Weakened Eastern Pacific El Niño Predictability in the Early Twenty-First Century

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(Manuscript received 9 December 2015, in final form 15 May 2016)

ABSTRACT

Predictive skill for El Niño in the equatorial eastern Pacific across a range of forecast models declined sharply in the early twenty-first century relative to what was achieved in the late twentieth century despite ongoing improvements of forecast systems. This decline coincided with a shift in Pacific climate to an enhanced east–west surface temperature gradient across the Pacific and a stronger Walker circulation at the end of the twentieth century. Using seasonal forecast sensitivity experiments with the Australian Bureau of Meteorology coupled model POAMA2.4, the authors show that this shift in background climate acted to weaken key ocean–atmosphere feedbacks that amplify eastern Pacific El Niño, thus resulting in weaker variability that is less predictable. These results indicate that extreme El Niños, such as those that occurred in 1982/83 and 1997/98, were conditioned by the background climate and so were favored to occur in the late twentieth century. However, anticipating future changes in El Niño variability and predictability is an outstanding challenge because causes and prediction of low-frequency variations of Pacific climate have not yet been demonstrated.

1. Introduction

El Niño and La Niña cause major changes to rainfall, temperature, and severe weather in many parts of the world, with impacts on health, agriculture, water resources, and ecosystems (e.g., McPhaden et al. 2006). Fortunately, the occurrence of El Niño/La Niña can usually be predicted two to three or more seasons in advance with modern operational prediction systems (e.g., Barnston et al. 2012), which helps in preparing for their impacts. However, long-lead predictive skill of El Niño/La Niña, as measured by forecast skill of sea surface temperature anomalies in the equatorial eastern Pacific, was reported to have declined in the early twenty-first century relative to what was achieved in the last two decades of the twentieth century across a range of dynamical and statistical prediction models (Barnston et al. 2012; Kumar et al. 2015). Unraveling the cause of this decline, despite ongoing improvements of seasonal forecast models and assimilation systems (e.g., Balmaseda et al. 2013; Saha et al. 2014; Zhao et al. 2013, 2014) and ocean initial conditions as a result of the advent of the Argo float profiling program after 2000 (e.g., Balmaseda et al. 2007), is important to guide development of observing and prediction systems and to inform the level of climate predictability that might be achieved in the future.

Interannual variability of the tropical eastern Pacific surface temperature was also observed to decrease in the early twenty-first century compared to the last two decades of the twentieth century (e.g., Hu et al. 2013), and this has been offered as an explanation for the reduced forecast skill of El Niño/La Niña in the eastern Pacific: the signal-to-noise ratio dropped (Barnston et al.
2012; Kumar et al. 2015). Weaker, more irregular El Niño/La Niña events are more difficult to predict than stronger, more regular events (e.g., Kirtman and Schopf 1998; Chen et al. 2004; Wen et al. 2014). Similar decadal covariations of forecast skill and El Niño variability have also been found using retrospective forecasts across the entire twentieth century (Tang et al. 2008) and based on model simulations (e.g., Kirtman and Schopf 1998).

An outstanding question then is why El Niño variability (used here to mean both La Niña and El Niño activity) in the eastern Pacific recently declined. One possibility is that it simply could have been by chance—for instance, because of variations in stochastic noise that interacts with El Niño (e.g., Kirtman and Schopf 1998). However, there is growing evidence that the characteristics of El Niño/La Niña changed at the end of the twentieth century in addition to the drop in variability, with central Pacific El Niño becoming more prominent (Ashok et al. 2007; McPhaden et al. 2011; Chung and Li 2013; Xiang et al. 2013). Furthermore, the lead–lag relationship between El Niño and the recharge/discharge of heat along the equator across the Pacific, which is at the root of long-lead predictability of El Niño (e.g., Jin 1997), also was reported to have weakened and shortened (Horii et al. 2012; McPhaden 2012; Wen et al. 2014), indicating some fundamental change in behavior of El Niño occurred at the end of the twentieth century that would act to reduce its predictability.

These changes in El Niño behavior have been postulated to have occurred because of a change in the background climate of the Pacific at the end of the twenty-first century (e.g., McPhaden et al. 2011; Hu et al. 2013; Chung and Li 2013; Xiang et al. 2013; Wen et al. 2014). This change in background climate has characteristics of a swing of the interdecadal Pacific oscillation (IPO) from its warm phase in the 1980s and 1990s to the cold phase in the early twenty-first century (Merrifield et al. 2012; Chung and Li 2013; L’Heureux et al. 2013; Xiang et al. 2013; Henley et al. 2015). This swing to the IPO-like cold state also has previously been associated with the recent hiatus in global mean warming (Kosaka and Xie 2013; England et al. 2014). The key changes in background climate include warmer SST in the western Pacific, colder SST in the eastern Pacific, and stronger equatorial trade winds in the central Pacific, which together can be characterized as a strengthening of the mean Walker circulation. This change in background climate has previously been diagnosed to have weakened key coupled feedbacks that promote El Niño in the eastern Pacific while promoting increased El Niño activity in the central Pacific (Chung and Li 2013; Xiang et al. 2013; Hu et al. 2016).

Previous studies have also indicated that epochs of low El Niño predictability and variability coincide with similar cold IPO-like states in the Pacific as was observed in the early twenty-first century (e.g., Kirtman and Schopf 1998; Rodgers et al. 2004; Choi et al. 2011; Hu et al. 2013; Ogata et al. 2013). However, in these studies it is not clear whether the changes in background climate simply result from changes in El Niño activity (e.g., Kirtman and Schopf 1998; Rodgers et al. 2004) or whether there is a feedback form the change in background climate onto the changes in El Niño variability (e.g., Choi et al. 2011; Hu et al. 2013; Ogata et al. 2013; Wittenberg et al. 2014). The premise of the current study is that the changes in El Niño variability and predictability are, at least partly, in response to the mean state changes as observed at the end of the twentieth century (e.g., Fedorov and Philander 2000).

We will address this hypothesis by conducting a simple forecast sensitivity experiment whereby seasonal forecasts of the coupled climate during the early twenty-first century are repeated but initialized with the background climate as observed during the warm phase of the IPO in the late twentieth century. Similarly, the seasonal forecasts during the late twentieth century are rerun but initialized with the background climate during the IPO-like cold phase in the early twenty-first century. In this fashion, the impact of the change in background climate on the initial tendencies of El Niño/La Niña anomalies can be assessed and inferences about changes in predictability can then be drawn. We use the Australian Bureau of Meteorology coupled model seasonal forecast system POAMA2.4. The POAMA2.4 system is described in section 2 along with the observational datasets used and design of the forecast sensitivity experiment. We note that control forecasts from a similar version of POAMA were included in the Barnston et al. (2012) assessment, with forecast skill and its decadal variation from POAMA being comparable to the other contributing coupled model systems. Changes in forecast skill from the POAMA control forecasts during 1981–99 compared to 2000–13 are provided in section 3. Results of the forecast sensitivity experiment are presented in section 4, and causes of the change in variability and predictability are diagnosed in section 5. Conclusions are presented in section 6.

2. POAMA, observational datasets, and sensitivity experiment

a. Model and control hindcasts

Our key tool is the POAMA2.4 coupled model seasonal prediction system (Hendon et al. 2009; Hudson
et al. 2013; Zhao et al. 2014). The POAMA2.4 system consists of a coupled atmosphere–ocean model and data assimilation/initialization systems. The coupled model consists of modest-resolution atmospheric (T47/L17) and ocean (2° longitude by 0.5° latitude) GCMs that are coupled once per day. Forecasts are initialized from observed atmosphere and ocean states as provided by assimilation/initialization systems. For this study, we use a 10-member ensemble of 9-month control hindcasts from version POAMA2.4 that are initialized on the first of each month for January 1981 to December 2013. Greenhouse gases are fixed at year-1985 levels. Atmospheric initial conditions are provided by nudging prognostic fields [zonal and meridional wind (\(u, v\)), temperature (\(T\)), and humidity (\(q\))], strongly to daily global atmospheric reanalysis (Hudson et al. 2011). ERA-40 (Uppala et al. 2005) is used during 1980–2002, while the NCEP-1 reanalysis (Kalnay et al. 1996) is used for 2003–13. The nudging approach for generating atmospheric initial conditions was designed so as to help reduce impacts from systematic changes in atmospheric fields as supplied by the different reanalyses (Hudson et al. 2011). Ocean initial conditions are provided by the POAMA Ensemble Ocean Data Assimilation System (PEODAS; Yin et al. 2011), which is an assimilation of available in situ observations of subsurface temperature and salinity into the ocean model that is driven by daily atmospheric fluxes. The surface forcing of the ocean model (stress, heat, and freshwater fluxes) in the assimilation cycle is also provided by ERA-40 and NCEP-1. During the assimilation cycle, SST is nudged strongly to the daily analyses of Reynolds et al. (2002). The PEODAS ocean reanalysis of \(T, S, u, v, w\), available on a 0.5° by 2.0° latitude–longitude grid, are reported to be of comparable or better quality to other operational ocean reanalyses generated for initializing seasonal predictions (Xue et al. 2012).

Ensemble mean forecasts are obtained by averaging 10 ensemble members that are initialized using coupled atmosphere–ocean perturbations generated via a breeding process (Hudson et al. 2013). We refer to these hindcasts based on observed atmosphere/ocean states as the control forecasts. Prediction skill of El Niño using the control hindcasts is on par with other state-of-the-art coupled model seasonal forecast systems (Barnston et al. 2012).

b. Verification data

Forecasts of El Niño–related sea surface temperature variations are verified using the Reynolds OI-v2 surface temperature analyses (Reynolds et al. 2002). We also assess changes in background climate using the monthly CMAP precipitation analyses (Xie and Arkin 1997) and NCEP-1 for mean sea level surface pressure and atmospheric vertical motion. Decadal changes in surface stress are assessed using the stress that is input to the PEODAS reanalysis (i.e., stress is provided by ERA-40 and NCEP-1).

Significance of the difference in means is assessed using a standard \(t\) test, the difference in variance using an \(f\) test, and the differences in correlation (regression) using a \(t\) test after applying Fischer’s transform. Our null hypothesis is zero difference. For the observed differences we use a two-sided test but use a one-sided test for the experiment minus control differences. For the two experiments we use 11-yr epochs (1985–95 and 2000–10), for which there are 132 forecast start times using 10 ensemble members. There are 228 forecast start times for the expanded period 1981–99 and 168 for 2000–13 using 10 ensemble members for the control hindcasts.

c. Sensitivity experiment

We pursue the hypothesis that changes in background climate contributed to the recent drop in predictive skill of eastern Pacific El Niño by conducting a simple forecast sensitivity experiment. We rerun the seasonal hindcasts during 2000–10 (referred to as epoch E2) but initialize them with the background climate from 1985 to 1995 (referred to as epoch E1), and vice versa for the hindcasts in E1. The impact of the change in background climate on prediction of El Niño and La Niña events in each epoch can then be diagnosed. The ambiguity of whether the enhanced predictability in E1 was simply due to the random occurrence of stronger El Niño/La Niña events is removed because we will diagnose the impact of the change in background climate on the events that did occur in each epoch. A further strength of this approach is that the impact of observed changes in background climate are assessed using a forecast model that has proven skill for depicting and predicting El Niño, in contrast to other model studies that have explored the response of El Niño to simulated changes in background climate (e.g., Choi et al. 2011; Wittenberg et al. 2014).

To clarify, let \(X_c(0)\) represent an initial atmosphere–ocean state at \(t = 0\) during E1 and \(Y_c(0)\) represent an observed state during E2. The subscript \(c\) indicates the observed initial states for the control forecasts. With an overbar representing the time average over the respective epoch and a prime indicating a deviation from that mean, the initial conditions for the control forecasts in the two epochs are as follows:

\[
X_c(0) = X'(0) + X_c(0) , \quad \text{and} \\
Y_c(0) = Y'(0) + Y_c(0).
\]

The initial conditions in the experiments with the swapped background climates are then simply formed as follows:
Here $\Delta = \bar{Y}_c - \bar{X}_c$, and noting that $\bar{X}_c = \bar{Y}_c$ and $\bar{Y}_c = \bar{X}_c$. By this construct, the initial anomalies in the experiment and control are defined to be identical but relative to different background climates.

After swapping the initial mean states, we rerun the forecasts for all start months from the first of each month in the two 11-yr periods and then examine the experiment-minus-control differences. We define the forecast anomalies relative to the lead-time-dependent climatology for each epoch and for the control and experiment forecasts separately.

These mean state differences in the initial conditions are depicted in Figs. 1 and 2. We purposely exclude the two big El Niňo events (1982/83 and 1997/98) from the definition of the mean state in E1; however, there is little difference in the mean state change or in the impact on the forecast experiment if these two events are included in the definition of the earlier epoch mean (e.g., Xiang et al. 2013). These epochal differences are similar in pattern and in magnitude inferred from the trends computed across the full period 1981–2013, as shown, for instance, in Xiang et al. (2013) and England et al. (2014). The salient changes in climate between E2 and E1 include warmer Indian and western Pacific Oceans with a strengthened east–west surface temperature gradient across the tropical Pacific (Fig. 1a) and stronger equatorial trade winds in the central Pacific (Fig. 1b). The increased trade winds in the central and western Pacific are indicative of a stronger mean Walker circulation with increased rainfall (Fig. 2a), increased tropospheric upward motion (Fig. 2b), and lower surface pressure (Fig. 2c) over the warmer western Pacific and Maritime Continent and reduced rainfall, higher pressure, and stronger subsidence over a colder central Pacific. In contrast to typical cold IPO conditions, the Indian Ocean during E2 is also warmer than normal, which could further contribute to the intensified Walker circulation and equatorial trade winds in the central Pacific (e.g., Luo et al. 2012).

Coincident with the stronger easterlies in the central-western equatorial Pacific, equatorial upwelling is shifted westward (Fig. 1b). The anomalous easterly stress also acts to drive a more steeply tilted equatorial thermocline across the Pacific (Fig. 1c), although the total change in thermocline slope is small (cf. epochal differences in depth of 20°C isotherm in Fig. 1c). In the eastern Pacific, a more modest decrease of upwelling occurs just to the north of the equator, which is coincident with veering of the surface stress anomalies from southeasterlies south of the equator to weak southwesters north of the equator.

This east–west pattern of upwelling change (increased in the western Pacific and decreased in the eastern Pacific), which we will show below to have an impact on coupled feedbacks associated with El Niňo.
development, is also evident in the ECMWF Ocean Reanalysis System 4 (ORAS4; Balmaseda et al. 2013; not shown) and is inferred from the decreased role for mean upwelling cooling in the eastern Pacific (110°–150°W) during E2 based on NCEP GODAS reanalyses (Hu et al. 2016).

These mean state changes in the initial conditions are applied to the full three-dimensional atmosphere (vorticity, divergence, $T$, moisture, surface pressure), land (temperatures and wetness), and ocean ($u$, $v$, $T$, and salinity) prognostic fields. However, the results are largely insensitive to changing the mean state only in the ocean because the atmosphere/land rapidly adjusts to the ocean.

The success of this forecast experiment depends on the capability of the experiment forecasts to maintain the epochal mean state changes long enough into the forecast in order to have a detectable impact on the behavior of El Niño. We assess the maintenance of the mean state difference by comparing the mean difference of SST (Fig. 3) and surface stress (Fig. 4) for all forecasts starts in E2 and in E1 using the control hindcasts and the mean difference between the experiment forecast during E1 and experiment forecasts during E2. The evolution of the mean state difference between the two epochs in both the control and experiment forecasts is similar and shows that the observed enhanced zonal temperature gradient across the Pacific and enhanced equatorial easterlies (strengthened Walker circulation) during E2 (i.e., Fig. 1) is well maintained for at least the first 3 months of the forecast and the broadscale contrast of SST across the Pacific basin is still maintained to at least 6-month lead time. These results suggest that the key differences in the atmosphere–ocean mean state between E2 and E1 that could be of relevance to altered El Niño behavior are maintained long enough so as to impact El Niño behavior during the forecasts.

There is also potential for shock in these experiment forecasts because we have artificially initialized with the mean climate from a different epoch. However, the evolution of the mean state differences is nearly identical in the control and experiment (Figs. 3 and 4), indicating little difference in behavior of the mean state in the control and experiments. We further show below little evidence of any abrupt change in standard deviation of surface temperature anomalies right after the initial time, together suggesting little shock in the experiment forecasts. Little shock is generated presumably because the imposed mean state differences are small relative to the interannual El Niño/La Niña anomalies (typically <20%), and the mean state changes are dynamically in balance because they are taken from the assimilated analysis.

3. Changes in control skill and ENSO variability

a. Control skill

We display in Fig. 5a the anomaly correlation coefficient and in Fig. 5b the normalized root-mean-square error (RMSE) for the monthly Niño-3 index for the two epochs using the control hindcasts. Note that in Barnston et al. (2012) forecast skill was assessed using a 3-month running mean; hence, forecast skill in their results is generally higher and falls off more slowly than reported here. RMSE for Niño-3 in Fig. 5b is normalized by the standard deviation of the observed Niño-3 index so that normalized RMSE < 1 is indicative of a skillful forecast relative to a climatological forecast. A similar message is provided by both measures in Fig. 5: the level of forecast skill that was achievable to a 9-month lead time during the earlier epoch E1 is only attained to a
3–4-month lead during E2. Kirtman and Schopf (1998) and Tang et al. (2008) found similarly large differences in predictive skill between epochs of high and low skill using an idealized ENSO models.

Breaking down the difference in forecast skill by start month [not shown, but see, e.g., Barnston et al. (2012)] shows that forecast skill declined for all start months, but the biggest decline was for forecasts across the “spring barrier”; that is, the biggest decline in skill occurred for forecasts that were initialized in boreal spring and verified in boreal summer and autumn.

Forecast skill is seen to be even lower during 2000–13 (dashed red curve in Fig. 5a) as compared to 2000–10 (solid red curve), indicating that the previously reported decline in predictive skill during the early 2000s continued through at least 2013. Skill in the earlier period E1 is high even with the exclusion of the two super EI Niños of 1982/83 and 1997/98 (dashed green curve for 1981–99 and solid green curve for 1985–95 in Fig. 5a). Hence, higher skill during E1 is not simply due to the (possibly random) occurrence of these two super–El Niño events.

Maps of the difference in RMSE for SST predictions in E2 and E1 (Fig. 6) show the primary drop in predictive skill of SST occurs in the eastern Pacific centered on the Niño-3 region. Forecast errors also increased in the off-equatorial western Pacific during E2, which is viewed to result from the teleconnection from the increased errors associated with El Niño in the eastern Pacific (e.g., Hu et al. 2013). At short lead times, there is...
little difference in forecast errors in the Niño-4 region of the equatorial central Pacific (area mean for 5°N–5°S, 160°E–150°W). If skill for the Niño-4 index is considered (not shown), forecast skill is slightly increased for the first 1–3 lead months during E2, but thereafter Niño-4 skill declined and forecast errors increased in the western Pacific relative to E1 (Fig. 6). The increase in forecast errors in the equatorial central and western Pacific at longer lead time in E2 presumably reflects model errors that act to extend variability associated with eastern Pacific El Niño into the central Pacific at longer lead time (Hendon et al. 2009).

b. ENSO variability

The recent drop in forecast skill for SST in the eastern Pacific coincides with a reduction in eastern Pacific El Niño activity during E2, as evidenced by a drop in standard deviation of SST in the Niño-3 region of the equatorial eastern Pacific (Fig. 1a; see also Barnston et al. 2012; Hu et al. 2013; Kumar et al. 2015). This drop in variability is quantified as a 38% decrease in the standard deviation of the Niño-3 index in 2000–13 compared to 1981–99 (significant \( p < 0.05 \)). Excluding the two big El Niño events in 1982/83 and 1997/98 results in a smaller but still highly significant decrease in Niño-3 standard deviation (16% decline for E2 compared to E1), so the decrease in standard deviation in E2 compared to E1 is not just due to the possibly random occurrence of the two super–El Niño events.

In contrast to the decrease in the eastern Pacific, variability of central Pacific surface temperatures appears to have slightly increased during E2 (Fig. 1a).
enhanced variability in the central Pacific is captured by the Niño-4 index (not shown), whose standard deviation increased in E2 relative to E1 by 5%, but this change is not significant. Taken together, these changes in SST variability are consistent with the previous reported decrease of eastern Pacific El Niño and increase of central Pacific El Niño after the end of the twentieth century (e.g., McPhaden et al. 2011; Hu et al. 2013; Xiang et al. 2013).

4. Impacts of changes in background climate

The impact on predicted El Niño variability of the imposed change in background climate is assessed first by examining the difference in standard deviation of the Niño-3 index as a function of forecast lead time for the experiment minus control (Exp−Ctrl) in each epoch (Fig. 7a). The differences are shown as the percentage change relative to the control. Initializing the forecasts during E2 with the background climate from E1 (red curve in Fig. 7a) results in increasing eastern Pacific El Niño amplitude and vice versa for the forecasts in E1 (green curve). By a 6-month lead time the differences in amplitude are comparable to the observed differences in standard deviation of the Niño-3 index between the two epochs (indicated by the asterisks on the y axis). The Exp−Ctrl differences after ~6 months are also comparable to the epochal differences in standard deviation from the control hindcasts (indicated by the blue dotted curve in Fig. 7a). The spatial pattern of the Exp−Ctrl differences in standard deviation of SST are shown in Fig. 8, which shows that the differences are concentrated in the Niño-3 region of the eastern Pacific, where the observed epochal differences in SST variability are the greatest (Fig. 1a).

We cannot directly assess changes in predictive skill as a result of changing the background climate in the initial conditions because changing the background climate will necessarily mean the predictive skill of observed events will be reduced. Hence, we assess impacts of changing the background climate on potential predictability. Potential predictability is estimated using the method of analysis of variance (Rowell et al. 1995) and is expressed as an explained variance (correlation coefficient squared), which is simply the ratio of the ensemble mean variance to the total ensemble variance:

\[ r^2 = \frac{\text{Var}_{\text{ensm}}}{\text{Var}_{\text{ensm}} + \text{Var}_{\text{spred}}} = \frac{\text{Var}_{\text{ensm}}}{\text{Var}_{\text{tot}}}. \]

An unbiased estimate of the ensemble mean variance is used (Rowell et al. 1995). The variance of the ensemble spread Var_{spred} is computed using the deviation of each of the 10 members about the ensemble mean. Potential predictability will increase as a result of an increase in ensemble mean variance (signal) relative to the spread variance (noise). Because we use a perfect model assumption, potential predictability is higher than actual prediction skill. Hence, for relative comparison, we also compute the difference in potential predictability using the control hindcasts for E2 and E1 expressed as a percentage.

In conjunction with increased Niño-3 amplitude when forecasts during E2 are initialized with E1 background climate (red curves Fig. 7a), potential predictability also increases with lead time (red curve Fig. 7b). Potential predictability increases because ensemble mean variance increases about twice as much as does the spread variance (not shown). Similarly, potential predictability decreases for forecasts during E1 when they are initialized with the background climate of E2 (green curve).
The changes grow with lead time because the forecasts in experiment and control are initialized with the same anomalies, so differences in variance and spread in the forecasts take time to develop. The changes in potential predictability in the experiments match well the differences diagnosed in the control hindcasts (dashed blue curve in Fig. 7b), suggesting that changes in potential predictability are a good indicator of changes in predictive skill.

By stratifying the forecasts by start month, the biggest changes in potential predictability are seen to occur for the control forecasts that are initialized in boreal spring season (Fig. 9a), which indicates that the biggest decline in predictability in E2 occurred across the “boreal spring predictability barrier” when El Niño is first growing and is most sensitive to noise (e.g., Fedorov et al. 2003). That is, the main drop in predictive skill in E2 resulted from the increased challenge of predicting El Niño for forecasts initialized just prior to and during boreal spring that verify in boreal summer and autumn prior to the peak of El Niño in boreal winter. This drop in predictability for forecasts across the spring barrier also reemerges at longer lead times (7–8 months) for forecasts initialized in October and November that verify in early boreal summer. In contrast, predictability is increased in E2 for forecasts initialized at the peak of El Niño in boreal winter and that verify 6–8 months later. This change in predictability across the “spring barrier” are well mimicked in the Exp−Ctrl for both epochs (Figs. 9b,c). This suggests that changes in the background climate have the greatest impact on El Niño behavior during the boreal spring.

5. Causes of changes in predictability

Why did eastern Pacific El Niño predictability and variability increase in E2 when the forecasts were initialized with the background climate of E1, and vice versa for the other epoch? Here we concentrate on the change in behavior in the first month of the forecast so as to best capture the impacts of the imposed change in background climate. We show in Figs. 10a,b the scatterplot of the Exp−Ctrl differences in predicted Niño-3 index at 1-month lead time versus the normalized observed initial Niño-3 anomaly. Recall that by construction the initial anomalies in both control and experiment forecasts are identical so we can construct the scatter of the differences in predicted Niño-3 anomalies versus the initial Niño-3 anomaly. To first order, we see that both El Niño (positive Niño-3) and La Niña (negative Niño-3) temperature anomalies tend to get stronger during E2 in the presence of the background climate from E1 (Fig. 10b) and vice versa during E1 in the presence of the background climate in E2 (Fig. 10a).

We interpret the slope of the scatter in Figs. 10a,b to be indicative of the change in growth rate of Niño-3 temperature anomaly. This is understood by assuming that the initial growth of a Niño-3 temperature anomaly in experiment and control forecasts is exponential:

\[ T_e(t) = T_e(0) \exp(\alpha_e t) \quad \text{and} \quad T_c(t) = T_c(0) \exp(\alpha_c t). \]

![Fig. 6. Differences in RMSE of monthly predicted SST (°C) from control hindcasts for 2000–10 minus 1985–95 for lead times of (a) 1, (b) 3, and (c) 6 months. Significant differences (p < 0.1; n = 132) are hatched and the Niño-3 region is boxed.](image-url)
The experiment minus control difference in initial tendency can then be expressed as follows:

\[ \Delta \frac{\partial T^e}{\partial t} = \frac{\partial T^c}{\partial t} \Delta T^e(0) = \alpha_r T^e(t) - \alpha_r T^c(t). \]

Using forward finite differences and making use of our construct whereby the initial anomalies in experiment and control are equal \([T^e(0) = T^c(0) = T(0)]\), the difference in growth rate for month 1 of the forecast is then approximated simply as follows:

\[ \Delta \frac{\partial T^e}{\partial t}(t = 1) = \frac{T^e(1) - T^c(1)}{\Delta t} = \beta T^e(0) \]

Here, \(\Delta t = 1\) month.

The quantity \(\beta\) is estimated by regressing the series of differences (experiment minus control) of predicted Niño-3 anomalies at lead time 1 month onto the corresponding series of standardized Niño-3 anomalies at the initial time. The value of \(\beta\) then has units of degrees Celsius per month and is interpreted as the difference in growth rate of an El Niño anomaly in response to the change in background climate.

The resulting regression slopes (indicated in the top right of Figs. 10a,b) are nearly equal in magnitude but with opposite sign for the two experiments. The magnitude of the change in growth rate (~0.05°C month\(^{-1}\)) is about 15% of the typical growth rate for a typical El Niño or La Niña event (e.g., Fedorov et al. 2003), which when compounded over ~6 months can account for the epochal difference in observed amplitude of Niño-3 (Fig. 7a). The negative slope in Fig. 10a shows that predicted El Niño and La Niña anomalies in the earlier epoch both weaken in response to initializing with the mean state from the later epoch. The positive slope in Fig. 10b shows that predicted El Niño and La Niña anomalies during the later epoch both strengthen in response to the background climate from the earlier epoch.

The difference in growth rate of predicted SST anomalies can be computed at each grid point in a similar fashion (Figs. 10c,d). We see that the change in growth rates is maximum in the Niño-3 region and matches well the resulting epochal differences in the pattern of surface temperature standard deviation from the experiments (Fig. 8).

The upper-ocean heat budget provides insight as to why the growth rates for El Niño/La Niña are changed in response to the change in background climate. We consider the mixed layer heat budget (averaged over 0–45 m) along the equator (averaged over 5°N–5°S). To good approximation and confirmed below, the difference in growth of an eastern Pacific El Niño temperature anomaly between the two epochs is governed by
differences in thermocline feedback and zonal advective feedback (e.g., Choi et al. 2011):

$$\frac{\partial T'}{\partial t} \approx -\overline{W} \frac{\partial T'}{\partial z} - u' \frac{\partial T}{\partial x}. \quad (1)$$

Overbars denote epochal means and primes are perturbations from those means. Here $T$ is the temperature averaged over the mixed layer of depth $H = 45\text{ m}$. The quantity $W$ is the vertical velocity (upwelling) at base of mixed layer $H$, and $u$ is the zonal current averaged over depth $H$. The vertical temperature gradient is computed at depth $H$ using the difference of the mean temperature in the mixed layer and the temperature at the base of the mixed layer. The first term on the right-hand side is referred to as the thermocline feedback, and the second term is referred to as the zonal advective feedback. As shown by Choi et al. (2011) and further justified below, we have neglected difference in the roles for 1) nonlinear terms, 2) advection of the mean vertical temperature gradient by anomalous vertical velocity (the Ekman feedback term, which is typically large only in the far-eastern Pacific), 3) advection of anomalous zonal temperature gradient by mean zonal currents, 4) meridional advection, and 5) surface heat fluxes and the residual terms. All of these neglected terms are important for growth, equilibration, and decay of El Niño/La Niña, but they do not significantly contribute to the epochal differences in El Niño behavior under investigation here.
Following the approach of Dinezio et al. (2012), we form the approximate heat budget from Eq. (1) for the experiment and control forecasts for month 1 using forward time differences and then difference the two budgets:

\[
\Delta \frac{\partial T}{\partial t} = \frac{T_e'(1) - T_e'(0)}{\Delta t} - \frac{T_c'(1) - T_c'(0)}{\Delta t} = \frac{T_e'(1) - T_e'(0)}{\Delta t} - \Delta \frac{\partial T}{\partial t} 
\]

where again we have made use of the construction that the initial anomalies are identical for experiment and control \([T_e'(0) = T_c'(0)]\).

The delta operator for the differences of means and perturbations is defined, for example, as follows:

\[
\Delta w(1) = w_e(1) - w_c(1), \quad \text{and} \quad \Delta \frac{\partial T}{\partial z} = \frac{\partial T_e'(1)}{\partial z} - \frac{\partial T_c'(1)}{\partial z}.
\]

The left-hand side of Eq. (2) is the total difference in tendency at month 1 as a result of imposing the change in mean state at the initial time. The right-hand side of Eq. (2) consists of two components for the thermocline feedback [terms (a) and (b)] and two components for the zonal advective feedback [terms (c) and (d)]. The thermocline feedback is composed of (a) the Exp−Ctrl difference in mean vertical velocity acting on the perturbation vertical temperature gradient and (b) the mean vertical velocity acting on the induced change in perturbation vertical temperature gradient between experiment and control. The zonal advective feedback is composed of (c) the anomalous zonal current acting on the Exp−Ctrl difference in mean zonal temperature gradient and (d) the induced change in anomalous zonal current between experiment and control acting on the mean zonal temperature gradient.

As for the estimation of the difference in growth rate, we highlight how El Niño/La Niña anomalies react to the imposed change in background climate by regressing all terms in Eq. (2) onto the normalized Niño-3 anomaly at the initial forecast time. Each term is formed using monthly output after smoothing anomalies in time and longitude with a three-point running mean and averaging about the equator (5°N–5°S). The regression of each term in Eq. (2) onto the initial Niño-3 anomaly is then formed at each longitude along the equator.

Fig. 9. Epochal differences in potential predictability (expressed as percentage change of explained variance) of Niño-3 index for (a) control forecasts 2000–10 minus 1985–95, (b) Exp−Ctrl forecasts for 1985–95, and (c) Exp−Ctrl forecasts for 2000–10. Differences are shown as a percentage change relative to the control. Difference in predictability is shown as a function of forecast start month (y axis) and lead time (x axis). Dotted sloping lines indicate a constant verification month.
We display the regression coefficients for the total tendency and the sum of the three terms labeled (a), (c), and (d) of Eq. (2) (Fig. 11a). The Exp–Ctrl difference in growth rate of the temperature anomaly in the eastern Pacific associated with an initial El Niño/La Niña anomaly is seen to be well approximated by the sum of these three terms and so justifies the approximation of the difference heat budget Eq. (2). The two primary terms for causing the change in El Niño amplitude in the eastern Pacific are the change in thermocline feedback due to the change in mean upwelling [term (a); Fig. 11b], which dominates the change in the eastern Pacific, and the change in zonal advective feedback as a result of changed zonal current anomalies during the forecast in response to the changed background climate [term (d); Fig. 10d], which dominates the changes in the central Pacific. Term (b), the change in thermocline feedback due to the change of the vertical gradient of anomalous temperature during the forecast, is found to be small and is not shown.

The sense of these changes is that the weakened mean upwelling in the eastern Pacific during E2 (i.e., Fig. 1b) acts to reduce the thermocline feedback (green curve in Fig. 11b). The opposite occurs for forecast during E2 in response to the mean change in upwelling during E1 (red curve in Fig. 11b). These changes are consistent with the weakened thermocline feedback diagnosed by Hu et al. (2016). We also see that the initial zonal current anomalies are weakened in the central Pacific during the forecasts in E1 in response to the background climate of E2, thus resulting in weaker zonal advective feedback in the central Pacific (green curve in Fig. 11d). Strengthened zonal advective feedback in the far-western Pacific for forecast during E1 as a result of strengthened mean zonal temperature gradient in the western Pacific during E2 is also detected (green curve in Fig. 11c). This change in zonal advective feedback in the western Pacific as a result of the mean strengthening of the zonal temperature gradient across the Pacific has previously been associated with the recent increase of central Pacific El Niño (Chung and Li 2013; Xiang et al. 2013; Hu et al. 2016). However, we note here the more dominant term is the change in zonal advective feedback in the central Pacific as a result of a weakening (strengthening) of the zonal current anomalies during the forecasts in response to the mean climate during E2 (E1). At longer lead
times (not shown), term (d) in Eq. (2) is found to dominate and so leads to the change in SST standard deviation that is maximized in the central-eastern Pacific as seen in Fig. 8.

The change in El Niño growth rates due to the changes in mean upwelling [term (a) in Eq. (2)] is easy to understand. However, why did the change in background climate cause a change in zonal current anomalies during the forecast, thus resulting in increased zonal advective feedback [term (d)] in the central Pacific during E1 and decreased feedback during E2? Chung and Li (2013) and Xiang et al. (2013) have previously argued that the change in background climate toward a strengthened mean Walker circulation with intensified east–west SST gradient across the Pacific during E2 would act to reduce the sensitivity of the atmospheric response to the surface temperature anomalies in the central and eastern Pacific. That is, for a given SST anomaly during E2 a weaker rainfall and surface zonal wind anomaly would develop compared to during E1, hence resulting in weaker induced zonal currents.

We diagnose this tendency for the surface zonal wind anomalies to weaken during the forecasts during E2 relative to E1 in a fashion similar to how we diagnosed the difference in SST growth rates (Figs. 10c,d). That is, we regress the difference in surface zonal stress anomalies between the experiment and control forecasts at month 1 onto the initial normalized Niño-3 anomaly. We do this regression at each grid point (Fig. 12), which we interpret as the difference in surface zonal stress growth rate per initial unit Niño-3 anomaly. The pattern of growth rate differences are negative (indicating relative damping) on the western edge of the Niño-3 region for the forecasts during E1 that are reinitialized with the background climate of E2 (Fig. 12a). In contrast, the growth rates are positive there for forecasts during E2 that are reinitialized with the background climate of E1. That is, the background climate during E1 relative to the background climate of E2 favors strengthening of the

Fig. 11. Regression onto the initial Niño-3 anomaly of the differences in predicted upper-ocean temperature tendency (Exp – Ctrl; °C month⁻¹) for month 1 averaged in latitude (5°N–5°S) and over depth (0–45 m). (a) Differences in total temperature tendency (solid curves) and tendency approximated by the sum of the three components shown in (b), (c), (d) (dotted-dashed curves); (b) difference in thermocline feedback tendency due to mean change in background upwelling; (c) difference in zonal advective tendency due to mean change in background zonal temperature gradient; and (d) difference in zonal advective tendency due to the difference in zonal current anomalies during forecast. Red curves are Exp – Ctrl forecasts for 2000–10 and green curves for 1985–95.
surface zonal wind stress anomalies associated with the El Niño SST anomaly.

Another way to diagnose the difference in surface zonal wind response between the two epochs is to regress the surface zonal wind along the equator onto the observed normalized Niño-3 anomaly separately for the two epochs (as opposed to regressing the differences in the anomalies). We can do this for the observed behavior in the two epochs (Fig. 13a) and using the control and experiment forecasts at 1 month lead time (Fig. 13b). Consistent with Chung and Li (2013) and Xiang et al. (2013), the zonal wind anomaly associated with a Niño-3 anomaly is weaker and shifted westward during E2, which would result in weaker surface zonal current anomalies in the central and eastern Pacific during E2 (and vice versa in E1), thus resulting in weaker zonal advective feedback. This observed epochal change in zonal wind response to an El Niño temperature anomaly is well depicted in the control and experiment forecasts (Fig. 13b).

This weakened zonal wind response to an El Niño temperature anomaly during E2 comes about because 1) an eastern Pacific El Niño/La Niña surface temperature anomaly acts on a colder mean eastern Pacific during the cold phase of the IPO and so produces a weaker and westward-shifted rainfall/zonal wind response and 2) stronger mean subsidence in the eastern Pacific (e.g., Fig. 2b) during E2 due to the strengthened mean Walker circulation acts to suppress the rainfall/wind response to an eastern Pacific surface temperature anomaly (e.g., Chung and Li 2013; Xiang et al. 2013). In summary, the likelihood and predictability of El Niño in the eastern Pacific during E2 decreases because the shift to stronger mean Walker circulation and strengthened east-west temperature gradient act to promote weaker events that are more susceptible to noise.

6. Conclusions

Eastern Pacific El Niño variability and predictability was weaker in the early twenty-first century compared to the late twentieth century. We have argued that the change in background climate, characterized as a swing
to the cold phase of the IPO at the end of the twentieth century, contributed to the weaker eastern Pacific El Niño/La Niña variability, and hence predictability. The change in background climate acted to weaken key coupled air–sea feedbacks that promote El Niño/La Niña in the eastern Pacific, consistent with other analyses (e.g., Hu et al. 2016). The key impacts of the change in background climate were to reduce the thermocline feedback in the eastern Pacific, as a result of a westward shift of mean upwelling, and a reduction of zonal advective feedback in the central Pacific as a result of weakened air–sea coupling due to a colder eastern Pacific under stronger mean sinking motion that acts to reduce the atmospheric response to a surface temperature anomaly. Although these impacts of the change in background climate on the stability of El Niño might seem counterintuitive (i.e., a more steeply tilted thermocline as occurred during E2 might be assumed to promote stronger air–sea coupling), they are consistent with previous diagnosed impacts of changes in background climate on El Niño stability (e.g., Kirtman and Schopf 1998; Rodgers et al. 2004; Choi et al. 2011; Hu et al. 2013; Ogata et al. 2013; Hu et al. 2016).

Our results make the case that the change in background climate affected eastern Pacific El Niño variability and predictability. An important implication of our study is that likelihood of a super El Niño, such as occurred during 1982 and 1997, appears to be pre-conditioned by the background climate. However, we have provided no insight as to what caused the change in background climate. We have not precluded the possibility of a two-way feedback such that the change in El Niño variability then acted to promote or sustain the change in background climate. There is ample evidence from other simulations that reduced El Niño variability can cause an IPO-like cold state such as occurred in the early twenty-first century (Kirtman and Schopf 1998; Rodgers et al. 2004; Choi et al. 2011; Ogata et al. 2013). Such background climate changes result from asymmetries in the structure and evolution of El Niño compared to La Niña, thereby yielding a rectified mean state change as a result of random changes in El Niño variability. Our results do not preclude a primary role for this pathway of the observed changes in background climate that occurred at the end of the twentieth century, but our results suggest that at a bare minimum a two-way feedback is occurring (i.e., the mean state change is affecting El Niño behavior and variability that then further promotes the mean state change). An avenue of future research then is to understand how the change in El Niño activity in response to a change in background climate then feeds back onto the background climate. Equally important, the cause of the swing from one background state to the other needs to be addressed.

Further, the robust impact of variations in background climate on eastern Pacific El Niño variability and predictability suggest we should expect similar decadal variations in El Niño behavior in the future, including changes in the likelihood of super El Niño. However, we have not provided insight as to whether such changes in background climate might be predictable. If they stem largely from a residual or nonlinearity due to stochastically driven changes in El Niño variability, then they might be largely unpredictable (e.g., Wittenberg et al. 2014). However, this swing to the cold IPO phase at the end of the twentieth century may be in part a response to forced climate change such that the eastern Pacific warms more slowly than the other oceans (Clement et al. 1996; Luo et al. 2012). If this is the case, some predictability of changes in El Niño behavior should be expected, assuming this interbasin change in background climate can be well simulated and predicted. At a longer time scale, although a consensus is emerging about expected changes of El Niño impacts in a warming climate (e.g., Power et al. 2013), there is as yet little insight as to how El Niño predictability might change because there is little agreement as to how El Niño activity might change in a warmer climate (e.g., Collins et al. 2010).

A key caveat of this current study is that it is based on a single forecast model that has systematic errors, especially in maintaining the distinction between eastern Pacific El Niño and central Pacific El Niño beyond a 3-month lead time (Hendon et al. 2009). Confidence in our results, however, is provided by the faithful representation of the observed dominant changes in eastern Pacific El Niño behavior in both the control and experiment forecasts and the consistency with other studies regarding the association of weakened eastern Pacific El Niño variability and predictability with the recent cold IPO-like state (e.g., Wen et al. 2014; Hu et al. 2016). Nonetheless, confirmation of these results with other prediction systems is warranted.

Acknowledgments. Support for this study was provided by the Victorian Climate Initiative and Managing Climate Variability programs. We thank D. Hudson, Y. Yin, and E.-P. Lim for technical assistance and J.-J. Luo, S. B. Power, A. Santoso, and the anonymous reviewers for comments on an earlier version of the manuscript.

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