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The role of forcing anomalies and climate shifts in seasonal forecasts

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Abstract: We devise a new method for determining the effects of model forcing anomalies and climate shifts on seasonal predictions. The role of model bias, due to anomalous forcings, and climate shift on forecast skill is studied for coupled ocean-atmosphere general circulation models (CGCMs) during different phases of the El Niño Southern Oscillation (ENSO) cycle. Biases due to anomalies or errors in the model forcing functions in simulations produce changes in the attractor of the thermo-dynamical system and shifts in the consequent climate state. We examine how such biases and climate shifts affect seasonal predictions.

We employ an efficient intermediate complexity model with established forecast skill in a standard configuration and analyse seasonal predictability during a 20-year period of intense El Niño and La Niña events starting in January 1980 and ending December 2000. Firstly, we use reanalysed data from the observations to perform seasonal forecasts using our intermediate model with the optimised forcings for the standard configuration. Forecasts for one year are produced starting each month of the analysis period. The same initial conditions are then used by the intermediate complexity model, together with changed forcings that closely reproduce climates from selected complex CGCMs, to produce two additional control forecasts. We then determine the effects of the anomalous CGCM forcings, or model biases, and climate shifts, by comparing how well the forecasts with these configurations perform in situations of developing and large amplitude El Niños and La Niñas. We calculate the forecast error of the 50m ocean temperatures in the Pacific Ocean region and show the model's variability in forecast error growth during the annual cycle. Larger amplitudes of error are seen during the development of El Niño events in all cases, with the seasonal predictions with CGCM determined forcings showing evidence of drift towards the shifted model climate with overall increased forecast error.

Keywords: *Seasonal forecasts, model bias, model climate, El Niño Southern Oscillation*

1. INTRODUCTION

Forecast errors in seasonal predictions of the regional climate state are dominated by coupled ocean-atmosphere model biases that lead to a systematic shift in the model climate state from the true climate state (Meehl et al., 2001; Kirtman and Pirani, 2008; Hermanson et al., 2018). Other significant sources of error are internal thermo-dynamical errors due to the chaotic nature of the coupled ocean-atmosphere system and to errors in the initial conditions for the forecasts (Frederiksen et al., 2010a, b; O'Kane et al., 2019). O'Kane et al. (2019) detail methods of data assimilation for the complex coupled system and they also provide a simple illustrative set of nine coupled equations – three for each of the atmospheric tropics and extratropics and the ocean – based on the Lorenz (1963) model of chaotic dynamics. Data assimilation reduces the sampling error in the initial conditions and the resulting analysis lies closer to the correct point on the attractor of the system ensuring a smoother integration without spurious oscillations that may otherwise occur. Internal thermo-dynamical errors are due to the exponential growth of perturbations in chaotic systems that may be particularly large when the system state approaches a bifurcation point on the attractor. At such a point the system state, like a planet transiting between two suns, may be deflected into orbiting about one or the other by a small perturbation. For example, in the atmosphere, the onset of blocking from a largely zonal flow state, or the reverse transition, is often associated with limited predictability and large forecast errors (Frederiksen et al., 2004 and references therein). Similarly, in the coupled system the transition in or out of an El Niño or La Niña state may have limited predictability while forecast skill may increase in these anomalous states before another regime transition occurs (Frederiksen et al., 2010a, b; Hermanson et al., 2018; O'Kane et al., 2019).

Systematic model biases result in the attractor of the model and its consequent climate state being different or displaced from the physical system. This climate shift between the model and physical systems (resulting in climate drift of the simulations) is generally a dominant source of errors and forecast failures. Despite this our understanding of model biases and how to ameliorate them is rather limited (Hermanson et al., 2018) and the World Climate Research Group has made this a project of current and future focus.

In a recent study, Osbrough et al., (2019) examined the internal error growth and potential predictability in coupled ocean-atmosphere models with different climate forcings and hence different attractors and climates. The models were variants of the Primitive Equation Coupled Ocean and Atmosphere Model (PECOCAM) formulated by Frederiksen et al., (2010a, b; 2013a, b). In the work of Osbrough et al., (2019) each model formulation was regarded as a 'perfect' model and the initial conditions or analyses for control forecasts were taken from long integrations of the models. The error growth was determined primarily by internal thermo-dynamics in the model variants with different forcing formulations.

In this article our focus is on how model biases, and the consequent climate shifts, affect forecasts when the initial conditions are from analysed observations and thus in general are displaced from the model attractor. We are particularly interested in how forecast skill (in hindcasts) relates to the changing El Niño Southern Oscillation (ENSO) cycle observed in the recent past.

2. MODEL SETUP

In this study, the PECOAM has been used with different radiative forcing functions derived from reanalysed observations and from two CGCMs. PECOAM is an intermediate complexity coupled ocean-atmosphere model ideally suited for investigative analysis of ENSO. It is highly computationally efficient and in standard configuration is skilful in the prediction of ENSO events (Frederiksen et al., 2010a, b). The model has prognostic equations that describe the dynamics and physics involved in the coupling between a Pacific Basin ocean, with levels at 50m and 150m, and a global atmosphere with pressure levels at 250hPa and 750hPa. The horizontal resolution is 2.3^{o} latitude by 3.75^{o} longitude, which is adequate for studying the variability and predictability of ENSO. Coupling is through wind stresses and heat fluxes over the ocean basin.

Representation of radiative forcing in the prognostic equations for the mean and shear atmospheric potential temperatures ensures that the reanalysed climatological annual cycle of mean and shear atmospheric temperature is reproduced. This is done in such a way as to produce the best simulation of ENSO-like variability and prediction (Frederiksen et al 2010a, Figures 5 and 16). As a result, because this climatological state includes a contribution from the climatological sea surface temperature (SST), an anomalous surface heat flux is applied to the atmospheric temperature equation. The formulation results in a model with a good climatology, little oceanic drift and good ENSO predictability. Full details of the model and its performance can be found in Frederiksen et al. (2010a, b; 2013a, b). In this study, we also run PECOAM with radiative forcings derived from the two CGCMs to investigate the differences in ENSO variability and predictability between the models. We make comparisons with the ENSOs generated using the reanalysed observations.

This model can be used to emulate the variability and predictability of more complex coupled models by determining forcing functions that closely reproduce the climatology of the CGCMs in simulations with PECOAM (Osbrough et al., 2019). Here, we compare the National Center for Atmospheric Research (NCAR) Community Climate System Model 4.0 (CCSM4) (Gent et al., 2011), and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and Bureau of Meteorology's (BOM) Australian Community Climate and Earth-System Simulator ACCESS1.3 (Rashid et al., 2013) models in their ability to predict observed ENSO variability over the period 1980-2000. Osbrough et al. (2019) compared the ENSO variability and potential predictability inherent within each model using reanalysed data from the models themselves. These models were chosen for their ability to reproduce the large scale dynamics of the Southern Hemispheric atmospheric circulation and reproduce 20th century trends in baroclinicity (Frederiksen et al., 2017; Grainger et al., 2014).

Here, we will use reanalysed data from the observations to investigate how well the models, initialised with observed reanalysis, perform seasonal forecasts including at times of developing and large amplitude El Niños and La Niñas. The Reanalysis 1 dataset used for the observed atmosphere is a joint product from National Centers for Environmental Prediction (NCEP) and NCAR (Kalnay, E. et. al., 1996), with the sub surface ocean temperatures taken from the Australian Government's Bureau of Meteorology Marine observations (2019).

3. METHODOLOGY

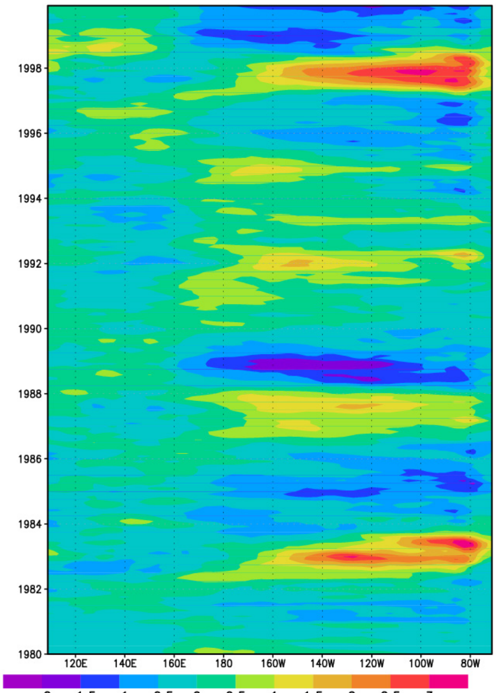

Figure 1. 50m ocean temperature anomalies averaged over 5°S-5°N (C) for analysis runs from 1980 to 2000 with NCEP/NCAR reanalysis data.

In order to generate initial conditions for predictability studies, we have performed an analysis run of PECOAM in which we have assimilated observed 50 and 150 metre ocean temperatures and surface wind stresses. Our interest is in the forecast of the anomalous temperature and circulation features from the climatology. We have therefore used a methodology for generating the analysis run that assimilates the observed anomalies, by nudging the model anomalies towards the observed values over 1980-2000 (see Frederiksen et al., 2010a, b for details). This period includes the El Niños of 1982-83, 1987-88 and 1997-98 and La Niñas of 1983-85, 1988-89 and 1998-2000.

Figure 1 shows the Hovmoller diagram for the 50m Pacific Ocean temperature anomalies averaged over 5°S to 5°N latitude for each month of the 20-year analysis run. The three El Niños and La Niñas are clearly seen.

4. FORECASTS

For each month between January 1980 and December 2000 we carry out yearly forecasts using the PECOAM with the reanalysed observation dataset. We take this to be our 'Standard' control run and compare this to our PECOAM runs that have identical initial conditions created from the observed reanalysis but are forced with CGCM forcing functions. Figure 2 compares the forecast root mean square (rms) errors of the 50m ocean temperatures in the NINO 3+ (10°S-10°N, 90°W-150°W) region for the Standard, ACCESS1.3 and CCSM4 control runs. Each of the three cases has the same initial conditions and, in particular, show large magnitudes of forecast error during the development of the three major El Niño events in 1982, 1987 and 1997. In both the CGCM cases we see an increase in forecast error compared to the Standard case, and this is most evident in the case of CCSM4 with peak error values reaching 3.6 °C. This tells us that the climate shift, namely the displacement of the CCSM4 model attractor from the observed reanalysis, is greater than for ACCESS1.3. It appears that the model bias in CCSM4 is having a significant detrimental effect on the quality of the forecasts as further discussed in Section 5.2.

Figure 3 examines the yearly averaged rms forecast errors over the 20-year period in order to analyse the seasonal dependence of predictability. The least skill is found in forecasts during March-April-May, which is a well-known problem in models called the boreal spring predictability barrier. ACCESS1.3 emulates this well, with slightly larger peak values but structure similar to the Standard configuration result, and a reduction in error showing a recovery in the months following northern spring. The averaged CCSM4 forecast rms error depicts similar values during the boreal spring months, with the most error 12 months on from forecast starting in October and November. It is however, expected that as time goes on, forecasts will generally decline in skill.

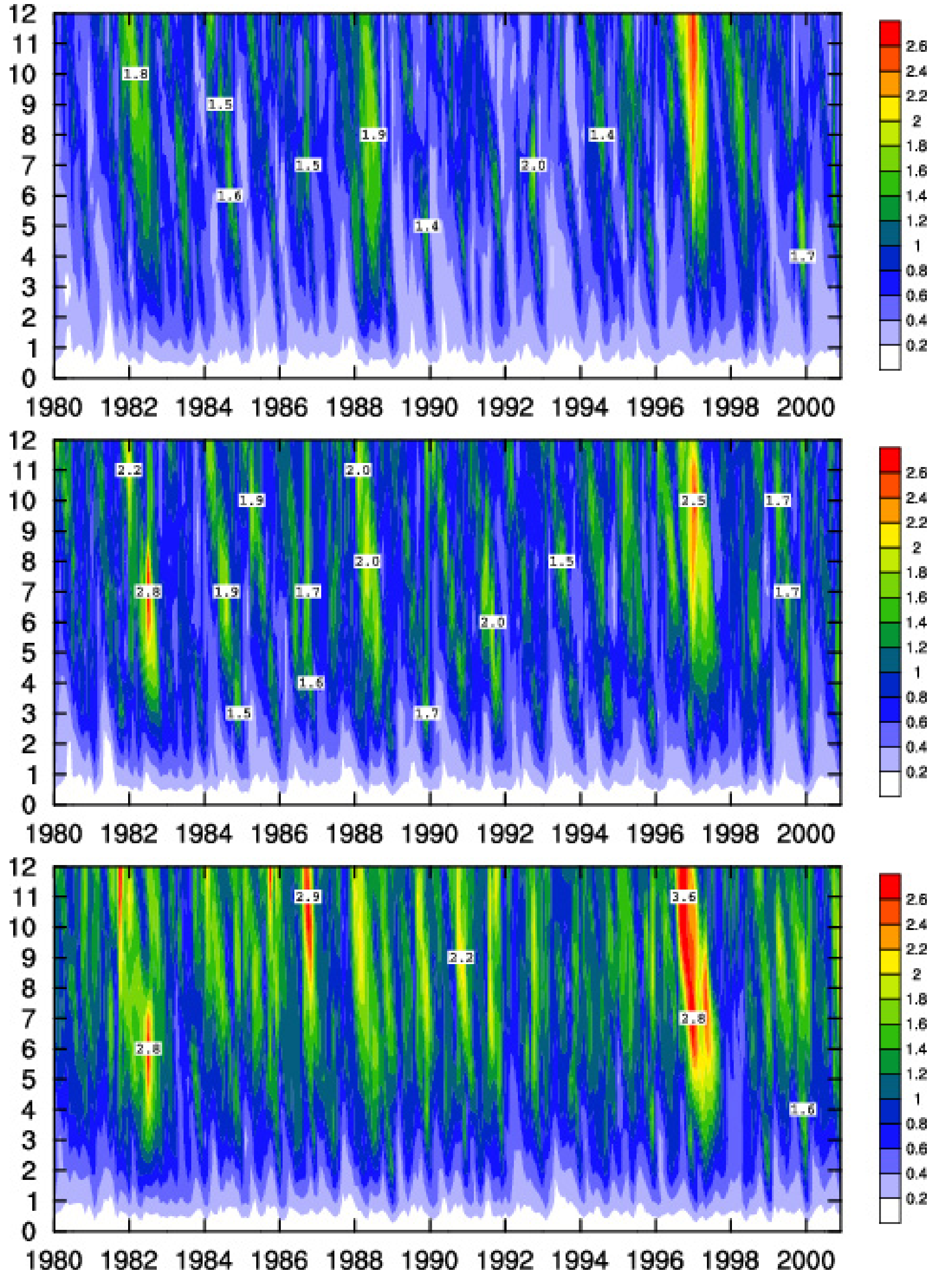

Figure 2. Error calculated for 12 month control forecasts starting each month during 1980-2000 for Standard (top), ACCESS1.3 (middle) and CCSM4 (bottom).

5. CLIMATE BIASES IN ACCESS1.3 AND CCSM4

Here we discuss the climate biases of the ACCESS1.3 and CCSM4 coupled ocean atmosphere models which affect the growth of errors in seasonal forecasts.

5.1 The ACCESS1.3 Model

Predictability on the seasonal time scale is affected by systematic shifts in the climatological mean state as well as biases in the annual cycle of the climate state that considerably impact on the realism of the simulated ENSO cycle. Rashid et al., (2013) detail the important biases in the ACCESS1.3 (and ACCESS1.0) model. In common

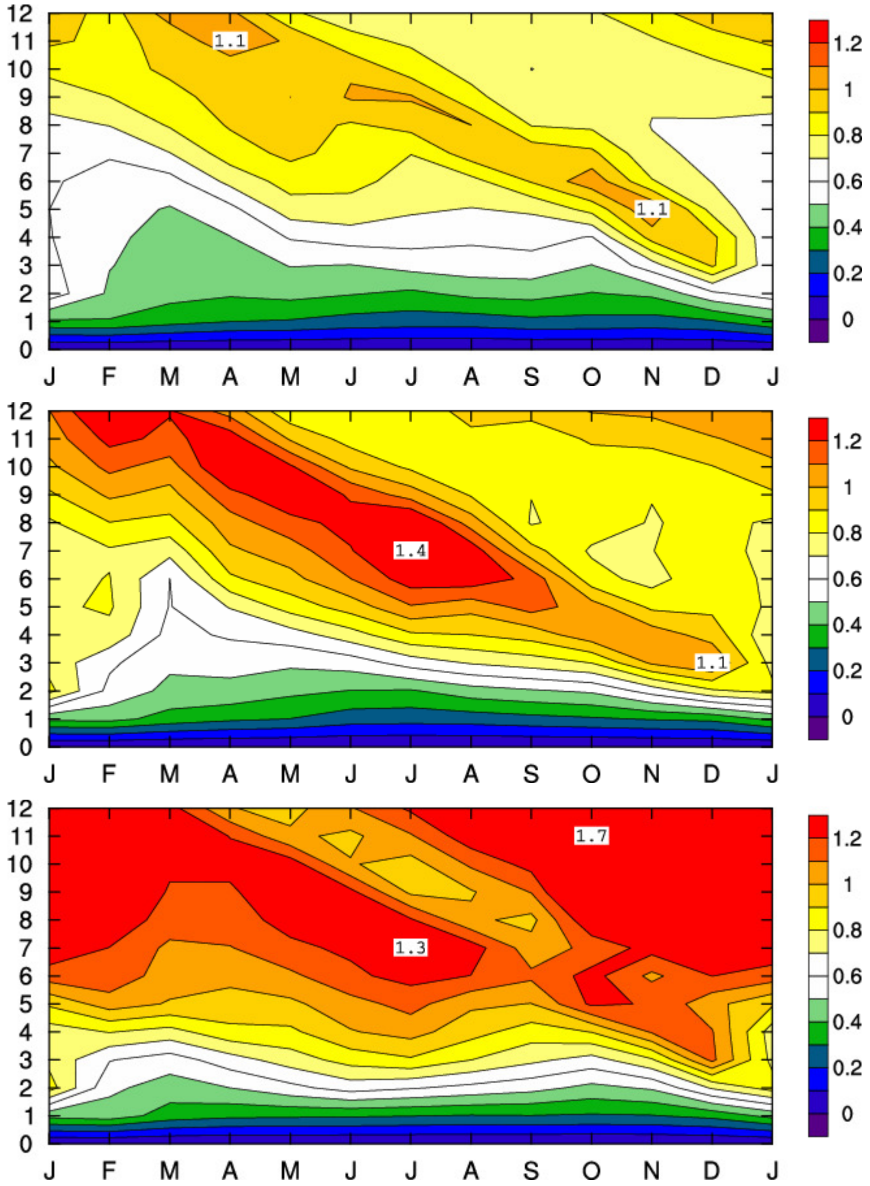

Figure 3. Yearly averaged rms forecast errors in Control run for each month over all years 1980-2000 for Standard (top), ACCESS1.3 (middle) and CCSM4 (bottom) of 50m ocean temperatures in the NINO3+ region.

with most CGCMs, ACCESS1.3 suffers from a so-called 'cold tongue' bias in which the SSTs are too cold by up to 1ºC across the central equatorial Pacific in the latitude band between 5ºS-5ºN and up to 2ºC too warm along the west coast of South America (Figure 1d of Rashid et al. 2013). These biases are nevertheless less pronounced than typical systematic shifts in most CGCMs used for climate variability and climate change prognoses, which is one of the reasons for choosing it for this study. The zonal (longitudinal) wind stress of the atmosphere on the ocean is also a significant determinant of the properties of the simulated ENSO variability. Again, like most CGCMs ACCESS1.3 has significant easterly wind stress bias across the Indian, and particularly Pacific, ocean regions (Figure 2d of Rashid et al. 2013). As noted by Meehl et al., (2001) ENSO characteristics are also especially affected by the structure and biases in the model thermocline – the temperatures in the equatorial Pacific upper ocean to a depth of 300m. Figure 3d of Rashid et al., (2013) shows the biases in the depth of the 20ºC isotherm surface, which approximates the thermocline, while their Figure 4d show vertical profiles of climatological potential temperatures in the Pacific ocean between 5ºS-5ºN. In the equatorial regions the anomalies in the 20ºC isotherm are small with larger biases located further from the equator in a pattern similar to that for zonal wind stress anomalies. The ACCESS1.3 model is cooler than observed in the upper equatorial Pacific Ocean and with larger (~2.5ºC) warm anomalies in the subsurface between 75m and 175m in the eastern Pacific.

The annual cycle of equatorial (5ºS-5ºN) SST and zonal wind stress for the ACCESS1.3 model has broadly similar behaviour in the Pacific basin compared with observations (Figure 5d of Rashid et al. 2013) but there are errors in the strengths and their location. The simulated ENSO SSTs (Figure 6d of Rashid et al. 2013) extend somewhat further east than in the observations in common with the CCSM4 model (discussed next). The power spectra and wavelet spectra of ACCESS1.3 NINO3 (5ºS-5ºN, 90ºW-150ºW) SST indices (Figures 7b and 8d of Rashid et al. 2013) have realistic magnitudes and show peaks in the 3 to 7-year timescales as in the observations and this is another strength of this model.

5.2 The CCSM4 Model

As mentioned in section 2, the CCSM4 CGCM, like ACCESS1.3, is able to reproduce the broad features of the Southern Hemisphere circulation and the twentieth century changes in baroclinicity that determines the strength and location of extra-tropical storm formation. The CCSM4 model has reduced biases compared to earlier versions of the model but still shares many systematic anomalies with the ACCESS1.3, described above, and other CGCMs. The cold tongue SST bias in the central Pacific Ocean is considerably reduced compared with an earlier version (Figure 1 of Gent et al., 2011) although the model SSTs are up to 2ºC too warm along the west coast of South America, as for ACCESS1.3. Capotondi (2013, Figures 6 and 7) compares the CCSM4 zonal wind stress and thermocline depth for different flavours of ENSO with observations and finds broad agreement between the two.

The annual cycle of SST for CCSM4 is qualitatively similar to that of the observations (Figure 7 of Gent et al. 2011) but its strength is considerably reduced. Like the ACCESS1.3 model, the CCSM4 has peak ENSO variability, measured by the NINO3 index, between 3 and 6 years. However, the CCSM4 ENSO variability is considerably larger than for the observations (Figure 8 of Gent et al. 2011) or the ACCESS1.3 model (Figure 7 of Rashid et al. 2013). This appears to be a particular source of the error growth in seasonal forecasts we found in section 4. Again, the CCSM4 simulated ENSO SSTs extend further eastward than observed and as well have an anomalously cold region in the west Pacific just north of the equator.

6. CONCLUSION

A new method using an efficient intermediate coupled ocean-atmosphere model with established forecast skill has been developed to evaluate the effect of model biases and climate shifts, in comprehensive global climate models, in predicting ENSO events. A period of intensive El Niño and La Niña events has been chosen for this study spanning twenty years beginning in January 1980.

Firstly, we have performed an analysis run to create the initial conditions used to produce the forecasts. The Standard control run uses this analysis as input to create 12 month forecasts for each month until December 2000. Next, we repeat this process using the same initial conditions in the PECOAM but with forcings that closely reproduce each of ACCESS1.3 and CCSM4 model climates, respectively. We have compared the skill of the resulting forecasts of 50m ocean temperatures in the NINO3+ region by calculating the root mean square error. Larger amplitudes of error occur during the development of El Niño events and is seen in all cases. However, generally increased forecast errors with ACCESS1.3 and CCSM4 model forcings show evidence of model climate drift. We have continued our study by examining the variability of forecast error growth during the annual cycle. In all cases there is evidence of the boreal spring predictability barrier, with ACCESS1.3 showing forecast error amplitude and structure more closely resembling that of the Standard run than that of CCSM4. The CCSM4 ENSO variability is known to be considerably larger than for the observations as discussed in section 5.2 and may be a contributing factor to this model’s larger ocean temperature forecast errors than those of ACCESS1.3. CCSM4 yearly averaged forecast error results show that it has potential to improve its forecasts during this period by reducing the model’s evident climate shift.

Our work in this area is continuing, with studies on the effect of climate shift using ensemble prediction methods in progress. Further discussion on this topic is beyond the scope of this paper, other than to say initial results show overall improvement in the ensemble forecast error when compared against the model’s control run. This indicates the model attractor is sufficiently close to the observed reanalysis to produce perturbations that result in an ensemble average that improves the forecast.

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