A Hindcast Approach to Diagnosing the Equatorial Pacific Cold Tongue SST Bias in CESM1

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ABSTRACT

An ensemble seasonal hindcast approach is used to investigate the development of the equatorial Pacific Ocean cold sea surface temperature (SST) bias and its characteristic annual cycle in the Community Earth System Model, version 1 (CESM1). In observations, eastern equatorial Pacific SSTs exhibit a warm phase during boreal spring and a cold phase during late boreal summer–autumn. The CESM1 climatology shows a cold bias during both warm and cold phases. In our hindcasts, the cold bias during the cold phase develops in less than 6 months, whereas the cold bias during the warm phase takes longer to emerge. The fast-developing cold-phase cold bias is associated with too-strong vertical advection and easterly wind stress over the eastern equatorial region. The antecedent boreal summer easterly wind anomalies also appear in atmosphere-only simulations, indicating that the errors are intrinsic to the atmosphere component. For the slower-developing warm-phase cold bias, we find that the too-cold SSTs over the equatorial region are associated with a slowly evolving upward displacement of subsurface ocean zonal currents and isotherms that can be traced to the ocean component.

1. Introduction

The tropical Pacific Ocean climate is governed by the interactions of winds, convection, and sea surface temperature (SST) at the atmosphere–ocean interface and is modulated by the seasonal variation of insolation. The complex interplay among these processes results in zonal and meridional asymmetries that characterize the tropical Pacific region. Along the equator, a band of cold SSTs forms the so-called equatorial cold tongue that extends westward from the eastern to the central Pacific. The equatorial cold tongue exhibits a strong annual cycle in SST that has its warmest and coldest phases when insolation is maximum at the equator, during March and September, respectively (Mitchell and Wallace 1992). This equinoctial contrast is largely understood to be a consequence of atmosphere–ocean coupling as expressed in the response of SSTs to wind forcing over the ocean surface (Xie 1994; Wang and McPhaden 1999). As the intertropical convergence zone (ITCZ) migrates northward in boreal summer, cross-equatorial winds over the eastern Pacific develop and drive westward upper-ocean Ekman transport and upwelling along the coast of South America (Hastenrath and Lamb 2004). This produces a negative SST zonal gradient at the western edge, forcing easterlies that in turn generate colder SSTs through equatorial upwelling (Nigam and Chao 1996). SST over the equatorial cold tongue reaches its minimum in boreal autumn, following the northernmost location of the ITCZ and strongest zonal and meridional winds. During boreal spring, surface winds are weakest and SST over the equatorial cold tongue is warmest.

Year-to-year fluctuations in the annual cycle of the equatorial cold tongue occur as part of El Niño–Southern Oscillation (ENSO), a major mode of tropical variability over the Pacific (Jin et al. 1994; Tziperman et al. 1994;
A realistic representation of the mean state and annual cycle of equatorial Pacific SSTs is thus key to an accurate simulation of ENSO (AchutaRao and Sperber 2006; Wittenberg et al. 2006; Jin et al. 2008). However, current atmosphere–ocean general circulation models (AOGCMs) struggle to capture the magnitude and annual cycle of the SST over the equatorial Pacific. Models show an equatorial Pacific cold tongue that is too cold and extends too far west (Mechoso et al. 1995; Davey et al. 2002; Wittenberg et al. 2006; Lin 2007; Li and Xie 2014). While observations show a warm phase of eastern equatorial Pacific SSTs in boreal spring and a cold phase in boreal autumn, models exhibit biases such as an early termination of the cold phase (Wittenberg et al. 2006), a delay of the warm phase (Small et al. 2014), and a spurious cooling in boreal spring (de Szoeke and Xie 2008).

Diagnosing the root cause of the equatorial cold tongue bias is challenging due to the complex interactions and feedbacks involved. The equatorial cold tongue bias is typically accompanied by the so-called double-ITCZ bias, which appears as deficient precipitation along the equatorial Pacific straddled by two zonal bands of excessive precipitation (Mechoso et al. 1995; Davey et al. 2002; Meehl et al. 2005). Precipitation and SST biases are further amplified by air–sea feedbacks such as the Bjerknes feedback (Bjerknes 1969) in the zonal direction, with excessive precipitation in the western Pacific driving overly strong easterlies that increase equatorial upwelling in the eastern Pacific (Lin 2007; Woelfle et al. 2018), and the stratus–SST feedback (Philander et al. 1996) in the meridional direction, with deficient stratus causing too-warm SSTs and excessive precipitation over the southeastern Pacific (Ma et al. 1996; Yu and Mechoso 1999; Li and Xie 2014; Zuidema et al. 2016). That the interplay of these processes changes from one season to another adds another layer of complexity.

Previous studies on the equatorial cold tongue and double-ITCZ bias have employed the classical approach of analyzing multimodel ensembles (Mechoso et al. 1995; Davey et al. 2002; Meehl et al. 2005; de Szoeke and Xie 2008; Li et al. 2015) and comparing biases in the fully coupled model ensemble with biases in their atmosphere-only counterparts (Lin 2007; Li and Xie 2014; Xiang et al. 2017). While this approach can help to identify which biases are robust and which errors are intrinsic to the atmospheric model, it does not allow us to understand the mechanisms and time scales through which the biases emerge. In addition, different models may have different pathways of how the biases develop. For instance, de Szoeke and Xie (2008) find that models with the eastern Pacific double-ITCZ bias also have a cold tongue cold bias and anomalous northerly winds during boreal spring. Using an SST-override approach, Song and Zhang (2016, 2017) investigated the remote impacts of tropical North Atlantic and southeastern Pacific SSTs on the equatorial Pacific cold tongue and double-ITCZ simulations. Other studies, however, suggest that the double-ITCZ and cold tongue bias are not always related and that a reduction in one bias does not necessarily improve the other (Li and Xie 2014; Woelfle et al. 2018). An approach through which we can study when the biases are initiated and how they develop would thus be useful.

Significant efforts have made use of climate model hindcast experiments, which are initialized from an operational analysis or reanalysis, to identify specific model deficiencies before the compensation of multiple errors masks the deficiencies (Phillips et al. 2004; Williams et al. 2013). In this way, the evolution of systematic errors of cloud processes in climate models can be studied. One can analyze how systematic biases associated with fast-developing model physics errors arise in the models as the large-scale state remains close to observations. This technique has been used extensively in a number of AGCM studies with focus on atmospheric moist processes (Xie et al. 2004; Williamson et al. 2005; Klein et al. 2006; Rodwell and Palmer 2007; Xie et al. 2012; Ma et al. 2014, among many others). In recent years, the climate model hindcast approach has been extended to fully coupled models in order to better understand SST biases (Vannière et al. 2013; Toniazzo and Woolnough 2014; Voldoire et al. 2014; Vannière et al. 2014; Woelfle et al. 2018). Using multimodel ensemble seasonal hindcasts, Vannière et al. (2013) find that the equatorial cold tongue bias exhibits a strong seasonality that differs from model to model. Some models have a pronounced cold bias during the warm phase of equatorial Pacific SSTs in boreal spring, whereas others develop the cold bias during the cold phase in boreal autumn. In one of the five models examined, the seasonality is further found to be modulated by ENSO—the cold bias develops during the warm phase in La Niña and during the cold phase in El Niño years.

In this study, we investigate the equatorial cold tongue bias in the Community Earth System Model, version 1 (CESM1), using ensemble seasonal coupled hindcasts. Building on previous studies that highlight the seasonality of the cold tongue bias and its seasonally varying interaction with precipitation and wind biases, we look at the annual cycle of the cold tongue bias growth in CESM1 in more detail. The aim of this paper is twofold: 1) to examine the growth of the cold bias and its characteristic annual cycle in CESM1 and 2) to diagnose the possible mechanisms that drive the anomalous cooling. We begin by first testing the hindcast approach by evaluating the correspondence between the biases that develop in the hindcasts and the systematic biases found in the long-term climate simulations in terms of the mean state and
of the annual cycle. The development of the cold bias, its time scale, and associated processes are then explored.

The remainder of the paper is organized as follows. Section 2 describes the model, the hindcast initialization procedure, and the reference datasets used in this study. The bias correspondence between the hindcasts and the climatology is presented in section 3. In section 4, we explore the possible drivers of the cold bias during the cold and warm phases of the cold tongue. Conclusions are provided in section 5.

2. Methods

a. Model

The hindcasts were performed using CESM, version 1.1.2. The model consists of the Community Atmosphere Model, version 5 (CAM5), for the atmosphere component (Neale et al. 2010); the Parallel Ocean Program, version 2 (POP2), for ocean (Smith et al. 2010); the Community Land Model, version 4 (CLM4), for land (Lawrence et al. 2011); and the Los Alamos Sea Ice Model (CICE) for sea ice (Hunke et al. 2010). The resolution used here is a $0.9^\circ \times 1.25^\circ$ grid for CAM and CLM and a 1° Greenland pole grid for POP2 and CICE. In the vertical direction, CAM5 is used with the standard 30 levels, whereas POP2 has 60 levels with a 1-m resolution in the upper 200 m. The CESM Coupler, version 7 (Craig 2014), controls the interaction among the individual component models and performs flux calculations and remapping at interfaces. The air–sea fluxes are computed from Large and Yeager (2009) bulk formulas. Details on the CESM1 model and its components are described in Hurrell et al. (2013).

b. Hindcast initialization and integration

In summary, initial conditions (ICs) for atmosphere and land are generated following the Cloud-Associated Parameterizations Testbed (CAPT) procedure described in Ma et al. (2015). Atmospheric ICs are derived from the European Centre for Medium-Range Weather Forecasts reanalysis (ERA-Interim; Dee et al. 2011). Land ICs are taken from an offline CLM simulation forced by observed precipitation, winds, and surface fluxes. Ocean ICs are taken from the Data Assimilation Research Testbed (DART) reanalysis from the National Center for Atmospheric Research (Karspeck et al. 2013). The DART reanalysis dataset is produced by applying a 48-member ensemble adjustment Kalman filter (EAKF) data assimilation system to POP2. Observations of subsurface temperature and salinity from the World Ocean Database 2009 (Johnson et al. 2009) are assimilated into the ocean model at a daily frequency from 1998 to 2005. The atmospheric forcing for the ocean model comes from an independently generated EAKF analysis with CAM, version 4 (Raeder et al. 2012), prescribed with Reynolds et al. (2002) optimally interpolated SSTs (OISST), version 2. We tested hindcasts using both 24 and 48 members with one starting date, and the hindcast results of cold tongue bias evolution and magnitude are very similar. To save computational resources, we only performed hindcasts with the first 24 ensemble members for all starting dates.

Applying the initial conditions to CESM1, 6-month-long coupled hindcasts are started on the first day of every month at 0000 UTC from August 2000 to December 2005. For each start date, an ensemble with 24 members is generated, using the DART ensemble of ocean ICs, but with the same atmospheric and land ICs in each ensemble member. As will be discussed in more detail in section 3, the cold bias during the warm phase is not clearly present within 6 months of lead time. The hindcasts started in February 2004 onward are therefore extended to 12 months to examine whether the bias needs a longer time to develop. Data from the simulations are available as monthly means and additionally as daily means for hindcasts with start dates between August 2004 and December 2005.

The simulation setup allows us to reconstruct a time series of monthly mean data on the basis of hindcast lead-time composites. A schematic diagram is shown in Fig. 1. The lead-time-based reconstructed monthly data from 2001 to 2005 are used to analyze the mean state and annual cycle of the SST bias growth.

c. Reference datasets

To evaluate the bias correspondence between the coupled hindcasts and the long-term climatology, we use historical simulations from the CESM1 Large-Ensemble (CESM1 LENS) Project (Kay et al. 2015) as the model climatology. The climatology is computed on the basis of 25 years, from 1980 to 2005, to be comparable with available observational datasets. SST biases are calculated with respect to OISST, version 2, data (Reynolds et al. 2002). Ocean subsurface variables in the hindcasts are compared with the DART reanalysis (Karspeck et al. 2013). Surface wind stress is evaluated using observations from the Quick Scatterometer (QuikSCAT) aboard the SeaWinds instrument (IFREMER/CERSAT 2002).

3. Bias correspondence

a. The mean state

Figure 2 shows the observed climatological mean SSTs over the tropical Pacific and the corresponding
biases in the model climatology and hindcasts. A cold bias along the equatorial Pacific is present in the climatology, together with a larger cold bias over the northern subtropical Pacific and warm biases south of the equator and along the coast of South America (Fig. 2b). In the hindcasts with 1-month lead (Fig. 2d), the SST over the tropical Pacific region remains close to the observed. The biases that are present in Fig. 2d can be traced to preexisting biases in the DART reanalysis that was used to initialize the hindcast (Fig. 2c). At 3 months of lead time, the spurious cooling over the equator emerges, starting at the eastern Pacific around 130°W (Fig. 2e). The bias subsequently extends westward and increases in magnitude at later lead times (Figs. 2f–h). In addition to the equatorial cold bias, the warm bias south of the equator also becomes apparent as well as the cold bias in the northern subtropical region. The SST bias patterns at later lead times are comparable to the climatological bias pattern, although differences in magnitude exist. Note that the sampling periods are also different, with the climatology covering 25 years, whereas the hindcast biases in Figs. 2d–h are calculated for 2005 (the year with hindcasts extended to 12-month lead).

The SST mean bias correspondence between the climatology and hindcasts for 2005 (12-month-long hindcasts), as well as for 2001–04 (6-month-long hindcasts), are summarized in a Taylor diagram (Taylor 2001) in Fig. 3. Here, we use the climatological bias pattern of CESM1 with respect to OISST as the reference field in order to quantify how well the hindcast bias corresponds to the climatological bias. The Taylor statistics are computed over the equatorial Pacific (the black box in Fig. 2b), between 10°S and 10°N and 150°E and 90°W. The spatial standard deviations in the 2002–05 hindcasts with lead times greater than 4 months are larger than the climatology because of the larger magnitude of the bias in the hindcasts than in the climatology. The small standard deviations in 2001 are consistent with the relatively smaller bias magnitudes that result from the 2000–01 La Niña (i.e., weaker cold bias in cold years). Similarly, the largest standard deviations are in 2002 and 2003, which are moderate El Niño years. For the bias correlation, all years show increasing correlation with increasing lead time, with correlation coefficients of ~0.85 at 6-month lead. The increasing correlation with lead time indicates that the hindcasts have bias patterns that grow toward the climatological pattern and can thus be used to study the bias emergence and growth. As seen in extended hindcasts in 2005, the bias correlations seem to saturate after 7 months of lead time. The bias correspondence in the extended 2005 hindcasts in the present study is consistent with the correspondence found in multiyear (1980–2014) 12-month hindcasts for CESM1 from the North American Multimodel Ensemble (NMME) project (Kirtman et al. 2014), despite differences in simulation period coverage and initialization procedures (H.-Y. Ma et al. 2019, unpublished manuscript). Note also that the characteristics of the strong correspondence in SST biases as seen in Figs. 2 and 3 are also shown in fast-physics-related atmospheric fields (e.g., clouds and precipitation) although systematic climate errors in the latter emerge much faster, often in just 3–5 days of hindcast lead time (Xie et al. 2012; Ma et al. 2014).

We further evaluate the annual mean subsurface ocean temperature in the hindcasts. Figure 4 shows the zonal-vertical cross section of the temperature difference between the hindcasts and the DART reanalysis in the upper 250 m along the equatorial Pacific. We see that
the subsurface ocean temperature structure is consistent with the SST bias growth in the hindcasts. A cold bias develops over the eastern Pacific at around 3 months of lead time and is largest at ~75-m depth centered around 100°W. The cold bias is accompanied by the shoaling of the mixed layer (denoted by the dashed line for the hindcast and solid line for the reanalysis). At longer lead times, the cold bias extends upward and westward. A warm bias concurrently develops over the western Pacific, associated with the deepening of the mixed layer.

b. The seasonal cycle

The annual mean bias consists of biases that occur within the annual cycle. Here, we examine how the equatorial cold tongue cold bias develops through the annual cycle by evaluating the monthly mean bias growth in the hindcasts. Figure 5 shows the zonally averaged annual cycle of SST over the eastern Pacific (90°–150°W) in OISST and the corresponding biases in the model climatology and hindcasts with various lead times. Along the equator, observations show a warm phase during boreal spring and a cold phase during late boreal summer–autumn. The CESM1 climatology shows a cold bias through most of the year, with the bias at its maximum during the warm and cold phases (Fig. 5c). The cold bias is minimum during the transition from boreal spring to summer. The cold bias maximum during March followed by a minimum during May–June results in an apparent delay in the warm phase, whereas the maximum during September results in a too-strong cold phase in the climatological annual cycle of CESM1 (Fig. 5b). In the hindcasts, the cold-phase cold bias develops earlier, within 6 months of lead time, whereas the warm-phase cold bias takes longer than 6 months to emerge. The cold-phase cold bias at the equator is present as early as 3 months of lead time, intensifying and extending...
through November at 6 months lead. During the warm phase, a cold bias can be found at 10°–15°N, but not at the equator in the 3–6 months of lead time (Figs. 5e,f). It is by 9–12 months of lead time that the annual cycle of the cold bias becomes more similar to that of the climatology (Figs. 5c,g,h). The 12-month hindcast, however, shows a stronger cooling during January–February and a spurious warming during December as compared with the climatology.

The earlier emergence of the cold-phase cold bias indicates that hindcasts that are initialized around the cold phase drift more quickly than those initialized outside this period. Figure 6 shows the SST averaged over the Niño-3 region (the red box in Fig. 2b) for hindcasts initialized in February, May, August, and November, with each set composed of 24 ensembles. We see that hindcasts with start dates outside the cold phase, such as February and November, stay close to observations. In contrast, in hindcasts with start dates preceding and during the cold phase, such as May and August, a stronger drift occurs. The May and August hindcasts also show increasing ensemble spread with lead time, but nevertheless develop the cooling shortly after initialization for all ensemble members.

Vannière et al. (2013) find a similar seasonality and start-date dependence of the cold bias in other AOGCMs from the ENSEMBLES-FP6 Project (Weisheimer et al. 2009). For instance, they show that models such as the Institut für Meereskunde (Institute of Marine Sciences) in Kiel, Germany (IFM-Kiel; Keenlyside et al. 2005; Jungclaus et al. 2006), and Météo-France (Salas Mélia 2002; Daget et al. 2009) models show a warm-phase cold bias, whereas the Met Office (Collins et al. 2008) model exhibits a cold-phase cold bias. The INGV-CMCC (Alessandri et al. 2010) model shows a too-strong cooling over the cold tongue during its warm and cold phases, a behavior similar to CESM1. They further find that such seasonality depends on the ENSO phase. In El Niño years, INGV-CMCC hindcasts started in May exhibit strong drifts, whereas those started in November remain close to observations. The opposite occurs during La Niña years: hindcasts started in May are closer to observations than those started in November. In Fig. 6, the 2000–01 La Niña and 2002–03 El Niño are marked by blue and red boxes, respectively, on the x axis. The weak El Niño in 2004–05 is denoted by a light-red box. Given the 5-yr period of our CESM1 hindcasts, it is difficult to clearly diagnose an ENSO phase dependence. That November hindcasts stay close to and May hindcasts drift from observations and reanalysis for all years, regardless of the ENSO phase, would, however, suggest that there is a weak relationship between the seasonality of the cold bias in CESM1 with ENSO.

4. Mechanisms behind the cold bias

In this section, we will investigate the mechanisms associated with the development of the cold bias in the hindcasts. We will start the analysis with the earlier emerging cold-phase cold bias, followed by the warm-phase cold bias.

a. The cold-phase cold bias

To investigate the processes that contribute to the SST cold bias during the cold phase, we look at the temperature budget over the upper 100 m of the ocean over the Niño-3 region (5°S–5°N, 90°–150°W). This layer covers the depth of the cold bias and mixed layer over the eastern equatorial Pacific (see Fig. 4). Focusing on the cold phase from May to October, we compute the budget following Zheng et al. (2010, 2012):

$$\int_{\text{May}}^{\text{Oct}} \frac{\partial T}{\partial t} dt = \int_{\text{May}}^{\text{Oct}} \left( \frac{Q_{\text{net}}}{\rho c_p H} \rho \left( \frac{\partial T}{\partial x} + \frac{\partial T}{\partial y} + \frac{\partial T}{\partial z} \right) \right) dt + \text{residual},$$

where $Q_{\text{net}}$ is the net surface heat flux input into the ocean, $c_p$ is the specific heat of the ocean, $\rho$ is the density of seawater, and $H$ is the depth of the layer, taken here to be 100 m. The square brackets denote vertically averaged terms. In Eq. (1), the total cooling from May to October is expressed as a sum of the net surface heat flux.
and ocean advection. The effects of neglected processes such as diffusion and of unresolved terms such as eddy heat flux divergence are computed as a residual. The budget is first calculated using monthly mean fields that are available for both the DART reanalysis and the hindcasts. Daily fields, available for May 2005 hindcasts, are then used to further evaluate the role of submonthly transients.

Figure 7 shows the temperature budget of the ensemble mean of hindcasts started from 1 May to 31 October 2005 and of the DART reanalysis, averaged over the upper 100 m of the Niño-3 region. Consistent with Fig. 6, the May 2005 hindcast shows a stronger cold-phase cooling relative to the reanalysis. The net surface heat flux is a warming term, following the semiannual cycle of the solar radiation over the equatorial region. It is larger in the hindcast than in the reanalysis, which implies that the cold bias is driven by other processes related to ocean transport. Indeed, much of the cooling over the equatorial Pacific comes from vertical advection, which is stronger in the hindcast as compared to the reanalysis. The zonal advection acts as a secondary cooling term in the hindcast, thus contributing to the cold bias. The meridional advection is a weak cooling term in the hindcast, whereas it is a weak warming term in the reanalysis. When daily output from the same period is used for the budget calculation in the hindcast, cooling from zonal and meridional advection decreases, together with a decrease in residual warming (not shown), implying that submonthly transients partly contribute to a warming tendency.

The difference in the partitioning of the May to October cooling between the hindcast and the reanalysis shows that the cold bias in the hindcast is largely driven by a too-strong equatorial upwelling. The too-strong upwelling is consistent with the strong easterly wind stress bias over the Niño-3 region, which is present as early as the first month of lead time and precedes the onset of the cold SST bias (Fig. 8a). At 3 months of lead time, the easterly bias is larger and extends westward around 150°W along the equator, with the cold bias at its eastern edge (Fig. 8b). This is in accordance with the westward expansion mechanism of Nigam and Chao (1996): Easterly winds drive equatorial upwelling, resulting in cold SST anomalies. A zonal SST gradient
develops, with easterlies generated at the western edge of the cold SST anomalies. These easterlies generate new cold SST anomalies at the western edge of the previous ones and this cycle can repeat again. In Fig. 8b, the easterly wind bias leads the cold SST bias by 1–2 months, as can be expected from the Ekman equatorial upwelling time scale (Neelin 1991; Nigam and Chao 1996).

To demonstrate the role of wind stress on the SST bias, we perform ocean-only hindcasts with and without biased zonal wind stress. The hindcasts are forced at the surface using the Coordinated Ocean Research Experiments (CORE), version 2 (Large and Yeager 2009), dataset. The simulations are initialized on 1 January of every year from 2001 to 2005 using initial conditions from DART.

Fig. 6. SST over the Niño-3 region in OISST (black), in the DART reanalysis (gray), and in the ensemble hindcasts with start dates in February (blue), May (green), August (orange), and November (light blue). The blue box on the x axis marks La Niña; red boxes mark El Niño, with a lighter shading denoting a weaker event.
and are run for 12 months with 10 ensemble members (based on a subset of the DART ensemble). In the experiment simulation with biased zonal wind stress, we override the zonal wind stress passed by the coupler to the ocean model and replace it with the global, monthly mean zonal wind stress field extracted from the 1-month lead-time coupled hindcast. This means that for each month, the zonal wind stress is taken from a hindcast simulation that is no more than 1 month after its initialization. The experiment is designed such that the wind stress modification impacts the SST directly through its dynamical effect. The turbulent heat fluxes are still calculated based on wind and near-surface temperature and humidity from COREv2, similar to the control simulation, but are indirectly impacted by the SST change from the wind stress modification.

Figure 9 shows the monthly mean wind stress and SST over the Niño-3 region in the ocean-only hindcast simulations averaged over 5 years. We see that the ocean-only control simulation shows wind stress and SST values comparable to observations. The prescribed biased zonal wind stress in the experiment is, by design, stronger than the CORE-based wind stress in the control starting in boreal summer. Colder SSTs develop in the experiment from late boreal summer to autumn, with magnitudes around 2°C less than the control. This SST difference is comparable to the cold-phase cold bias magnitude in the coupled hindcasts of about 3°C, thus confirming that the cold-phase cold bias is primarily driven by the dynamical impact of an anomalous easterly wind stress.

The boreal summer easterly wind stress bias over the eastern equatorial Pacific in our fully coupled hindcasts (Fig. 8) is a bias that is also present in atmosphere-only simulations with prescribed observed SSTs. Figure 10 shows the zonally averaged annual cycle of precipitation and wind stress over the eastern Pacific in observations and models, as well as the corresponding model biases. In boreal summer, cross-equatorial winds flow toward the northward migrating ITCZ (Fig. 10a). On the equator, the zonal component of this flow is overestimated in the CESM1 climatology (Fig. 10d) and in the coupled hindcasts (Figs. 10g–k) during May–August. The bias can be traced to easterly anomalies present in CAM5, the atmospheric component of CESM1 (Fig. 10e). The wind anomalies in CAM5 are accompanied by excessive precipitation at the southern edge of the northern ITCZ around 5°N.

Additional uncoupled hindcast simulations with the atmospheric component CAM5 are performed to

![Figure 7](image-url)  
**Fig. 7.** Temperature budget, averaged over the upper 100 m of the Niño-3 region, integrated from May to October 2005 for the hindcast ensemble mean initialized from 1 May 2005 (light blue) and DART reanalysis (gray). Contributions to the total cooling (c) from net surface heat flux, vertical advection, zonal advection, meridional advection, and residual are indicated as QNET, VADV, ZADV, MADV, and RES, respectively.

![Figure 8](image-url)  
**Fig. 8.** The 2005 boreal summer (June–August) mean surface wind stress and SST bias in the hindcasts with respect to QuikSCAT and OISST.
diagnose over which time scale the easterly wind bias develops. The atmosphere-only hindcast simulations follow the atmosphere and initialization procedure (Ma et al. 2015) in section 2, with the SST prescribed using the OISST (Reynolds et al. 2002) dataset. The simulations are started every day at 0000 UTC and run for 50 days covering 1997–2012. Figure 10f shows that the CAM5 hindcasts develop precipitation and easterly wind stress biases very quickly, within 5 days of lead time, although the causes of the wind bias are still unknown. The short time scale indicates that processes associated with fast physics in the atmosphere are involved.

b. The warm-phase cold bias

In contrast to the boreal summer easterly wind bias that originates from the atmosphere model, the boreal spring northerly wind bias found in CESM1 (Fig. 10d) is much weaker in CAM5 (Fig. 10e). The precipitation structures are also different. In CAM5, a weak double ITCZ occurs during boreal spring, similar to observations, although the precipitation intensities are overestimated (Fig. 10c). When coupled to the ocean, the northern branch of the ITCZ weakens considerably as the southern branch enhances (cf. Fig. 10b with Fig. 10c). This suggests that the wind and precipitation biases in boreal spring develop through interactions with SST biases. Previous studies have suggested the strong coupling between the spurious southward ITCZ and the equatorial cold tongue SST bias (Lin 2007; de Szoeke and Xie 2008). However, the exact mechanisms are unclear, with some studies indicating that the spurious southward ITCZ and equatorial cold tongue SST bias can in fact develop independently (Li and Xie 2014; Woelfle et al. 2018). Other studies emphasize the role of off-equatorial biases, such as the cold bias over the northeastern Pacific, the warm bias over the southeastern Pacific (de Szoeke and Xie 2008; Wang et al. 2015; Song and Zhang 2016, 2017), and the warm bias over the tropical North Atlantic (Song and Zhang 2017). In the following, we explore the relationships between these three biases in boreal spring: the spurious southward ITCZ, the equatorial cold tongue SST bias, and the off-equatorial SST biases. By examining how these biases develop in the coupled hindcasts, we aim to determine whether they occur together or independently.

During the warm phase, the equatorial cold SST bias does not emerge until lead times greater than 6 months (Figs. 5g,h). At earlier lead times, a cold bias is instead found north of the equator (Figs. 5e,f). This cold bias is collocated with the locally warmest waters over the northeastern Pacific region (blue box in Fig. 11a and Fig. 2a). Similar to the findings of Wang et al. (2015), we note that this northeast Pacific cold bias is associated with an anomalous weakening of the North Equatorial Countercurrent at 5°–10°N (not shown). The northeast Pacific cold bias is accompanied by a warm bias south of the equator (Fig. 11a). The cold SST bias in the northeast and the warm SST bias in the south occur together with anomalous northerlies and a spurious southward...
ITCZ that also develop at 3 to 6 months of lead time (Figs. 5e,f and 10h,i). We therefore see that the off-equatorial SST biases and the spurious southern ITCZ bias, present at early lead times, develop independent of the warm-phase cold bias at the equator, which emerges at later lead times. This supports the results of Li and Xie (2014) and Woelfle et al. (2018), which show that the boreal spring spurious southward ITCZ bias is not always tied to the equatorial cold bias.

Why then does the warm-phase equatorial cold bias take more than 6 months of lead time to emerge? Unlike the cold-phase cold bias, the later emergence of the warm-phase cold bias means that it is more difficult to diagnose. It develops farther away from initialization, and, as such, feedbacks and compensation of ocean–atmosphere biases would tend to mask the sources of the warm-phase equatorial cold bias. An upper-ocean temperature budget analysis for the warm phase is also unsuitable, as the temperature tendencies would be influenced by the already present cold-phase cold bias. With these limitations in mind, we attempt to gain further insight on the warm-phase cold bias by considering at least two possibilities: First, the warm-phase equatorial cold bias can only develop after the cold-phase equatorial cold bias. The May–November cold bias would change the ocean–atmosphere state, setting the stage for the cold bias in the following January–April months. Second, the warm-phase equatorial cold bias occurs separately from the cold-phase cold bias but has a slower time scale because slower processes related to the ocean component are involved.

A simple way to test the two hypotheses is to use the ocean-only control hindcast simulations from section 4a. Recall that the ocean-only control hindcasts are forced at the surface with the COREv2 dataset and hence do not develop a cold-phase cold bias. We take the ocean-only control hindcast that is started on 1 January of 2005 and
run for 12 months with 10 ensembles. We refer to this initial 12-month simulation as the first cycle. In the first cycle, the January–April months are only 1–4 months away from the initialization date and as such, the warm-phase equatorial cold bias is not expected to fully develop. The ocean-only hindcast is then extended to another 12 months, referred to as the second cycle, such that the prescribed surface forcings are the same as the first cycle but the January–April months are now 13–16 months away from the initialization date.

Figures 11d and 11e show the boreal spring SST bias in the first and second cycles of the ocean-only hindcasts, respectively. A small cold bias a few degrees north of the equator in the eastern Pacific can be seen in the first cycle, with a magnitude of less than 0.5°C. In the second cycle, a larger cold bias in the eastern equatorial Pacific develops, with a magnitude of about 1.5°C–2°C, comparable to that in Fig. 11c. The ensemble spread is much smaller than the SST biases in the first and second cycles (not shown). The second cycle of the ocean-only hindcasts shows that the warm-phase cold bias develops even without a pre-existing cold-phase cold bias, provided the simulation is far enough away in time from the initialization date. The cold bias over the eastern equatorial Pacific is thus traced to the ocean component of the model, supporting our second hypothesis on the role of slow ocean processes. This also suggests that the first hypothesis is not correct, since boreal spring cold bias develops without the presence of the May to November cold bias in cycle 1. Interestingly, over the western equatorial Pacific (160°E–150°W) as well as over the northeast Pacific (blue box in Fig. 11a), the 9- and 12-month coupled hindcasts show cold biases (Figs. 11b,c) that are not present in the second cycle of the ocean-only hindcast (Fig. 11e). This suggests that for the western and northeast Pacific cold biases, coupling with the atmosphere is an important factor for bias development.

Figure 12 shows the subsurface ocean temperature structure and zonal current along the equatorial Pacific (2°S–2°N) for the ocean-only hindcasts. Over the eastern Pacific, the isotherms in the second cycle are shifted upward as compared with those in the first cycle, resulting in colder waters at the uppermost layers up to the surface. The upward tilt of the isotherms is consistent with the stronger and higher core of the Equatorial Undercurrent (EUC), an eastward-flowing current linking the deeper cold waters in the west to shallower cold waters in the eastern equatorial Pacific. These upward displacements in the isotherms and EUC structure likely take several months to occur, in line with the slower time scale of the warm-phase equatorial cold bias over the eastern Pacific. Thus, we attribute the boreal spring cold bias to a 6–12-month adjustment of the EUC into a biased state.

In theory, the strength and structure of the EUC is determined by a seasonally varying balance between the eastward zonal pressure gradient force in the upper ocean and the westward surface stress (Philander 1973; McPhaden and Taft 1988; Drenkard and Karnaukas 2014). Biases in the simulated EUC in models can thus come from errors in the surface forcing, in the ocean circulation, or parameterizations. That ocean-only simulations (Fig. 12) exhibit biases in the EUC suggest that the latter two may be more important. For instance, past studies have attributed the EUC anomalies that develop in ocean-only models to uncertainties in the magnitudes of the lateral viscosity and diffusivity coefficients, which impact the depth and strength of EUC, along with the

![Figure 11](image-url)
thermocline structure and vertical mixing in the ocean (Stockdale et al. 1993; Maes et al. 1997; Jochum et al. 2008; Danabasoglu et al. 2012). A detailed analysis of the EUC bias and its associated anomalous ocean processes would require additional research and is beyond the scope of this paper.

5. Conclusions

This study investigated the equatorial Pacific cold tongue bias in the coupled climate model CESM1 through the use of ensemble seasonal hindcasts. The too-cold cold tongue problem is shared by other models and is particularly challenging to diagnose because of the coupled atmosphere–ocean interactions and feedbacks involved. This close coupling is typified by the fact that the cold bias occurs together with biases in other fields such as surface winds and precipitation (Mechoso et al. 1995; Davey et al. 2002; Meehl et al. 2005; Lin 2007; Li and Xie 2014). Another source of difficulty is that these interactions change from one season to another and may be represented differently from one model to another. Given these complexities, our approach is to use ensemble seasonal hindcasts with CESM1, initialized from a reanalysis, as a means of diagnosing how errors in long-term climatological simulations emerge and grow.

We first tested the hindcast approach by examining the correspondence between biases in the short-term hindcasts and those in the long-term climatology. We found that in the mean state, the equatorial Pacific cold tongue cold bias emerges by 3 months of hindcast lead time. The cold bias starts over the eastern region and subsequently extends westward at later lead times. With increasing lead time, the spatial correlation of the hindcast and climatological biases increases. The mean state equatorial cold bias becomes comparable to its climatological counterpart from 6 months of lead time onward, showing that hindcasts performed over a few months can indeed be used to study some long-term climatological biases. The bias correspondence in the mean state is also evident in the annual cycle. In the climatology, CESM1 shows a cold bias during boreal spring (warm phase) and during late boreal summer–autumn (cold phase). Our analysis revealed that in the hindcasts, the warm and cold-phase cold biases over the eastern equatorial Pacific have different time scales of development. The cold-phase cold bias emerges earlier, within 6 months of lead time, whereas the warm-phase cold bias takes more than 6 months to emerge. This seasonality is consistent with the dependence of the bias growth on the initialization month: hindcasts started around the cold-phase period drift more quickly than those initialized outside the cold phase.

The rapid emergence of the cold-phase cold bias suggests that fast processes in the atmosphere and upper ocean are involved. Analyzing the upper-ocean heat budget, we found that the cold bias during this period comes from too-strong vertical advection. The vertical advection bias is in turn associated with the too-strong easterly wind stress, which emerges as early as the first month of lead time, preceding the onset of the cold SST bias. An ocean-only hindcast with erroneous prescribed zonal wind stress taken from the coupled hindcast with 1-month lead confirms that the cold SST bias develops in response to too-strong easterly wind stress. In contrast, the later emerging warm-phase cold bias is found to be related to slower ocean processes such as the upward

FIG. 12. February–April longitude–depth plots along the equatorial Pacific (2°S–2°N) of the (top) mean subsurface ocean temperature and (bottom) zonal current in the (left) first (right) second cycles of the ocean-only control simulation.
displacement of isotherms and the Equatorial Undercurrent maximum over the eastern Pacific.

Comparison of the annual cycle of SST, wind, and precipitation biases over the eastern Pacific between the fully coupled CESM1 and its atmosphere component CAM5 shows that the easterly wind bias that drives the cold-phase cold tongue bias in the coupled model originates from the atmosphere model. Atmosphere-only hindcasts further show that the easterly wind bias develops quickly, within 5 days of lead time, although the causes of the wind bias are still unknown. On the other hand, the anomalous northerlies and the southward ITCZ bias during the warm phase are considerably enhanced in CESM1 as compared to CAM5, indicating that these are biases that result from air–sea coupling and feedbacks. Based on the bias growth as seen in the coupled hindcasts and on the comparison of the accompanying wind and precipitation biases between the fully coupled and atmosphere-only model, the annual cycle progression of the cold tongue bias is summarized as follows. First, boreal summer easterly anomalies, originating from the atmosphere model, develop quickly within a few days after initialization. The easterly wind anomalies drive strong vertical and zonal ocean advection that leads to a too-cold equatorial cold tongue in late boreal summer–boreal autumn by 3 months of lead time. At 3–6 months from initialization, the cold-phase cold bias is larger and extends through late autumn. Meanwhile, during late boreal winter to boreal spring, off-equatorial SST biases (cooling over the northeastern Pacific and warming south of the equator) develop and induce excessive precipitation over the southern ITCZ and anomalous northerlies. Unrelated to this, anomalies in the subsurface temperature and zonal current structure reach the surface at lead times greater than 6 months, resulting in the warm-phase equatorial cold bias.

On the basis of the above findings, we conclude that 1) the cold bias develops at different time scales depending on the season, with the cold bias during the cold phase evident within 6 months of lead time but does not emerge until well after 6 months during the warm phase; and 2) biases in SST associated with atmosphere–upper-ocean interactions, as in the wind-driven cold-phase cold bias, develop faster than those that arise as a result of subsurface ocean biases, as in the case of the warm-phase cold bias. We also note that the seasonality of equatorial Pacific cold tongue bias shown in this paper may differ from model to model.

This study demonstrates that the hindcast approach is a valuable method for the diagnosis and attribution of SST biases. This method allows one to study the SST bias growth and determine the time scales and mechanisms through which the bias develops. Because the hindcasts require only a few months of integration, they also provide a computationally cost-effective way of assessing and improving our climate models.

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