate models, in which marine and terrestrial biogeochemical processes are added into coupled atmosphere–ocean general circulation models (AOGCMs). Compared with offline OBGCMs, which are driven by prescribed atmospheric data, ESMs characterize the interaction between the carbon cycle and the physical climate system. Owing to these features, the ESMs can simulate the physical, chemical, and biological processes on Earth, and hence ESMs are powerful tools for understanding and projecting changes in the global carbon cycle ([Wang et al. 2016](#); [Li et al. 2016](#); [Li and Ilyina 2018](#); [Kwiatkowski and Orr 2018](#)). Because of the nonlinear carbon cycle and climate feedbacks in ESMs, the complex coupling between biogeochemical processes and the physical processes may also cause some unknown biases in the air–sea CO_2 flux in ESMs ([Boer and Arora 2009](#); [Zhou et al. 2014](#); [Schwinger et al. 2014](#)). Therefore, before using ESMs to perform climate projections, including the study of carbon cycle and climate feedbacks, their accuracy in reproducing the air–sea CO_2 fluxes for the present climate should be assessed.

Evaluation of the ocean carbon cycle in 18 ESMs from phase 5 of the Coupled Model Intercomparison Project

(CMIP5) showed that models agree on the sign and magnitude of the CO_2 flux, but they show weaker year-to-year variability than the observations ([Anav et al. 2013](#)). [Dong et al. \(2016\)](#) examined the interannual variability of global air–sea CO_2 flux in 18 CMIP5 models and found that 12 models fail to represent the observed ENSO-related pattern over the tropical Pacific owing to the stronger interannual variability in the Southern Ocean and inconsistent period of air–sea CO_2 flux with the period range of ENSO events. However, it is unclear whether the mechanism of ENSO-related air–sea CO_2 flux interannual variations can be reproduced by CMIP5 ESMs. As a key component of the global carbon cycle, the air–sea CO_2 flux over the tropical Pacific Ocean, especially the prominent relation with ENSO, is necessary for system evaluation. In this study, the physical and biogeochemical processes of the interannual variations in the air–sea CO_2 flux over the tropical Pacific associated to ENSO were evaluated quantitatively by decomposing the anomalous $p\text{CO}_2^{\text{sea}}$ into contributions from salinity, SST, DIC, and alkalinity (Alk). The objectives of this study are as follows: 1) to evaluate the performances of CMIP5 ESMs in the simulation of the air–sea CO_2 flux over the tropical Pacific Ocean; 2) to address whether the coupled ESMs can reproduce the interannual variability of the air–sea CO_2 flux related to ENSO; and 3) to understand why some ESMs fail to reproduce the relation between CO_2 flux and ENSO.

The remainder of the paper is organized as following. [Section 2](#) introduces the model, data, and analysis methods. Major results are presented in [section 3](#). [Section 4](#) summarizes our major findings.

2. Model, data, and analysis method

a. CMIP5 models

Fourteen ESMs from the CMIP5 were used based on the availability of monthly outputs of the emission-driven historical experiment (esmhistorical). Different from traditional concentration-driven historical experiment, forced by the historical atmospheric CO_2 concentration, esmhistorical is forced by spatially distributed CO_2 emissions reconstructed using estimated fossil fuel consumption from 1850 to 2005, which is more like the processes of global carbon cycle in nature. The atmospheric CO_2 concentration freely varies with human emission and is modulated by carbon exchange between air, ocean, and the terrestrial biosphere ([Taylor et al. 2012](#)). [Table 1](#) summarizes the model names, ocean carbon cycle components, horizontal and vertical resolutions of ocean models, and corresponding references. Only one ensemble member for each ESM is

TABLE 1. Names, ocean resolutions, and ocean carbon cycle components of the 14 CMIP5 ESMs used in this study. Bold type indicates models used to analyze sources of model bias (see section 2a). OCMIP2 = Ocean Carbon-Cycle Model Intercomparison Project version 2; iBGC = idealized ocean biochemistry; BEC = Biogeochemical Elemental Cycling model; TOPAZ2 = Tracers of Ocean Phytoplankton with Allometric Zooplankton code version 2.0; Diat-HadOCC = diatom version of the Hadley Centre Ocean Carbon Cycle model; PISCES = Pelagic Interactions Scheme for Carbon and Ecosystem Studies; NPZD-type = nutrients (N), phytoplankton (P), zooplankton (Z), and detritus (D); HAMOCC = Hamburg ocean carbon cycle model; other acronyms are available online at <http://www.ametsoc.org/PubsAcronymList>.

Models	Source	Ocean carbon cycle component	Ocean resolution (lon $\times$ lat, levels)	Reference
BCC-CSM1.1	Beijing Climate Center, China	OCMIP2	$1^\circ \times (1/3^\circ\text{--}1^\circ)$, L40	Wu et al. 2013
BCC-CSM1.1-m	Meteorological Administration, China			
BCC-CSM1.1-m	Beijing Climate Center, China	OCMIP2	$1^\circ \times (1/3^\circ\text{--}1^\circ)$, L40	Wu et al. 2014
BNU-ESM	Meteorological Administration, China			
BNU-ESM	Beijing Normal University, China	iBGC	$\sim 1^\circ \times \sim 0.6^\circ$, L50	Ji et al. 2014
CanESM2	Canadian Centre for Climate Modeling and Analysis, Canada	CMOC	$1.41^\circ \times 0.94^\circ$, L40	Arora et al. 2011
CESM1(BGC)	National Centre for Atmospheric Research, United States	BEC	$\sim 1.12^\circ \times (0.27^\circ\text{--}0.53^\circ)$, L60	Long et al. 2013
FIO-ESM	First Institution of Oceanography, State Oceanic Administration, China	OCMIP2	$\sim 1^\circ \times (0.3^\circ\text{--}0.5^\circ)$, L40	Qiao et al. 2013
GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory, United States	TOPAZ2	$1^\circ \times \sim 0.6^\circ$, L63	Dunne et al. 2012
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, United States	TOPAZ2	$1^\circ \times \sim 0.6^\circ$, L50	Dunne et al. 2012
HadGEM2-ES	Met Office Hadley Centre, UK	Diat-HadOCC	$1^\circ \times (0.3^\circ\text{--}1^\circ)$, L40	Collins et al. 2011
IPSL-CM5A-LR	Institut Pierre Simon Laplace, France	PISCES	$2^\circ \times (0.5^\circ\text{--}2^\circ)$, L31	Dufresne et al. 2013
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Japan; Atmosphere and Ocean Research Institute, Japan; National Institute for Environmental Studies, Japan	NPZD-type	$1.406\ 25^\circ \times \sim 0.9375^\circ$, L44	Watanabe et al. 2011
MPI-ESM-LR	Max Planck Institute for Meteorology, Germany	HAMOCC	$1.5^\circ \times \sim 1.5^\circ$, L40	Hyina et al. 2013
MRI-ESM	Meteorological Research Institute, Japan	NPZD-type	$1^\circ \times 0.5^\circ$, L40	Adachi et al. 2013
NorESM-ME	Norwegian Climate Centre, Norway	HAMOCC	$\sim 1^\circ \times \sim 0.5^\circ$, L53	Tjiputra et al. 2013

used. Seven (bold in Table 1) out of these 14 models are used to analyze sources of model bias depending on whether the data are available.

b. Data

Observational and reanalysis datasets include 1) a well-structured climatological mean distribution of the air–sea CO₂ fluxes with a resolution of $4^\circ \times 5^\circ$ (Takahashi et al. 2009); 2) monthly mean air–sea CO₂ fluxes and $p\text{CO}_2^{\text{sea}}$ derived from neural network technique based on observation for the period from 1982 to 2011 and with a resolution of $1^\circ \times 1^\circ$ (Landschützer et al. 2015); 3) surface wind fields from the European Centre for Medium-Range Weather Forecasts (ERA-Interim) (Dee et al. 2011); and 4) the SST dataset from National Oceanic and Atmospheric Administration Extended Reconstructed SST version 3b (ERSSTv3b) (Smith et al. 2008).

Although the observation-based products are used as “observational metrics” to gauge the performance of the models, these types of products rely heavily on data

interpolation; for example, the product of Takahashi et al. (2009) employed an advection-based algorithm, whereas Landschützer et al. (2015) used a neural network interpolation.

For evaluating the climatology, since the observation-based products employ the reference year of 2000, the modeled results are averaged from 1990 to 2005 to match with the observation-based product. In the study of interannual variability, we focus on the boreal winter [December–February (DJF)] from 1982 to 2005, which is available in both the observation-based and model results. To focus on interannual variability, we filtered out variations longer than eight years from the original datasets using a Lanczos filter.

The upward ocean mass transport (kg s^{-1}), a standard output of CMIP5 models, is used to analyze physical processes related to model biases. Its unit is different from that of the upward velocity (m s^{-1}) in CMIP3. To make the upward ocean mass transport with different spatial resolutions in CMIP5 ESMs comparable, we

transformed the upward ocean mass transport (kg s^{-1}) to upward velocity (m s^{-1}) by dividing the ocean gridcell area (m^2) and seawater density (1025 kg m^{-3}) for each model.

c. Analysis method

The air–sea CO_2 fluxes (fgCO_2) are calculated as follows:

$$\text{fgCO}_2 = k\alpha\Delta p\text{CO}_2 = k\alpha(p\text{CO}_2^{\text{sea}} - p\text{CO}_2^{\text{air}}), \quad (1)$$

where k is gas transfer coefficient (cm h^{-1}). As in Landschützer et al. (2014, 2015), we now use ERA-Interim 10-m wind speeds U_{10} and the quadratic gas transfer formulation of Wanninkhof (1992) rescaled to a global mean gas transfer velocity of 16 cm h^{-1} [to match a recent estimate by Wanninkhof et al. (2013)]. The method used to calculate the coefficient for the gas transfer velocity is described by Wanninkhof et al. (2013) as $k/\langle U^2 \rangle$. Therefore, the optimal coefficient for the gas transfer velocity parameterization is $0.36 \text{ cm h}^{-1} (\text{m s}^{-1})^{-2}$ and

$$k = 0.36 \times U_{10}^2 \times \sqrt{660/\text{Sc}_t}. \quad (2)$$

The Schmidt (Sc_t) number is calculated as follows:

$$\text{Sc}_t = 2073.1 - 125.62T + 3.6276T^2 - 0.043219T^3, \quad (3)$$

where α is the CO_2 solubility ($\text{mol m}^{-3} \text{ atm}^{-1}$; $1 \text{ atm} = 1013.25 \text{ hPa}$) influenced by SST T ($^\circ\text{C}$) and salinity S (psu) (Weiss 1974):

$$\ln\alpha = A_1 + A_2(100/T) + A_3 \ln(T/100) + (S/1000) \times [B_1 + B_2(T/100) + B_3(T/100)^2], \quad (4)$$

where A_1 , A_2 , A_3 , B_1 , B_2 , and B_3 are constants.

The term $\Delta p\text{CO}_2$ is the difference in CO_2 partial pressure between the surface seawater ($p\text{CO}_2^{\text{sea}}$) and air ($p\text{CO}_2^{\text{air}}$). The interannual variability of $\Delta p\text{CO}_2$ is controlled primarily by $p\text{CO}_2^{\text{sea}}$ because of the relatively small interannual variations of $p\text{CO}_2^{\text{air}}$.

To examine the mechanisms driving $p\text{CO}_2^{\text{sea}}$, a linear decomposition was applied in this study (Lovenduski et al. 2007; Doney et al. 2009; Jin et al. 2017):

$$p\text{CO}_2^{\text{sea}'} \approx \frac{\partial p\text{CO}_2}{\partial T} T' + \frac{\partial p\text{CO}_2}{\partial \text{DIC}} \text{nDIC}' + \frac{\partial p\text{CO}_2}{\partial \text{Alk}} \text{nAlk}' + \frac{\partial p\text{CO}_2}{\partial S} S'. \quad (5)$$

The terms on the right side represent the effect of variability in SST, salinity-normalized DIC (nDIC),

TABLE 2. Range of the factors for calculating partial derivatives.

Factor	Range
Sea surface salinity (SSS)	(−3, 3) psu
Sea surface temperature (SST)	(−2, 2) $^\circ\text{C}$
Dissolved inorganic carbon (DIC)	(−200, 200) mmol m^{-3}
Alkalinity (Alk)	(−200, 200) mmol m^{-3}

salinity-normalized alkalinity (nAlk), and sea surface salinity (SSS). The partial derivatives are estimated from the variation of $p\text{CO}_2^{\text{sea}}$ due to the change of individual forcing variables, while keeping all other forcing variables constant. These partial derivatives are derived from the isolated code for calculating $p\text{CO}_2^{\text{sea}}$ in an ocean carbon cycle model (Ilyina et al. 2013). We perturb a variable 50 times equidistantly around its climatology, keeping the others constant, and then use the least squares fitting to estimate the corresponding partial derivative. The perturbed ranges of variables are listed in Table 2. The climatological winter mean (DJF) during 1982–2005 is used.

Since every grid point of the spatial pattern is independent, when testing statistical significance on the spatial pattern correlation, we evaluate the effective sample sizes N_{eff} for correlations of X and Y as

$$N_{\text{eff}} = N / \max \left[1, 1 + 2 \sum_{\tau=1}^{\tau_{\max}} (1 - \tau/N) r_X(\tau) r_Y(\tau) \right], \quad (6)$$

where N represents data length, and $r_X(\tau)$ is an autocorrelation of time series X with a lag of τ . In this study, the estimate of the effective sample size is 18.

3. Results

a. Annual mean

The annual-mean air–sea CO_2 fluxes over the tropical Pacific Ocean in the observation-based products and multimodel ensemble (MME) are shown in Fig. 1. Positive values indicate that CO_2 fluxes go upward from ocean to the atmosphere. The modeled air–sea CO_2 fluxes are averaged in the period 1990–2005, matching with the observation-based product in reference year 2000 in Takahashi et al. (2009). In the observation-based product, the spatial pattern of air–sea CO_2 fluxes shows a large contrast between the domains of the eastern and western tropical Pacific Ocean (Fig. 1a). Evidently, the eastern Pacific is characterized by larger efflux than that in the western Pacific. This feature is reproduced reasonably by MME (Fig. 1b). The spatial correlation coefficient between observation-based product and MME is 0.84, which is statistically significant at the 1% level.

FIG. 1. Annual-mean air-sea CO₂ fluxes ($\text{g C m}^{-2} \text{yr}^{-1}$) in the period 1990–2005 over the tropical Pacific based on (a) an observation-based product (Takahashi et al. 2009) and (b) the MME. (c) Annual-mean air-sea CO₂ fluxes (Pg C yr^{-1}) over the tropical Pacific (TP), western tropical Pacific (WP; west of 160°W), and eastern tropical Pacific (EP; east of 160°W). Blue (brown) bars represent the MME (observed results). The MME is constructed by using the first realizations from 14 CMIP5 ESMs (black dots). Positive fluxes indicate that CO₂ fluxes go upward from ocean to the atmosphere.

In the observation-based product, the climatological annual-mean air-sea CO₂ flux over the tropical Pacific (18°S–18°N, 120°E–80°W) is $0.47 \text{ Pg C yr}^{-1}$ (Fig. 1c, brown bar), which mainly originates from the eastern tropical Pacific ($0.43 \text{ Pg C yr}^{-1}$). The annual CO₂ flux ($0.35 \text{ Pg C yr}^{-1}$) simulated by the MME is about 25% less than the observation-based products, owing to less efflux over the eastern tropical Pacific in the MME ($0.32 \text{ Pg C yr}^{-1}$). However, the intermodel spread is large. Among the CMIP5 models, some models (BCC-CSM1.1, BCC-CSM1.1-m, BNU-ESM, CanESM2, IPSL-CM5A-LR, MPI-ESM-LR, and NorESM1-ME) reasonably reproduce the observed magnitude, while others cannot.

The Taylor diagram is presented in Fig. 2 to quantitatively assess the individual performance of CMIP5

models in the simulation of annual-mean air-sea CO₂ flux. Better model performance is indicated by a higher pattern correlation coefficient and a normalized standard deviation nearer to 1.0. For the tropical Pacific (Fig. 2, black dot), the pattern correlation coefficients of most models with the observation-based product are statistically significant at the 5% level (correlation coefficient > 0.5), except for MIROC-ESM (0.15) and HadGEM2-ES (0.31), indicating that the overall characteristics of the spatial distribution of climatological air-sea CO₂ flux over the tropical Pacific Ocean are reasonably reproduced by most of the ESMs; the details, however, are not well captured. Although the ratios of the standard deviations between model and observation-based product show large spread (from 0.55 for HadGEM2-ES to 2.64 for MRI-ESM), they are distributed symmetrically around 1.0. The pattern correlation coefficient (0.84) and the ratio of standard deviation (1.02) in MME are better than the individual ESM, which implies that the ratio of noise-to-signal in MME is lower than that for the individual ESM. For the western tropical Pacific (Fig. 2, red dot), the spatial correlation coefficients exceed 0.65 except for MIROC-ESM (0.30). However, the ratios of the standard deviations are generally higher than 1.0, indicating a stronger spatial variation than the observation-based product. The pattern correlation coefficients in the 14 ESMs of the eastern tropical Pacific (Fig. 2, blue dot) are less than those of the western tropical Pacific, and the MME yields better performances in terms of both the spatial distribution (0.75) and standard deviation (0.97) over the eastern tropical Pacific.

b. Interannual variability

Previous modeling studies have indicated that the interannual variability of the global air-sea CO₂ flux is primarily determined by the interannual variability over the tropical Pacific (account for approximately 70% of the global variance; Le Quéré et al. 2000; McKinley et al. 2004; Obata and Kitamura 2003). However, an offline biogeochemical model indicates that the contribution of the tropical Pacific variability is approximately 40% of the global variance (Valsala et al. 2014). Here the averaged contribution from the 14 ESMs is 25%, ranging from 11% in MPI-ESM-LR to 46% in CESM1(BGC), showing large intermodel spread (figure not shown).

The monthly interannual variability intensity of the air-sea CO₂ flux over the tropical Pacific Ocean simulated by CMIP5 MME is shown in Fig. 3. The interannual standard deviation for the period 1982–2005 is calculated as the anomalies relative to the mean annual cycle for each month of the year. Two peaks were observed (one each in the winter and summer); they are associated with the peak phase and developing phase of

FIG. 2. Taylor diagram for displaying the pattern statistics during annual-mean air-sea CO_2 fluxes averaged from 1990 to 2005. The observation-based product is considered as the reference (REF), and the angular coordinate indicates the pattern correlation between the model and observation-based product. The vertical coordinate represents the ratio of the standard deviations of the model and observation-based product. The smaller the distance between a number and REF, the better is the performance of the corresponding model. Numbers represent 14 CMIP5 models and the MME. As in Fig. 1, the WP is west of 160°W , and the EP is east of 160°W .

ENSO, respectively. Since the highest interannual variability intensity of the air-sea CO_2 flux occurs in ENSO mature winter, we focus on the first leading mode of the air-sea CO_2 flux in DJF.

The EOF analysis was performed to examine whether the ESMs can reproduce the leading mode of interannual variability of the air-sea CO_2 flux in winter over the tropical Pacific Ocean (20°S – 20°N , 120°E – 80°W). In the observation-based product, the first leading mode (EOF1) exhibits negative anomalies over the central tropical Pacific, and this explains 49.8% of the variance (Fig. 4a). The first principal component (PC1) correlates with the Niño-3.4 index (the area-averaged SSTA over 5°S – 5°N , 120° – 170°W) with a high correlation coefficient of 0.92 (Fig. 5a), indicating the dominant influence of ENSO. In the CMIP5 ESMs, the correlation coefficients between the PC1 and Niño-3.4 index calculated based on the model SST range from 0.59 (IPSL-CM5A-LR) to 0.96 (CanESM2) (Fig. 5), and all values are statistically significant at the 1% level. The correlations between PC1 and the Niño-3.4 index are intended to be positive to ensure that the corresponding EOF1 patterns are comparable across models. Hence, the high correlations between PC1 and the Niño-3.4 index calculated based on the model SST show that ENSO also

plays dominant role in determining the air-sea CO_2 flux variability in the ESMs.

Biases in the simulated atmospheric CO_2 concentration in CMIP5 ESMs were reported in several recent studies (Hoffman et al. 2014; Friedlingstein et al. 2014). To exclude the possible influence of biases in atmospheric CO_2 on the interannual variability of air-sea CO_2 flux, we repeated the EOF analysis on concentration-driven

FIG. 3. Monthly interannual standard deviation of the air-sea CO_2 flux in the period from 1982 to 2005 over the tropical Pacific Ocean simulated by CMIP5 MME. The shaded area indicates one standard deviation across CMIP5 ESMs. The datasets have been filtered through an 8-yr high-pass filter.

FIG. 4. Spatial pattern of the first EOF of the winter mean (DJF) air-sea CO_2 flux ($\text{g C m}^{-2} \text{yr}^{-1}$) in the period from 1982 to 2005 over the tropical Pacific. The percent variance (%) captured by EOF1 is noted. The datasets have been filtered through an 8-yr high-pass filter.

historical simulations in the corresponding 13 models; FIO-ESM was excluded as it did not have any air-sea CO_2 flux output (see the online supplemental material, Figs. S1 and S2 therein). The EOF results of emission-driven and concentration-driven simulations differ only slightly. Hence, the influence of biases in simulated atmospheric CO_2 concentration in ESMs can be neglected in this study.

The observed negative anomalies in the central Pacific are well captured by several ESMs [CESM1(BGC),

FIO-ESM, GFDL-ESM2M, and MRI-ESM], but not so by some other ESMs, and some models (BNU-ESM, HadGEM2-ES, and MPI-ESM-LR) even exhibit positive anomalies in the spatial pattern of EOF1 (Fig. 4). The key question is what causes the biases in response of the air-sea CO_2 flux to El Niño in some ESMs. Therefore, based on the availability of the model output fields related to the ocean carbon cycle, seven models are selected to examine the related physical processes and

FIG. 5. The principal component of the first EOF modes of the winter mean air-sea CO_2 flux (red line) and Niño-3.4 index (black line). The correlation of PC1 and the Niño-3.4 index is shown.

potential causes of biases. The high-skill models [CESM1(BGC) and GFDL-ESM2M], low-skill models (HadGEM2-ES and MPI-ESM-LR), and medium-skill models (CanESM2, GFDL-ESM2G, and NorESM1-ME) are distinguished by the pattern correlation coefficients shown in Fig. 4 between each model and observation-based product (Table 3).

Based on Eq. (1), the variations in the air-sea CO_2 flux can be attributed to the gas transfer coefficient k , CO_2 solubility α , and $p\text{CO}_2^{\text{sea}}$. Regression of these three

factors with respect to Niño-3.4 index is shown in Fig. 6. In the observations-based result, the negative gas transfer coefficient anomalies locate at the central tropical Pacific (Fig. 6a2), associated with the westerly wind anomalies at the equator induced by El Niño warming. The observed gas transfer coefficient pattern is reproduced reasonably by six [CanESM2, CESM1(BGC), GFDL-ESM2M, GFDL-ESM2G, HadGEM2-ES, and NorESM1-ME] of seven ESMs (Figs. 6b2–h2), whereas weak positive anomalies over the central tropical Pacific

TABLE 3. Pattern correlation coefficients of the spatial pattern of EOF1 between each model and observation-based result shown in Fig. 4.

Model	Pattern correlation coefficient
CanESM2	0.05
CESM1(BGC)	0.56
GFDL-ESM2G	0.18
GFDL-ESM2M	0.51
HadGEM2-ES	−0.29
MPI-ESM-LR	−0.43
NorESM1-ME	0.36

are seen in MPI-ESM-LR (Fig. 6g2). For CO_2 solubility, the observed negative anomalies (Fig. 6a3) associated with the warm SST anomalies during El Niño [Eq. (4)] are captured well by all the seven ESMs

(Fig. 6). The westward shift of the anomalous solubility center in CanESM2, GFDL-ESM2G, MPI-ESM-LR, and NorESM1-ME (Figs. 6b3,e3,g3,h3) is expected to result from biases in ENSO-related anomalous SST and SSS based on Eq. (4). The largest contrast among the seven ESMs, however, is in the $p\text{CO}_2^{\text{sea}}$ anomalies (Figs. 6a4–h4). The spatial patterns of the $p\text{CO}_2^{\text{sea}}$ response to ENSO in the seven ESMs are similar to those of the air–sea CO_2 flux, with negative anomalies in CanESM2, CESM1(BGC), and GFDL-ESM2M (Figs. 6c4 and 6d4) and weak anomalies in GFDL-ESM2G and NorESM1-ME (Figs. 6e4 and 6h4) but positive anomalies in HadGEM2-ES and MPI-ESM-LR (Figs. 6f4 and 6g4). Therefore, the biases in the $p\text{CO}_2^{\text{sea}}$ response to ENSO are the dominant factors for the biases of the air–sea CO_2 flux variations, especially

FIG. 6. Regression coefficients of the (a1)–(h1) air–sea CO_2 flux ($\text{g C m}^{-2} \text{yr}^{-1}$), (a2)–(h2) gas transfer coefficient (cm h^{-1}), (a3)–(h3) CO_2 solubility ($\text{mmol m}^{-3} \text{atm}^{-1}$), and (a4)–(h4) surface ocean $p\text{CO}_2$ (ppm) with respect to the normalized Niño-3.4 index in the period 1982–2005. The dotted regions are statistically significant at the 5% level based on the Student's t test. The datasets have been filtered through an 8-yr high-pass filter.

the reverse sign biases in HadGEM2-ES and MPI-ESM-LR (Figs. 6f1 and 6g1).

To further understand the causes of biases of the $p\text{CO}_2^{\text{sea}}$ response to ENSO in the several ESMs, a linear decomposition [Eq. (5)] was applied to diagnose contributions of SSS, SST, nDIC, and nAlk based on carbonate chemistry. All models indicate that the apparent $p\text{CO}_2^{\text{sea}}$ anomalies result from the compensation between the positive effect of SST and negative effect of DIC; the effects of SSS and Alk are negligible (Fig. 7). For a quantitative comparison, the area-averaged regression coefficients over the region with the maximum variations (10°S – 10°N , 180° – 70°W) are shown in Fig. 8. In CESM1(BGC) and GFDL-ESM2M, the DIC effect dominates the $p\text{CO}_2^{\text{sea}}$ anomalies; this result is consistent with previous studies (Long et al. 2013). The negative contributions to $p\text{CO}_2^{\text{sea}}$ from DIC are 2.1 and 1.8 times the positive contributions from SST in CESM1(BGC) and GFDL-ESM2M, respectively (Fig. 8). In contrast, the negative effects of DIC in HadGEM2-ES and MPI-ESM-LR are weaker than the positive effect of SST (Fig. 7f3), with 55% and 96% ratios of the contributions of the DIC and SST (Fig. 8); this is the main cause of the biases of $p\text{CO}_2^{\text{sea}}$ (Figs. 6f4 and 6g4). It indicates that the suppressed upwelling of DIC during El Niño in HadGEM2-ES and MPI-ESM-LR is not as evident as that in CESM1(BGC) and GFDL-ESM2M. In NorESM1-ME, although the negative contributions to $p\text{CO}_2^{\text{sea}}$ from DIC are 2.0 times the positive contributions from SST (Fig. 8), the positive contributions from Alk counteract with the negative effect of DIC (Fig. 7h4) and cause the weak anomalies of $p\text{CO}_2^{\text{sea}}$ (Fig. 6h4). The contributions of DIC and SST are equivalent in GFDL-ESM2G (Fig. 8), leading to the weak anomalies of $p\text{CO}_2^{\text{sea}}$ (Fig. 6e4). The biases of the $p\text{CO}_2^{\text{sea}}$ in CanESM2 (Fig. 6b4) result from both the underestimated DIC anomalies in the western Pacific and overestimated contributions of DIC and alkalinity in the eastern Pacific (Figs. 7b3 and 7b4).

Based on previous studies, the suppressed upwelling in the equatorial Pacific during El Niño is an important process that reduces upward transport of high-concentration DIC from deeper layers (McKinley et al. 2004; Long et al. 2013; Jin et al. 2017). This process can be expressed as $-w'\partial\text{DIC}/\partial z$, where w' is the anomalous upward motion of seawater related to ENSO and $\partial\text{DIC}/\partial z$ is the vertical gradient of climatological DIC. To understand why negative contribution to $p\text{CO}_2^{\text{sea}}$ from DIC is too weak in HadGEM2-ES and MPI-ESM-LR, we compare the simulated w' and DIC across different models. Vertical profiles of anomalous equatorial DIC, upward motion and seawater temperature in the upper ocean (above 250 m) over the tropical Pacific associated with Niño-3.4 index are shown in Fig. 9, as well as climatological upward motion, DIC, and its vertical gradient. The specific values of w' , $-\partial\text{DIC}/\partial z$, and their product averaged in the

tropical Pacific are shown in Fig. 10. A weakened upward motion ($w' < 0$; positive in the upward direction) induced by a deeper thermocline (Fig. 9c3; e.g., Christian et al. 2001) is observed at depths above 250 m in CESM1(BGC) and GFDL-ESM2M (Figs. 9b2 and 9c2). In the same region, the climatological DIC distributions show large vertical gradients ($-\partial\text{DIC}/\partial z > 0$) in both models with larger concentrations in the deeper layers (Figs. 9b4 and 9c4). Therefore, the upward transport of high-concentration DIC water to surface is evidently suppressed ($-w'\partial\text{DIC}/\partial z < 0$), which is expected during an El Niño year [Figs. 9b1 and 9c1, as previously reported by Feely et al. (2006) and Landschützer et al. (2014)]. This process of anomalous upward motion suppressing the transport of high-concentration DIC water to surface simulated by CESM1(BGC) and GFDL-ESM2M is also shown in Fig. 10. In contrast, the negative anomalies of upwelling are weak in HadGEM2-ES (Fig. 9d2) and shift westward in MPI-ESM-LR (Fig. 9e2). Correspondingly, the positive anomalies of seawater temperature over the eastern and central equatorial Pacific in the upper ocean are weak in HadGEM2-ES (Fig. 9d3) and extend westward in MPI-ESM-LR (Fig. 9e3), indicating the weak deepening of the thermocline in HadGEM2-ES and MPI-ESM-LR. In addition, the vertical gradients of climatological DIC are too weak in the region where reduced upward motion occurs (Figs. 9d4 and 9e4). The weak anomalous upwelling and the vertical gradients of climatological DIC simulated by HadGEM2-ES and MPI-ESM-LR are also shown in Fig. 10. Therefore, the concentration of the surface DIC in HadGEM2-ES and MPI-ESM-LR does not decrease as strongly as that in CESM1(BGC) and GFDL-ESM2M. Finally, the negative effect of decreasing DIC on $p\text{CO}_2^{\text{sea}}$ cannot overwhelm the positive effect of increasing SST (Fig. 8). These weak negative contributions arising from the insufficient reduction of vertical DIC transport to $p\text{CO}_2^{\text{sea}}$ are responsible for the positive response of air–sea CO_2 flux to El Niño in HadGEM2-ES and MPI-ESM-LR. In the medium-skill models (CanESM2 and NorESM-ME), although the vertical gradients of climatological DIC are as large as CESM1(BGC) and GFDL-ESM2M (Figs. 9a4,b4, c4,f4), the concentration of the surface IDC in CanESM2 and NorESM-ME cannot decrease as strongly as that in CESM1(BGC) and GFDL-ESM2M owing to the relatively weak negative anomalies of upwelling (Figs. 9a2,b2, c2,f2; see also Fig. 10).

4. Conclusions and discussion

The annual-mean climatology and interannual variability of the air–sea CO_2 fluxes over the tropical Pacific Ocean in the 14 CMIP5 ESMs were evaluated in this

FIG. 7. Regression of the contributions of surface ocean $p\text{CO}_2$ anomalies from (b1)–(h1) sea surface salinity, (b2)–(h2) SST, (b3)–(h3) surface-water salinity-normalized dissolved inorganic carbon, and (b4)–(h4) salinity-normalized alkalinity with respect to the Niño-3.4 index in the period 1982–2005. The dotted regions are statistically significant at the 5% level based on the Student's t test. The datasets have been filtered through an 8-yr high-pass filter.

study. We found that more than half of the models cannot reproduce well the spatial pattern of the tropical Pacific CO_2 flux response to ENSO, despite the reasonable performances in the simulation of the mean states. The underlying reason was analyzed by comparing the models with different skills.

The spatial pattern of the observed annual-mean air–sea CO_2 fluxes in the tropical Pacific can be reasonably reproduced in CMIP5 MME, despite large spreads in the magnitude and spatial gradient across the ESMs. The models also consistently show the controlling influence of ENSO on the interannual variability of the

FIG. 8. Regression coefficients in Fig. 7 averaged in the central-eastern tropical Pacific (10°S – 10°N , 180° – 70°W).

tropical Pacific air–sea CO_2 fluxes in DJF. However, the dominant interannual modes (i.e., the spatial pattern) exhibit even stronger outgassing during an El Niño year in several models, such as HadGEM2-ES and MPI-ESM-LR,

which is in contrast with the result obtained using observation-based data.

Further analysis show that the positive anomalies of air–sea CO_2 fluxes during the warm events of ENSO

FIG. 9. Equatorial anomaly profiles (2°S – 2°N) of (a1)–(f1) DIC (shadings; mmol m^{-3}), (a2)–(f2) upward velocity (10^{-3} m s^{-1}), and (a3)–(f3) seawater temperature ($^{\circ}\text{C}$) over the tropical Pacific Ocean with respect to the Niño-3.4 index in the period 1982–2005. The dotted regions are statistically significant at the 5% level based on the Student's t test. (a4)–(f4) Equatorial profile (2°S – 2°N) of the climatological DIC (mmol m^{-3}) and its vertical gradient ($\text{mmol m}^{-3} \text{ m}^{-1}$) in the period 1990–2005 over the tropical Pacific Ocean. The green line in (a3)–(f3) is the climatological thermocline depth, represented by the 20°C isotherm. The datasets have been filtered through an 8-yr high-pass filter.

FIG. 10. The anomalous upward velocity of seawater (x axis; 10^{-3} m s^{-1}), the vertical gradient of climatological DIC (y axis; $\text{mmol m}^{-3} \text{ m}^{-1}$), and their product ($-w' \partial \text{DIC} / \partial z$; blue circles). The values of $-w' \partial \text{DIC} / \partial z$ are identified on the circles, which are also shown as colors. The anomalous upward velocity averaged in the depth above 200 m and the tropical Pacific (160°E – 120°W). The vertical gradient of climatological DIC is calculated as the difference of upper level (above 100 m) DIC and medium level (100–200 m) DIC.

result from the positive response of surface-water partial pressure ($p\text{CO}_2^{\text{sea}}$). During El Niño, increasing SST (apt to increase $p\text{CO}_2^{\text{sea}}$) and decreasing surface DIC (apt to decrease $p\text{CO}_2^{\text{sea}}$) in the central-eastern Pacific play competing roles in determining the $p\text{CO}_2^{\text{sea}}$, in which the DIC effect should be larger. By calculating the contributions of SST and surface DIC variation to $p\text{CO}_2^{\text{sea}}$ anomalies, we found that the weaker DIC effect on negative $p\text{CO}_2$ anomalies associated with ENSO in HadGEM2-ES and MPI-ESM-LR is the main cause of the air–sea CO_2 flux biases. For HadGEM2-ES, the main cause is the weak vertical gradient of the climatological DIC, weak negative anomalies of upwelling, and weak deepening of thermocline. For MPI-ESM-LR, the westward shift of the negative anomalies of upwelling limits the DIC vertical transport, leading to weak surface DIC anomalies. Therefore, the negative effect of decreasing DIC on $p\text{CO}_2^{\text{sea}}$ cannot overwhelm the positive effect of increasing SST, leading to positive $p\text{CO}_2^{\text{sea}}$ and outgassing in HadGEM2-ES and MPI-ESM-LR.

In terms of the seasonal cycle, the equatorial Pacific $p\text{CO}_2^{\text{sea}}$ is mainly controlled by the SST evolution rather than by the surface DIC, which shows less fluctuations due to the subtle balance between the compensating individual components of physical transport, biological drawdown, and air–sea CO_2 flux (Feely et al. 2002; Jiang and Chai 2006). This subtle balance may be perturbed by

tropical oscillations, such as ENSO. This study supports the importance of DIC transport perturbation in response of $p\text{CO}_2^{\text{sea}}$ to ENSO, for which both the physical upwelling response and climatological DIC profile are crucial factors. Model developers should take care to reduce the biases in these two factors in future by observation-based calibration because biological processes can adjust and feedback dramatically to redistribution of carbon and nutrients; this is necessary to ensure good predictions of air–sea CO_2 flux and biological activities (Chavez et al. 1999). MPI-ESM-LR and NorESM1-ME, which employ a similar ocean biogeochemical module (Assmann et al. 2010; Ilyina et al. 2013), show similar vertical profiles of the DIC response to ENSO, indicating that the processes and parameters included in the CMIP5 ocean carbon cycle modules (Table 1) partly contribute to DIC and air–sea CO_2 flux biases in response to ENSO.

In the observation-based product, the spatial pattern of the first leading EOF of the air–sea CO_2 flux clearly exhibits negative anomalies over the central tropical Pacific (Fig. 4a), which appears like the pattern of El Niño Modoki (Ashok et al. 2007). However, we speculate that the physical mechanism of air–sea CO_2 flux anomalies over the central tropical Pacific is different from that of El Niño Modoki. The air–sea CO_2 flux anomalies over the central tropical Pacific result from the gas transfer coefficient anomalies (Fig. 6a2) and $p\text{CO}_2^{\text{sea}}$ anomalies (Fig. 6a4), which are regressed onto conventional ENSO index. The air–sea CO_2 flux anomalies related to ENSO diversity should be another topic and deserve to be studied further.

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REFERENCES

- Adachi, Y., and Coauthors, 2013: Basic performance of a new Earth system model of the Meteorological Research Institute (MRI-ESM1). *Pap. Meteor. Geophys.*, **64**, 1–19, <https://doi.org/10.2467/mripapers.64.1>.
- Anav, A., and Coauthors, 2013: Evaluating the land and ocean components of the global carbon cycle in the CMIP5 Earth system models. *J. Climate*, **26**, 6801–6843, <https://doi.org/10.1175/JCLI-D-12-00417.1>.
- Arora, V. K., and Coauthors, 2011: Carbon emission limits required to satisfy future representative concentration pathways of greenhouse gases. *Geophys. Res. Lett.*, **38**, L05805, <https://doi.org/10.1029/2010GL046270>.

- Ashok, K., S. K. Behera, S. A. Rao, H. Weng, and T. Yamagata, 2007: El Niño Modoki and its possible teleconnection. *J. Geophys. Res.*, **112**, C11007, <https://doi.org/10.1029/2006JC003798>.
- Assmann, K. M., M. Bentsen, J. Segsneider, and C. Heinze, 2010: An isopycnic ocean carbon cycle model. *Geosci. Model Dev.*, **3**, 143–167, <https://doi.org/10.5194/gmd-3-143-2010>.
- Boer, G. J., and V. K. Arora, 2009: Temperature and concentration feedbacks in the carbon cycle. *Geophys. Res. Lett.*, **36**, L02704, <https://doi.org/10.1029/2008GL036220>.
- Chavez, F. P., P. G. Strutton, G. E. Friederich, R. A. Feely, G. C. Feldman, D. G. Foley, and M. J. McPhaden, 1999: Biological and chemical response of the equatorial Pacific Ocean to the 1997–98 El Niño. *Science*, **286**, 2126–2131, <https://doi.org/10.1126/science.286.5447.2126>.
- Christian, J. R., M. A. Verschell, R. Murtugudde, A. J. Busalacchi, and C. R. McClain, 2001: Biogeochemical modelling of the tropical Pacific Ocean. I: Seasonal and interannual variability. *Deep-Sea Res. II*, **49**, 509–543, [https://doi.org/10.1016/S0967-0645\(01\)00110-2](https://doi.org/10.1016/S0967-0645(01)00110-2).
- Collins, W. J., and Coauthors, 2011: Development and evaluation of an Earth-system model—HadGEM2. *Geosci. Model Dev.*, **4**, 1051–1075, <https://doi.org/10.5194/gmd-4-1051-2011>.
- Dee, D. P., and Coauthors, 2011: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quart. J. Roy. Meteor. Soc.*, **137**, 553–597, <https://doi.org/10.1002/qj.828>.
- Dlugokencky, E., and P. Tans, 2018: Trends in atmospheric carbon dioxide. NOAA/ESRL, accessed 21 February 2018, <http://www.esrl.noaa.gov/gmd/ccgg/trends/global.html>.
- Doney, S. C., I. Lima, R. A. Feely, D. M. Glover, K. Lindsay, N. Mahowald, J. K. Moore, and R. Wanninkhof, 2009: Mechanisms governing interannual variability in upper-ocean inorganic carbon system and air–sea CO₂ fluxes: Physical climate and atmospheric dust. *Deep-Sea Res. II*, **56**, 640–655, <https://doi.org/10.1016/j.dsr2.2008.12.006>.
- Dong, F., Y. C. Li, B. Wang, W. Y. Huang, Y. Y. Shi, and W. H. Dong, 2016: Global air–sea CO₂ flux in 22 CMIP5 models: Multiyear mean and interannual variability. *J. Climate*, **29**, 2407–2431, <https://doi.org/10.1175/JCLI-D-14-00788.1>.
- Dufresne, J. L., and Coauthors, 2013: Climate change projections using the IPSL-CM5 Earth system model: From CMIP3 to CMIP5. *Climate Dyn.*, **40**, 2123–2165, <https://doi.org/10.1007/s00382-012-1636-1>.
- Dunne, J. P., and Coauthors, 2012: GFDL’s ESM2 global coupled climate–carbon Earth system models. Part I: Physical formulation and baseline simulation characteristics. *J. Climate*, **25**, 6646–6665, <https://doi.org/10.1175/JCLI-D-11-00560.1>.
- Feely, R. A., R. Wanninkhof, T. Takahashi, and P. Tans, 1999: Influence of El Niño on the equatorial Pacific contribution of atmospheric CO₂ accumulation. *Nature*, **398**, 597–601, <https://doi.org/10.1038/19273>.
- , and Coauthors, 2002: Seasonal and interannual variability of CO₂ in the equatorial Pacific. *Deep-Sea Res. II*, **49**, 2443–2469, [https://doi.org/10.1016/S0967-0645\(02\)00044-9](https://doi.org/10.1016/S0967-0645(02)00044-9).
- , T. Takahashi, R. Wanninkhof, M. J. McPhaden, C. E. Cosca, S. C. Sutherland, and M. E. Carr, 2006: Decadal variability of the air–sea CO₂ fluxes in the equatorial Pacific Ocean. *J. Geophys. Res.*, **111**, C08S90, <https://doi.org/10.1029/2005JC003129>.
- Friedlingstein, P., M. Meinshausen, V. K. Arora, C. D. Jones, A. Anav, S. K. Liddicoat, and R. Knutti, 2014: Uncertainties in CMIP5 climate projections due to carbon cycle feedbacks. *J. Climate*, **27**, 511–526, <https://doi.org/10.1175/JCLI-D-12-00579.1>.
- Hoffman, F. M., and Coauthors, 2014: Causes and implications of persistent atmospheric carbon dioxide biases in Earth system models. *J. Geophys. Res. Biogeosci.*, **119**, 141–162, <https://doi.org/10.1002/2013JG002381>.
- Ilyina, T., K. D. Six, J. Segsneider, E. Maier-Reimer, H. M. Li, and I. Núñez-Riboni, 2013: Global ocean biogeochemistry model HAMOCC: Model architecture and performance as component of the MPI-Earth System Model in different CMIP5 experimental realizations. *J. Adv. Model. Earth Syst.*, **5**, 287–315, <https://doi.org/10.1029/2012MS000178>.
- Ishii, M., S. Saito, T. Tokieda, T. Kavano, K. Matsumoto, and H. Y. Inoue, 2004: Variability of surface layer CO₂ parameters in the western and central equatorial Pacific. *Global Environmental Change in the Ocean and on Land*, M. Shiyomi et al., Eds., Terrapub, 59–94.
- , and Coauthors, 2014: Air–sea CO₂ flux in the Pacific Ocean for the period 1990–2009. *Biogeosciences*, **11**, 709–734, <https://doi.org/10.5194/bg-11-709-2014>.
- Ji, D., and Coauthors, 2014: Description and basic evaluation of BNU-ESM version 1. *Geosci. Model Dev.*, **7**, 2039–2064, <https://doi.org/10.5194/gmdd-7-1601-2014>.
- Jiang, M. S., and F. Chai, 2006: Physical control on the seasonal cycle of surface pCO₂ in the equatorial Pacific. *Geophys. Res. Lett.*, **33**, L23608, <https://doi.org/10.1029/2006GL027195>.
- Jin, C. X., T. J. Zhou, X. L. Chen, and B. Wu, 2017: Seasonally evolving dominant interannual variability mode of air–sea CO₂ flux over the western North Pacific simulated by CESM1-BGC. *Sci. China Earth Sci.*, **60**, 1854–1865, <https://doi.org/10.1007/s11430-015-9085-4>.
- Joos, F., and R. Spahni, 2008: Rates of change in natural and anthropogenic radiative forcing over the past 20,000 years. *Proc. Natl. Acad. Sci. USA*, **105**, 1425–1430, <https://doi.org/10.1073/pnas.0707386105>.
- Kwiatkowski, L., and J. C. Orr, 2018: Diverging seasonal extremes for ocean acidification during the twenty-first century. *Nat. Climate Change*, **8**, 141–145, <https://doi.org/10.1038/s41558-017-0054-0>.
- Landschützer, P., N. Gruber, D. C. E. Bakker, and U. Schuster, 2014: Recent variability of the global ocean carbon sink. *Global Biogeochem. Cycles*, **28**, 927–949, <https://doi.org/10.1002/2014GB004853>.
- , —, and —, 2015: A 30 years observation-based global monthly gridded sea surface pCO₂ product from 1982 through 2011. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Dept. of Energy, http://cdiac.ornl.gov/ftp/oceans/SPCO2_1982_2011_ETH_SOM_FFN.
- Le Quéré, C., J. C. Orr, P. Monfray, O. Aumont, and G. Madec, 2000: Interannual variability of the oceanic sink of CO₂ from 1979 through 1997. *Global Biogeochem. Cycles*, **14**, 1247–1265, <https://doi.org/10.1029/1999GB900049>.
- , and Coauthors, 2016: The global carbon budget 2016. *Earth Syst. Sci. Data*, **8**, 605–649, <https://doi.org/10.5194/essd-8-605-2016>.
- Li, H. M., and T. Ilyina, 2018: Current and future decadal trends in the oceanic carbon uptake are dominated by internal variability. *Geophys. Res. Lett.*, **45**, 916–925, <https://doi.org/10.1002/2017GL075370>.
- , —, W. A. Müller, and F. Siens, 2016: Decadal predictions of the North Atlantic CO₂ uptake. *Nat. Commun.*, **7**, 11076, <https://doi.org/10.1038/ncomms11076>.
- Li, Y. C., and Y. F. Xu, 2013: Interannual variations of the air–sea carbon dioxide exchange in the different regions of the Pacific Ocean. *Acta Oceanol. Sin.*, **32**, 71–79, <https://doi.org/10.1007/s13131-013-0291-7>.
- Long, M. C., K. Lindsay, and S. Peacock, 2013: Twentieth-century oceanic carbon uptake and storage in CESM1(BGC). *J. Climate*, **26**, 6775–6800, <https://doi.org/10.1175/JCLI-D-12-00184.1>.

- Lovenduski, N. S., N. Gruber, S. C. Doney, and I. D. Lima, 2007: Enhanced CO₂ outgassing in the Southern Ocean from a positive phase of the southern annular mode. *Global Biogeochem. Cycles*, **21**, GB2026, <https://doi.org/10.1029/2006GB002900>.
- McKinley, G. A., M. J. Follows, and J. Marshall, 2004: Mechanisms of air–sea CO₂ flux variability in the equatorial Pacific and the North Atlantic. *Global Biogeochem. Cycles*, **18**, GB2011, <https://doi.org/10.1029/2003GB002179>.
- Obata, A., and Y. Kitamura, 2003: Interannual variability of the air–sea exchange of CO₂ from 1961 to 1998 simulated with a global ocean circulation–biogeochemistry model. *J. Geophys. Res.*, **108**, 3337, <https://doi.org/10.1029/2001JC001088>.
- Qiao, F. L., Z. Y. Song, Y. Bao, Y. J. Song, Q. Shu, C. J. Huang, and W. Zhao, 2013: Development and evaluation of an Earth system model with surface gravity waves. *J. Geophys. Res.*, **118**, 4514–4524, <https://doi.org/10.1002/jgrc.20327>.
- Schwinger, J., and Coauthors, 2014: Nonlinearity of ocean carbon cycle feedbacks in CMIP5 Earth system models. *J. Climate*, **27**, 3869–3888, <https://doi.org/10.1175/JCLI-D-13-00452.1>.
- Smith, T., R. Reynolds, T. Peterson, and J. Lawrimore, 2008: Improvements to NOAA's historical merged land–ocean surface temperature analysis (1880–2006). *J. Climate*, **21**, 2283–2296, <https://doi.org/10.1175/2007JCLI2100.1>.
- Takahashi, T., and Coauthors, 2009: Climatological mean and decadal change in surface ocean pCO₂, and net sea-air CO₂ flux over the global oceans. *Deep-Sea Res. II*, **56**, 554–577, <https://doi.org/10.1016/j.dsr2.2008.12.009>.
- Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.*, **93**, 485–498, <https://doi.org/10.1175/BAMS-D-11-00094.1>.
- Tjiputra, J. F., C. Roelandt, M. Bentsen, D. M. Lawrence, T. Lorentzen, J. Schwinger, Ø. Seland, and C. Heinze, 2013: Evaluation of the carbon cycle components in the Norwegian Earth System Model (NorESM). *Geosci. Model Dev.*, **6**, 301–325, <https://doi.org/10.5194/gmd-6-301-2013>.
- Valsala, V. K., M. K. Roxy, K. Ashok, and R. Murtugudde, 2014: Spatiotemporal characteristics of seasonal to multidecadal variability of pCO₂ and air–sea CO₂ fluxes in the equatorial Pacific Ocean. *J. Geophys. Res. Oceans*, **119**, 8987–9012, <https://doi.org/10.1002/2014JC010212>.
- Wang, L., J. B. Huang, Y. Luo, and Z. C. Zhao, 2016: Narrowing the spread in CMIP5 model projections of air–sea CO₂ fluxes. *Sci. Rep.*, **6**, 37548, <https://doi.org/10.1038/srep37548>.
- Wang, X. J., J. R. Christian, R. Murtugudde, and A. J. Busalacchi, 2006: Spatial and temporal variability of the surface water–pCO₂ and air–sea CO₂ flux in the equatorial Pacific during 1980–2003: A basin-scale cycle model. *J. Geophys. Res.*, **111**, C07S04, <https://doi.org/10.1029/2005JC002972>.
- , R. Murtugudde, E. Hackert, J. Wang, and J. Beauchamp, 2015: Seasonal to decadal variations of sea surface pCO₂ and sea-air CO₂ flux in the equatorial oceans over 1984–2013: A basin-scale comparison of the Pacific and Atlantic Oceans. *Global Biogeochem. Cycles*, **29**, 597–609, <https://doi.org/10.1002/2014GB005031>.
- Wanninkhof, R., 1992: Relationship between wind speed and gas exchange over the ocean. *J. Geophys. Res.*, **97**, 7373–7382, <https://doi.org/10.1029/92JC00188>.
- , and Coauthors, 2013: Global ocean carbon uptake: Magnitude, variability and trends. *Biogeosciences*, **10**, 1983–2000, <https://doi.org/10.5194/bg-10-1983-2013>.
- Watanabe, R., and Coauthors, 2011: MIROC-ESM2010: Model description and basic results of CMIP5-20c3m experiments. *Geosci. Model Dev.*, **4**, 845–872, <https://doi.org/10.5194/gmd-4-845-2011>.
- Weiss, R. F., 1974: Carbon dioxide in water and seawater: The solubility of a non-ideal gas. *Mar. Chem.*, **2**, 203–215, [https://doi.org/10.1016/0304-4203\(74\)90015-2](https://doi.org/10.1016/0304-4203(74)90015-2).
- Wu, T. W., and Coauthors, 2013: Global carbon budgets simulated by the Beijing Climate Center Climate System Model for the last century. *J. Geophys. Res. Atmos.*, **118**, 4326–4347, <https://doi.org/10.1002/jgrd.50320>.
- , and Coauthors, 2014: An overview of BCC climate system model development and application for climate change studies. *J. Meteor. Res.*, **28**, 34–56, <https://doi.org/10.1007/s13351-014-3041-7>.
- Zhou, T. J., L. W. Zou, B. Wu, C. X. Jin, F. F. Song, X. L. Chen, and L. X. Zhang, 2014: Development of Earth/climate system models in China: A review from the Coupled Model Intercomparison Project perspective. *J. Meteor. Res.*, **28**, 762–779, <https://doi.org/10.1007/s13351-014-4501-9>.