Seasonal ENSO phase locking in the Kiel Climate Model: The importance of the equatorial cold sea surface temperature bias

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Abstract

The El Niño/Southern Oscillation (ENSO) is characterized by a seasonal phase locking, with strongest eastern and central equatorial Pacific sea surface temperature (SST) anomalies during boreal winter and weakest SST anomalies during boreal spring. In this study, key feedbacks controlling seasonal ENSO phase locking in the Kiel Climate Model (KCM) are identified by employing Bjerknes index stability analysis. A large ensemble of simulations with the KCM is analyzed, where the individual runs differ in either the number of vertical atmospheric levels or coefficients used in selected atmospheric parameterizations. All integrations use the identical ocean model. The ensemble-mean features realistic

seasonal ENSO phase locking. ENSO phase locking is very sensitive to changes in the mean-state realized by the modifications described above. An excessive equatorial cold tongue leads to weak phase locking by reducing the Ekman feedback and thermocline feedback in late boreal fall and early boreal winter. Seasonal ENSO phase locking also is sensitive to the shortwave feedback as part of the thermal damping in early boreal spring, which strongly depends on eastern and central equatorial Pacific SST. The results obtained from the KCM are consistent with those from models participating in the Coupled Model Intercomparison Project phase 5 (CMIP5).

1. Introduction

The El Niño/Southern Oscillation (ENSO) is the dominant mode of interannual climate variability in the tropics. ENSO is characterized by sea surface temperature (SST) anomalies of a few centigrade primarily in the eastern and central equatorial Pacific, which drive global teleconnections (e.g. Brönnimann et al. 2004). The warm phase of ENSO is termed El Niño, its cold phase La Niña. A robust feature of ENSO is its preference to exhibit peak SST anomalies in boreal winter and to depict only small anomalies in boreal spring. This behavior is referred to as seasonal ENSO phase locking (e.g. Tziperman et al. 1998; Neelin et al. 2000; McGregor et al. 2012).

Several previous studies have discussed the dynamics that cause the seasonal phase locking of ENSO (e.g. Chang et al. 1995; Tziperman et al. 1995; Jin et al. 1996; Harrison and Vecchi 1999; Neelin et al. 2000; Stuecker et al. 2013; McGregor et al. 2013; Zhu et al. 2015). Yet there are still significant gaps in our understanding of these dynamics. A majority of these studies provide an explanation in terms of stochastic forcing acting on a seasonally changing background state. Others argue in terms of feedbacks. For example, the termination of ENSO in boreal spring can be linked to the southward shift of wind anomalies (Harrison and Vecchi 1999; Stuecker et al. 2013 and McGregor et al. 2013) or to the relatively weak linkage between SST and thermocline depth in that season (Zhu et al. 2015). Results by Stein et al. (2010) on the basis of the recharge oscillator suggest that the seasonally varying growth rate is critical to ENSO phase locking, where damping by the mean flow field dominates the seasonally changing dynamics. Dommenget and Yu (2016) show that ENSO phase locking is strongly linked to seasonal changes in shortwave radiation due to changes in cloud cover.

In the past, significant progress has been made in understanding ENSO dynamics (see e.g. Wang and Picaut 2004 for a review) and in simulating ENSO (e.g. Bellenger et al. 2014). However, many coupled ocean-atmosphere general circulation models (CGCMs) still have difficulties in simulating seasonal ENSO phase locking as observed. Amongst others, ENSO phase locking is particularly important to ENSO forecast (Jin and Kinter 2009) and ENSO teleconnections. For example, the influence of ENSO on the Indian summer monsoon critically depends on the CGCMs′ ability to realistically represent ENSO phase locking (e.g. Webster et al. 1998). Typical problems in CGCMs are that ENSO extremes either peak in the wrong season (e.g. Ham et al. 2012; Ham and Kug 2014; Rashid and Hirst 2015) or that the annual variation of SST variability is too weak (Ham and Kug 2014; Bellenger et al. 2014).

Zheng and Yu (2007) link the spurious summer peak in ENSO variability in the FGCM model to the double Intertropical Convergence Zone (ITCZ) problem. This model bias sets conditions for heat content anomalies originating erroneously south of the equator and at the wrong time of the year. Ham et al. (2012) identify an excessively large SST gradient and resultant thermocline shoaling in boreal summer to enhance zonal advection feedback and thermocline feedback as reasons for spurious boreal summer variability in the GFDL CGCM. Similar results are obtained by Ham and Kug (2014) for a set of CMIP3 and CMIP5 models. Rashid and Hirst (2015) find an incorrect simulation of the shortwave feedback and thermocline feedback to cause variability to peak in March instead December-February in the ACCESS CGCM and link the biases to errors in long-term mean SST.

A number of studies have focused on finding reasons for too weak annual variation of interannual variability in CGCMs, but with the seasonal phase being overall correct. Xiao and Mechoso (2009) show that the seasonal warming of the cold tongue in January-April favors the onset of an El Niño or La Niña event, whereas the termination of an event is connected to a southward shift of surface zonal wind anomalies. Ham and Kug (2014) also link the importance of the southward shift of surface zonal wind anomalies to a models' ability to have ENSO phase-locked to the annual cycle. Furthermore, Bellenger et al. (2014) suggest that a better simulation of the shortwave feedback helps to simulate a more pronounced annual variation of equatorial Pacific SST variability in CMIP3 and CMIP5 models.

ENSO originates from large-scale ocean-atmosphere interactions and is based on a feedback cycle, as originally proposed by Bjerknes (1969). The Bjerknes stability index (BJ index) of Jin et al. (2006) is a powerful tool to examine feedbacks, positive and negative, relevant to ENSO and the relative importance of the contributing terms on the basis of a linearized SST equation. The BJ index therefore is a measure of coupled ocean-atmosphere stability or growth rate of SST anomalies. Stein et al. (2014) argue that the seasonal modulation of the coupled stability is responsible for the ENSO being phase-locked to the annual cycle. Hence, the BJ index would form a useful and comprehensive tool for investigating ENSO phase locking, particularly because it comprises those processes in both atmosphere and ocean that are known to determine interannual variability. This also is consistent with Stein et al. (2010) who use the seasonally changing BJ index to examine ENSO phase locking in a simple recharge oscillator model.

In the equatorial Pacific, a pervasive systematic bias in CGCMs is an excessive equatorial cold tongue (e.g. Davey et al. 2002; Zhang et al. 2007; Guilyardi et al. 2009). Although relatively small in magnitude compared to other tropical SST biases (e.g. the southeastern tropical Pacific warm SST bias), the cold equatorial Pacific SST bias has far reaching implications. Too cold sea surface conditions in the cold tongue region suppress precipitation at the equator (Li and Xie 2014), among others one reason for the double ITCZ problem, and thus reduce ocean-atmosphere coupling. Therefore it is not surprising that the cold SST bias influences a CGCM's ability to simulate ENSO (e.g. Kim et al. 2013) and in particular ENSO phase locking (Battisti and Hirst 1989; Ham and Kug 2014).

In this study, the controls of seasonal ENSO phase locking in the Kiel Climate Model (KCM) are investigated. A novel approach applied here is the usage of the BJ index to identify the processes that determine ENSO phase locking in a CGCM. The BJ index is calculated for each calendar month separately to investigate its seasonal variation. Analysis of the individual feedbacks contributing to the BJ index reveals the importance of specific physical processes that control ENSO phase locking in the KCM. Moreover, the feedbacks are linked to the long-term mean-state. Thus possible reasons for ENSO phase locking biases in the KCM are discussed in terms of both the feedbacks and mean-state. A set of 40 KCM experiments provides the basis for this study. The experiments differ in atmospheric parameters used in selected physical parameterizations and vertical atmospheric model resolution, whereas the ocean configuration is held fixed. In previous studies, similar changes to the atmospheric component were shown to have large influence on both climatology and interannual variability of the tropical regions (Kim et al. 2011; Ham et al. 2012; Harlaß et al. 2015). The results from the KCM are compared to those obtained from climate models participating in the CMIP5.

First results based on the ensemble-mean calculated over all experiments conducted with the KCM are discussed. Furthermore, all sensitivity experiments are compared with each other and thus factors critical to ENSO phase locking in the KCM are identified. This paper is structured as follows. Section 2 introduces the KCM, experiment setup, observational datasets and the methodology applied in the stability analysis. Section 3 briefly describes the performance of the KCM in simulating tropical Pacific mean-state. In Section 4, the main results about factors controlling the ENSO phase locking in the KCM are presented. Major conclusions, comparison with CMIP5 models and discussion of the main findings follow in Section 5 and conclude the paper.

2. Coupled model, data and method

We employ a version of the Kiel Climate Model (KCM; Park et al. 2009). The atmospheric component of the KCM is the European Centre for Medium Range Weather Forecasts (ECMWF) Hamburg atmospheric general circulation model version 5 (ECHAM5; Roeckner et al. 2003). The ECHAM5 model used in this study, differently from Park et al. (2009) where a prognostic cloud scheme (Tompkins 2002) is used, predicts cloud fraction on the basis of relative humidity (Sundqvist 1978) and uses a cumulus mass flux scheme that includes vertical transport by shallow and deep convective clouds (Nordeng 1994). ECHAM5 is coupled to the Nucleus for European Modeling of the Ocean (NEMO; Madec et al. 1998; Madec 2008) ocean-sea ice general circulation model via the Ocean Atmosphere Sea Ice Soil version 3 (OASIS3; Valcke 2006) coupler.

A set of 40 "present-day" integrations of the KCM (each 100 years long) is analyzed (see Table 1 for a list of all experiments), in which the atmospheric CO_2-concentration is constant at 348 ppm. The atmospheric horizontal resolution is T42 (~2.8°) in all experiments. The horizontal ocean resolution also is the same throughout the experiments and based on a 2° Mercator mesh (ORCA2 grid) and is on average 1.3° with increased meridional resolution of 0.5° near the equator and 31 levels in the vertical. The experiments differ in two respects. First, in atmospheric vertical resolution: experiments 1-28 use a model version with 19 vertical levels, experiments 29-34 a model version with 31 vertical levels, and experiments 35-40 a model version with 62 vertical levels. Second, the experiments differ in atmospheric parameters.

Cloud and radiation processes cannot be resolved in current climate models and are thus parameterized. A variation of the parameters in the corresponding schemes can produce rather different mean-states, as indicated by Kim et al. (2011) and Ham et al. (2012) by investigating model sensitivity to the Tokiaka parameter - a minimum entrainment rate threshold in the cumulus convection parameterization. Ham et al. (2012) further show how a variation of this parameter can lead to a dramatic change in ENSO phase locking. The three parameters changed in this study represent convective cloud conversion rate from cloud water to rain, entrainment rate for shallow convection and convective mass-flux above level of non-buoyancy (see Mauritsen et al. 2012 for a detailed discussion). The chosen parameter range corresponds to the suggested values by Mauritsen et al. (2012). The primary quantity to determine ENSO phase locking is SST.

CMIP5 model SST data is used for comparison with the KCM results. Historical simulations (1850-2005) are taken from 43 CMIP5 models (Taylor et al. 2012) and are interpolated to a 2.5° x 2.5° regular grid (see Table 2 for a list).

Additionally, we performed an atmosphere standalone experiment with the same atmospheric component as used in the KCM, ECHAM5 (T42, 31 levels), forced by observed daily SST and sea ice concentration (Reynolds et al. 2007). The time period of the simulation is 1982-2009.

Several observational and reanalysis datasets are used to evaluate the model results. For SST, the HadISST 1.1 dataset from the Met Office Hadley Centre (Rayner et al. 2003) is used for 1958-2001. For the BJ index calculation, output from the Simple Ocean Data Assimilation (SODA) ocean reanalysis product version 2.0.2 (Carton and Giese 2008) is used for ocean temperatures and velocities (1958-2001). SST and zonal wind stress are taken from SODA as well to provide consistency among the datasets for the BJ index calculation. Surface heat fluxes are taken from ERA40 (Simmons and Gibson 2000) that spans the same time period as SODA 2.0.2.

The BJ index calculation is based on the original formulation from Jin et al. (2006) with some modifications made by Lübbecke and McPhaden (2013) and references therein. The BJ index includes the zonal advection feedback (ZAF), Ekman feedback (EF), thermocline feedback (TF), dynamical damping (DD) and thermal damping (TD). The formulation of the positive feedbacks (ZAF, EF and TF) is based on mean-state variables and a series of coefficients that measure the sensitivity of the atmosphere (i.e. zonal wind stress) to SST changes, and the ocean (i.e. zonal currents, upwelling and thermocline tilt) to changes in the zonal wind stress. The negative feedbacks (DD and TD) describe the damping effects on SST anomalies (SSTa) from mean ocean currents and changes in atmospheric heat fluxes (see Table 3 for an overview of the contributing feedback terms to the BJ index). The sum of all feedbacks is defined as the BJ index which is therefore a measure of coupled ocean-atmosphere stability or growth rate of SSTa.

The region selection for computing area averages is adapted from Kim and Jin (2011a). The latitudinal range is 5°S-5°N. In the zonal direction, 120°E-180°E for western equatorial thermocline depth, 180°E-80°W for SST, subsurface ocean temperature, eastern equatorial thermocline depth, upper ocean currents and atmospheric heatfluxes and 120°E-80°W for zonal wind stress is taken. 90%-confidence intervals for the BJ index calculated from reanalysis data are estimated from linear regression via the standard error of the regression slope. For the analysis of interannual variability, the linear trend and the mean seasonal cycle were removed from all datasets.

When analyzing ENSO phase locking, the Niño3.4 index region (170°W-120°W; 5°S-5°N) is chosen, because it captures both a large part of the main region of SST variability as well as the area where coupling processes between ocean and atmosphere associated with ENSO are assumed to take place. A phase locking index (PLI) is defined after Bellenger et al. (2014):

$$\mathrm{PLI} = \frac{\mathrm{STD\ DEV}(\mathrm{SSTa}_{\mathrm{Nino3.4}})_{\mathrm{DJF}}}{\mathrm{STD\ DEV}(\mathrm{SSTa}_{\mathrm{Nino3.4}})_{\mathrm{AMJ}}}$$

With SSTa denoting interannual SST anomalies and STD the corresponding standard deviation. A larger

PLI is either determined by stronger variability in DJF or weaker variability in AMJ or both and therefore reflects stronger phase locking.

3. Mean-state SST

The long-term annual-mean SST in the tropical Pacific from observations is shown in Figure 1a and the ensemble-mean SST derived from all KCM simulations in Figure. 1b. The model captures the western Pacific warm pool, the zonal band of relatively high SST north of the equator as well as the equatorial cold tongue. Large spread among the model realizations exists, as indicated by the standard deviation among the individual ensemble members (contour lines). Ensemble-mean SSTs are too warm in several regions (Fig. 1c). Largest warm SST biases are observed in the coastal upwelling regions in the eastern Pacific, a problem that is seen in most climate models (Latif et al. 2001). The model spread is rather small in the coastal upwelling regions, indicating the changes applied to the KCM do not significantly influence the SST in these regions. SST biases in the equatorial region are considerably smaller, with the exception of the very eastern part. However, model spread is large, especially west of 140°W. This indicates that SST in this region is sensitive to the changes applied to the KCM. When the areal-mean SST is subtracted from the map (Fig. 1d) to obtain the relative SST biases, the equatorial cold bias becomes obvious (as indicated by the green color in Fig. 1d). Using relative temperatures has the advantage that it resembles the corresponding atmospheric circulation more accurately (Bayr and Dommenget 2013). The double-ITCZ problem is also seen in the SSTs, as bands of warm SST biases stretching from the western equatorial Pacific eastward in both hemispheres and merging with the warm SST biases in the subtropical coastal upwelling areas (Fig. 1c). We note that the model spread is strongly reduced when subtracting the areal-mean SST from the individual ensemble members.

Perturbing the physics (Section 2) has implications for the equatorial cold bias (Fig. 2). This is because the region of the equatorial cold tongue is characterized by boundary layer cloud cover (e.g. Klein and Hartmann 1993; Lacagnina and Selten 2013) and this is affected by our perturbations. First, we need to clarify the role of the perturbed parameters, which is explained in detail in Mauritsen et al. (2012). The perturbed atmospheric parameters of interest are the convective mass-flux above the level of non-buoyancy and the entrainment rate for shallow convection. They both control the updraft in shallow convective processes and thus the amount and thickness of boundary layer clouds. Increasing the first parameter increases the strength of the updraft and thus leads to a reduction of boundary layer cloud cover. This is because a stronger updraft is associated with more evaporation of cloud water in the boundary layer. Increasing the second parameter has the opposite effect, because a larger entrainment rate weakens the updraft and therefore increases boundary layer cloud cover. The effect of modifications in the cloud cover is to change the amount of solar radiation reaching the sea surface. Therefore, the cold SST bias could in principle be reduced by decreasing shallow cloud cover over the cold tongue region by increasing insolation at the surface. A considerably reduced cold SST bias can be achieved by increasing the convective mass-flux above the level of non-buoyancy (Fig. 2a) or with a less consistent but still visible effect by decreasing the entrainment rate for shallow convection (Fig. 2b). Changing the convective cloud conversion rate from cloud water to rain has no significant impact on the cold SST bias (not shown).

We also investigate the influence of changing the vertical atmospheric resolution, as motivated by Harlaß et al. (2015) who achieved a considerable reduction of SST biases in the tropical Atlantic by enhancing the vertical resolution. We find that varying the number of vertical levels in the atmosphere has no systematic effect on the strength of the cold bias in the equatorial Pacific (Fig. 2c). This may be partly due to the relative small number of sensitivity experiments (6 sets of KCM-experiments; each set differs in the cloud parameters). A reduction of the cold SST bias is achieved by increasing the resolution from 19 to 31 levels in 5 out of the 6 sets of sensitivity experiments, but at 62 levels the bias again increases. It should be mentioned in this context that horizontal and vertical atmosphere model resolution should be consistent with each other (Harlaß et al. 2015).

Figure 3 depicts the seasonal cycle of equatorial SST directly at the equator relative to the annual-mean SST calculated from observations (Fig. 3a) and the KCM (Fig. 3b). The ensemble-mean SST annual cycle is shown from the KCM (color shading in Fig. 3b). It captures the warming during the first half and the cooling during the second half of the year in the eastern equatorial Pacific as well as the westward propagation of the signal. However, the amplitude of the SST seasonal cycle is underestimated, and the cold phase terminates 3 months too early compared to the observations. The model spread is shown by contours in Figure 3b. Largest spread is found in the very eastern equatorial Pacific during the first half of the year.

4. Seasonal ENSO phase locking and feedback analysis

In the ensemble-mean, the KCM produces a seasonal ENSO phase locking comparable to observations (Fig. 4a), with largest variability in December to February and smallest in April to June. There are, however, several noticeable differences. First, the interannual variability is too strong in the model during all calendar months. In the KCM, ENSO is sensitive to the mean temperature of the tropical Pacific, with a warmer mean-state leading to stronger interannual variability. This has been shown by Park et al. (2009) and Latif et al. (2015), both describing the ENSO response to global warming in a T31-version of the KCM. Regarding this relationship, Figure 5 shows tropical Pacific mean (25°N-25°S) SST for each ensemble member of the T42-version of the KCM analyzed here together with annual mean ENSO amplitude as assessed by Niño3.4-averaged SSTa standard deviation. The correlation amounts to 0.59, consistent with the T31-version. Compared to observations (black cross), the KCM ensemble-mean shows higher tropical Pacific mean SST along with a stronger ENSO (red cross). Second, the seasonal variation of monthly SSTa is smaller than that in observations, as indicated by the much less accentuated minimum in boreal spring and by the less distinct maximum in boreal winter (Fig. 4a). This becomes especially clear when normalizing the seasonal cycle of SST variability by its annual mean (Fig. 4b). And third, there is significant spread about the ensemble-mean as shown by the individual realizations. This indicates that the seasonal cycle of interannual SST variability is rather sensitive to changes in vertical atmosphere model resolution and changes in cloud and convective parameters, as shown below.

A similar analysis has been carried out for the CMIP5 models (Fig. 4c, d). In the ensemble mean, the CMIP5 models exhibit similar biases as the KCM. Most noteworthy is the weak variability minimum in boreal spring. The spread is larger than that obtained from the KCM ensemble. This is expected, since the CMIP5 ensemble covers a wider range of resolutions and physical parameterizations.

In the following, the controls of seasonal ENSO phase locking in the KCM are investigated. Biases in seasonal ENSO phase locking may be linked to a flawed simulation of the mean-state SST seasonal cycle. We calculate from each member of the KCM ensemble the correlation (on the basis of the monthly values) of the simulated mean-state SST seasonal cycle in the Niño3.4 box with the observed seasonal cycle in this region. The PLI, which was introduced above, quantifies the strength of the annual variation of interannual SST variability. Figure 6 shows the PLI against the models’ ability to capture the mean-state SST seasonal cycle in the eastern equatorial Pacific. There is no significant relationship (correlation of 0.02). This agrees with Stein et al. (2014), in which it is found that the seasonal modulation of the coupled stability is responsible for the ENSO being phase-locked to the annual cycle rather than a periodic forcing by the annual cycle.

Next, we make use of the BJ index which measures the linear stability of the coupled atmosphere-ocean system and is hence a measure of SSTa growth rate. Figure 7 shows the BJ index and the individual feedbacks as a function of calendar month calculated from observations and the set of experiments with the KCM. Figure 7a-c displays the positive feedbacks, Figure 7d-e the damping terms, and Figure 7f the BJ index which is calculated as the sum of all feedbacks. Again, both the ensemble-mean and the individual experiments are shown from the KCM. Confidence intervals in the observations, as estimated from the standard error of the contributing terms (see Section 2 for more details), are quite large for the TF term, which is mainly attributed to the short time period of 44 years and the lack of subsurface data prior the TAO-array. First, we note that the annual-mean BJ index is negative in SODA (-0.18 yr^{-1}; close to the value calculated in Kim et al. 2013) and in the KCM ensemble mean (-1.24 yr^{-1}), which is expected since the coupled system should be overall stable. According to the BJ index calculated from observations, the coupled system is unstable from July through November, allowing SSTa to grow, and most strongly damped at the beginning of the year (Fig. 7f). This finding agrees with Stein et al. (2010) who assess the seasonal growth rate of ENSO via the BJ index and show that the coupled system is unstable around boreal fall and stable during the rest of the year. The seasonal cycle of the BJ index matches the seasonal cycle of interannual SST variability (Fig. 4) with a phase shift of a few months. This is reasonable, because SSTa, owing to the inertia of linear perturbations, may still grow after SSTa growth rate has reached its annual maximum. The BJ index can thus explain the seasonal ENSO phase locking.

The positive feedback terms derived from observations, namely EF and TF and to a lesser extent ZAF, tend to destabilize the system in late boreal summer and boreal fall. DD and TF on the other hand are strongest in early boreal spring. Together with the small positive feedbacks during that time, this contributes to stable conditions, giving rise to the so-called spring predictability barrier (Latif and

Graham 1992; Torrence and Webster 1998; Levine and McPhaden 2015). The ensemble-mean of the KCM runs reproduces the seasonal cycle of the BJ index quite well. All individual feedbacks peak approximately at the right time of the year. In boreal fall, however, the SSTa growth rate is not as strong as in observations, which results from too weak positive feedbacks at that time of the year. Furthermore, in the annual mean the system is too strongly damped compared to observations. This is mostly a result of too strong DD and overall too weak positive feedbacks. We note that the relatively small ensemble-mean BJ index cannot explain the too strong SST variability in the KCM (Fig. 4a), since low values of the BJ index would favor weak variability (Kim and Jin 2011b; Kim et al. 2013). Furthermore, it is noteworthy that TD is underestimated, especially at the beginning of the year.

Some of the feedback biases can explain why ENSO phase locking is overall too weak in the KCM:

(1) The too weak positive feedbacks (ZAF, EF and TF) explain why the annual maximum of SSTa growth rate is underestimated in boreal fall. This results in a too weak SST variability maximum in boreal winter.

(2) The too weak negative feedback TD at the beginning of the calendar year (February-March-April, FMA) can explain why SST variability in boreal spring does not decay as strongly as in observations.

Regarding the second point, it can be argued that too weak TD may be compensated by too strong DD. When adding TD and DD it becomes clear that in FMA, the total damping rate is underestimated with respect to observations, whereas during the remainder of the year there is compensation. Therefore the bias in TD is here considered as a potential cause for biasing ENSO phase locking.

To better assess the role of the feedbacks in controlling ENSO phase locking in the KCM, the feedbacks are computed for each single model experiment and plotted against the phase locking index, PLI. Figure 8 shows scatter diagrams of ZAF, EF, TF, TD, DD and the BJ index at their peak season with respect to the PLI. The results indicate that a stronger EF, TF and TD during September-December (SOND) and January-April (JFMA) is associated with stronger ENSO phase locking (Fig. 8b, c, e), and with significant correlations of 0.69, 0.54 and -0.67, respectively. ZAF is of less relevance for ENSO phase locking, being small in magnitude and exhibiting a correlation with PLI of only 0.21 (Fig. 8a). Also the DD is not correlated with PLI (-0.1; Fig. 8d). The highest correlation is found for the EF term. However, TF and TD are of greater magnitude and therefore may have an equivalent impact. This can be quantified by the slope of the fitted linear regression lines between PLI and EF, TF and TD in Figure 8b, c and e, amounting to 1.18 yr^{-1}, 1.21 yr^{-1} and -2.35 yr^{-1}, respectively. We also compare the PLI with the total BJ index by taking the difference of the simulated BJ index maximum and minimum season, i.e. in SOND and JFMA, respectively (Fig. 8f). This is because the BJ index measures both the instability towards the end of the calendar year as well as the stability at the beginning of the calendar year. The results show that the BJ index is in close relation to the PLI (correlation of 0.76), which supports our hypothesis that it can to a large extent explain seasonal ENSO phase locking.

We conclude that the major controls of seasonal ENSO phase locking in the KCM is mostly due to EF and TF around boreal fall and TD in late winter/early boreal spring. A stronger EF and TF in boreal fall increases the growth rate of the SST anomalies, which leads to larger SST variability in boreal winter. A stronger TD from the atmospheric heat fluxes in late winter/early boreal spring on the other hand stabilizes the coupled system, which keeps SST variability low in boreal spring.

ENSO stability is tightly linked to the mean-state (e.g., Battisti and Hirst 1989; Neelin et al. 1998; An and Jin 2000; Fedorov and Philander 2001; Guilyardi 2006; Bejarano and Jin 2008; Kim et al. 2013).

Therefore, as the next step we connect the feedback biases outlined above with the mean-state. The KCM exhibits a cold SST bias in the equatorial Pacific (Fig. 1d), which is common to many CGCMs (e.g. Zheng et al. 2012) and has previously been linked to feedback biases in terms of the BJ index (Kim et al. 2013).

Figure 9 displays the equatorial cold bias calculated over the region 160°E-80W; 5°S-5°N against the feedbacks which we identified to be important for controlling ENSO phase locking in the KCM, i.e. EF, TF and TD. The cold bias is computed for SOND and compared to EF and TF in SOND, and to TD in JFMA. A smaller cold bias in SOND goes along with an enhanced EF (correlation of 0.69; Fig. 9a) and TF (correlation of 0.70; Fig. 9b) in SOND, and an increased TD in JFMA (correlation of -0.87; Fig. 9c). Xiang et al. (2011) and Kim et al. (2013) discuss in detail what implications the equatorial cold SST bias can have for the feedbacks. For example, an equatorial cold tongue extending too far west places the deep convection too far west, thereby reducing the response of low-level winds to SST changes over the central equatorial Pacific. A weaker low-level wind response to SST forcing contributes to the underestimation of both the EF and TF (see Table 3 for the definition of the feedbacks). Furthermore, the cold SST bias reduces the thermal stratification in the upper ocean. This too affects EF which is proportional to the strength of the mean vertical temperature gradient. Kim et al. (2013) argue that in a weaker stratified upper ocean, wind stress-forced momentum is less confined towards the sea surface. This would result in a lower ocean-upwelling response sensitivity to wind stress forcing as part of the EF. Consistent with this, we find that in the KCM a smaller cold SST bias is associated with a stronger upwelling response to wind stress forcing in SOND (correlation of 0.64; not shown). Further, the weaker stratification can lead to an underestimation of the thermocline-subsurface temperature feedback (Xiang et al. 2011) and influences the thermocline slope response to wind forcing (Kim et al. 2013). The influences on TD likely result from biases in the shortwave feedback. Lloyd et al. (2012) and

Dommenget et al. (2014) show that the cold SST bias weakens the shortwave damping and can even reverses it to a positive feedback. We find in the KCM that a smaller cold bias is strongly related to a larger shortwave feedback in JFMA (correlation of -0.87; not shown). Finally, we analyze the results from an uncoupled ECHAM5 simulation forced by observed daily SSTs during 1982-2009. Here the shortwave feedback is stronger than that in any of the coupled simulations (not shown). This corroborates our hypothesis that the shortwave feedback is strongly controlled by the SST bias. Based on these results, we conclude that an excessive equatorial cold tongue is the main cause for too weak seasonal ENSO phase locking in the KCM.

5. Summary and discussion

In this study, processes controlling seasonal ENSO phase locking are identified in the Kiel Climate Model (KCM) and compared to observations. A large ensemble of simulations with the KCM has been conducted, which differ in vertical atmospheric resolution and physical parameterizations. ENSO phase locking in observations is explained by the seasonal variation of the coupled system′s stability and the associated feedbacks, here measured by the Bjerknes (BJ) index. Positive feedbacks are strongest towards the end of the calendar year, leading to a maximum in SST anomaly growth rate, whereas negative feedbacks are strongest at the beginning of the year, thereby setting relatively stable conditions. The ensemble-mean of the KCM simulations depicts ENSO phase locking and seasonal variation of the BJ index consistent with observations. The model spread, however, is rather large, as discussed below. A major result of this study is that the ability of a coupled model to realistically simulate seasonal ENSO phase locking is closely linked to the strength of the cold equatorial Pacific SST bias, with less biased models exhibiting more realistic phase locking owing to more realistic coupled feedbacks.

The KCM in the ensemble-mean features too weak seasonal ENSO phase locking compared to observations, that is a less accentuated SST variability maximum and SST variability minimum in December to February and April to June, respectively. This bias is induced by a too weak Ekman feedback (EF) and thermocline feedback (TF) towards the end of the year and too weak thermal damping (TD) at the beginning of the year. When comparing the individual KCM experiments from the ensemble with each other, we find that stronger EF and TF in SOND and TD in JFMA are associated with stronger seasonal ENSO phase locking. Improving these feedbacks holds great potential to enhance seasonal ENSO phase locking in the KCM.

It is suggested that an excessive equatorial cold tongue significantly affects the simulation of these feedbacks and thus seasonal ENSO phase locking not only in the KCM but also in the CMIP5 models. Figure 10 depicts results from all KCM runs and from the CMIP5 models. The scatter diagram shows for each simulation the seasonal ENSO phase locking index (PLI) and the strength of the cold equatorial Pacific SST bias. In both ensembles, a smaller cold SST bias corresponds to stronger seasonal ENSO phase locking, with significant correlations of 0.61 (KCM) and 0.48 (CMIP5). We note that the CMIP5 models tend to simulated overall warmer conditions.

We hypothesize that the link between seasonal ENSO phase locking and cold equatorial Pacific SST bias can be explained as follows: An excessive equatorial cold tongue weakens the low-level wind response to SST forcing (Xiang et al. 2011) and thus reduces the strength of both EF and TF. Furthermore, the cold SST bias weakens the thermal stratification in the upper ocean (Xiang et al. 2011; Kim et al. 2013). This also reduces the strength of EF, because subsurface temperature influence on SST and ocean upwelling response to wind forcing are reduced. Furthermore, a weaker stratification can reduce the thermocline-subsurface temperature feedback (Xiang et al. 2011) and the thermocline slope response to wind stress anomalies (Kim et al. 2013). Consequently, the total TF is reduced. Since these feedbacks are strongest in boreal fall, this lowers SST anomaly growth and eventually interannual SST variability in boreal winter. Further, the cold SST bias weakens the shortwave damping and can even cause it to be amplifying (Lloyd et al. 2012; Dommenget et al. 2014). This reduces TD and thus increases interannual SST variability in boreal spring. To summarize, the cold SST bias weakens seasonal ENSO phase locking by reducing SST variability in boreal winter and increasing SST variability in boreal spring.

We relate the strength of the equatorial cold SST bias to the perturbed physics in our set of experiments with the KCM. We show that changing specific parameters in the cloud scheme has an effect on the cold SST bias by altering the amount of low-level clouds over the cold tongue region, allowing realistic seasonal ENSO phase locking for specific parameter choices. We note that the applied changes to the convection scheme are specific to our atmospheric model, ECHAM5, and it is of interest whether this can be valid to other models. We also show that the vertical resolution in the atmosphere model has no systematic effect on the strength of the cold Pacific SST bias. However, it has to be kept in mind that atmospheric horizontal resolution has been kept fixed and consistency between horizontal and vertical resolution may be required. We note that a realistic seasonal ENSO phase locking can be achieved at coarse vertical atmosphere model resolution (e.g. experiment 28). This situation in the tropical Pacific is different to that in the tropical Atlantic: Harlaß et al. (2015) show that a reasonable seasonal phase locking of interannual SST variability in the equatorial Atlantic can only be achieved in the KCM at sufficiently high vertical and horizontal atmospheric resolution.

Previous studies have discussed the relationship between the equatorial Pacific cold SST bias, ENSO feedbacks and seasonal ENSO phase locking, which are consistent with this study. For instance, Bellenger et al. (2014) suggest that a larger shortwave feedback strengthens seasonal ENSO phase locking in CMIP3 + CMIP5 models. Furthermore, Rashid and Hirst (2015) point out the dependency of the shortwave feedback on local SST. Kim et al. (2013) also connect cold tongue biases to atmospheric and oceanic response biases, restricting the analysis, however, to annual mean conditions. Ham and Kug (2014) and Rashid and Hirst (2015) link the cold SST bias with phase locking biases via errors in the simulated feedbacks, but referring to a SST variability peak in the wrong season. We provide, with the aid of the BJ index, a comprehensive analysis of the importance of the cold equatorial Pacific SST bias for the seasonal variation of coupled feedbacks that control seasonal ENSO phase locking.

Due to its comprehensiveness, the BJ index is highly valuable for highlighting out significant processes that control ENSO-associated variability, especially in the ocean. Nevertheless, there are arguments about limitations of the BJ index in representing ENSO feedbacks. We find that the relatively small ensemble-mean BJ index cannot explain the too strong SST variability in the KCM (Fig. 4a), since low values of the BJ index would favor weak variability. Similar results are obtained by Kim et al. (2013) for a set of CMIP5 models. This suggests limitations of the BJ index in reflecting the overall strength of ENSO variability and should be the subject of further investigation. Furthermore, Graham et al. (2014) analyze the ability of the BJ index in representing ocean dynamics and point out the role of assuming linearity in the formulation, although ENSO processes can be inherently nonlinear (Lloyd et al. 2012; Bellenger et al. 2014). Duan et al. (2013) also underpin the important role of nonlinearities in seasonal ENSO phase locking. Yet the consistency between the results obtained from the KCM ensemble with those obtained from the CMIP5 ensemble is reassuring.

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Table 1 List of all KCM experiments which differ in three atmospheric parameters (column 2-4) and vertical atmospheric resolution (column 5).

Table 2 List of all CMIP5 models used in the analysis.

Table 3 Contributing feedbacks in the Bjerknes stability index and their formulation. μ_a denotes equatorial zonal wind stress response to eastern equatorial SSTa, β_u zonal ocean velocity response, β_w ocean upwelling response and β_h thermocline slope response to equatorial zonal wind stress anomalies. a_h is the ocean subsurface temperature response to thermocline depth anomalies and α the net surface heat flux response to SSTa. $\bar{u}, \bar{v}, \bar{w}$ denote mean zonal, meridional and vertical ocean velocities, $\bar{T}$ mean SST and H_m mean mixed layer depth. $\langle\cdot\rangle_E$ denotes volume-averaged quantities over the eastern equatorial regime with L_x and L_y as zonal and meridional extent. $H(\bar{w})$ is a step function to account only for upstream vertical advection. The responses are estimated via linear regressions. The methodology is adapted from Lübbecke and McPhaden (2013), region selection after Kim and Jin (2011a).

Figures

Fig. 1 (a) Long-term annual-mean SSTs from observations and (b) as given by the ensemble-mean calculated over all experiments with the KCM. (c) Total SST bias, (d) with regional mean SSTs (120°E-60°W; 15°S-15°N) subtracted. Contour lines depict the standard deviation over all model realizations. Unit is °C.

Fig. 2 Scatter plot of the cold equatorial SST bias (160°E-80°W; 5°S-5°N) with areal-mean (120°E-60°W; 15°S-15°N) subtracted versus different parameter values in the cloud parameterization of (a) the convective mass-flux above level of non-buoyancy and (b) the entrainment rate for shallow convection for a selection of KCM experiments. Model experiments 41 and 42 are not included in the set of experiments used in the previous part of the analysis due to their extreme parameter values. (c) Scatter plot of the cold equatorial SST bias versus atmospheric vertical resolution with color denoting same cloud parameters.

Fig. 3 Seasonal cycle of equatorial SST at the equator with the annual mean removed for (a) observations and (b) the ensemble-mean calculated over all experiments with the KCM. Contour lines depict the standard deviation over all model realizations. Unit is °C.

Fig. 4 Monthly standard deviation of Niño3.4 SSTa for (a) all 40 KCM experiments (blue) together with its ensemble-mean (red) and (b) normalized by the annual mean. The same for a set of (c) 43 CMIP5 models with (d) normalized by the annual mean. Observations are added in black.

Fig. 5 Scatter plot of Niño3.4-averaged SSTa standard deviation versus tropical Pacific mean SST (120°E-60°W; 25°S-25°N) for the set of 40 KCM experiments (blue) together with the annual-mean SST (red cross) and observations (black cross). The correlation over all KCM experiments is given and it is significant at the 90% level. A regression line is also added.

Fig. 6 Scatter plot of the phase locking index PLI versus the correlation of the mean SST seasonal cycle in the Niño3.4 between observations and the set of 40 KCM experiment (blue) together with the ensemble-mean (red cross) and observations (black cross). The correlation over all KCM experiments is given but not significant and a regression line also is added.

Fig. 7 Monthly (a) zonal advection feedback, (b) Ekman feedback, (c) thermocline feedback, (d) dynamical damping, (e) thermal damping and (f) the Bjerknes stability index for the set of 40 KCM experiments (blue) together with the ensemble-mean (red) and observations (black). Error bars for observations show 90% confidence intervals.

Fig. 8 Scatter plots of the phase locking index PLI versus (a) the zonal advection feedback in September-December, (b) the Ekman feedback in September-December, (c) the thermocline feedback in September-December, (d) the dynamical damping in January-April, (e) the thermal damping in January-April and (f) for the BJ index difference between September-December and January-April for the set of 40 KCM experiments (blue) together with the ensemble-mean (red cross) and observations (black cross). The correlation over all KCM experiments is given and it is significant at the 90% level. A regression line is also added.

Fig. 9 Scatter plots of (a) the cold equatorial Pacific SST bias (160°E-80°W; 5°S-5°N) with areal-mean (120°E-60°W; 15°S-5°N) subtracted in September-December versus the Ekman feedback in September-December, (b) the equatorial cold SST bias in September-December versus the thermocline feedback in September-December and (c) the equatorial cold SST bias in January-April versus the thermal damping January-April for the set of 40 KCM experiments (blue) together with its ensemble-mean (red cross) and observations (black cross). The correlation over all KCM experiments is given and it is significant at the 90% level. A regression line is also added.

Fig. 10 Scatter plot of the phase locking index PLI versus the cold equatorial SST bias (160°E-80°W; 5°S-5°N) with areal-mean (120°E-60°W; 15°S-15°N) subtracted in September-April for the set of 40 KCM experiments (blue) and the set of 43 CMIP5 models together with their ensemble-means (red crosses) and observations (black cross). The correlations over all KCM experiments and CMIP5 models are given and they are significant at the 90% level. A regression line is also added.