

1 Weakened El Niño Predictability in the Early 21st Century

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8 **Predictive skill for El Niño-Southern Oscillation (ENSO) during 2000-2013 declined**
9 **sharply relative to that achieved during 1980-1999¹ despite improvements of forecast**
10 **systems^{2,3} and initial conditions^{4,5}. This decline in skill coincides with a reduction of**
11 **ENSO activity⁶ and a shift in Pacific climate to a stronger Walker circulation^{7,8,9}, which**
12 **has previously been associated with the recent pause in global-mean surface**
13 **warming^{10,11}. We show using seasonal forecast sensitivity experiments that this shift in**
14 **Pacific climate also drove the drop in ENSO predictive skill because the atmosphere-**
15 **ocean feedbacks that sustain ENSO are weakened. Weakened atmosphere-ocean**
16 **coupling due to the ongoing strengthened Walker circulation helps explain the**
17 **unpredictable behaviour of El Niño in 2014. The recent decadal decline in ENSO**
18 **predictability is a sobering reminder that the long lead prediction achieved during**
19 **1980-1999 might not be achievable in the future, although the robust impacts of the**
20 **background Pacific climate variation on ENSO predictability indicate the potential for**
21 **prediction of decadal variations in ENSO activity. However, anticipating future changes**
22 **in ENSO predictability poses challenges because the causes and predictability of the**
23 **change in background tropical Pacific climate, including any contribution of**
24 **anthropogenic climate change, are as yet poorly quantified and simulated^{11,12,13}.**

25 ENSO causes major changes to rainfall, temperature, and severe weather in many
26 parts of the world, with impacts on agricultural production, water resources, and
27 ecosystems¹⁴. Fortunately, the occurrence of ENSO can be predicted up to 2-3 seasons in
28 advance¹⁴, which helps in preparing for ENSO-driven impacts. Hence, unravelling the
29 decline in ENSO predictive skill in the early 21st century, which has been reported across a

1 range of dynamical and statistical forecast systems¹, is important to guide future development
2 of prediction systems and to inform the level of climate predictability that might be achieved
3 in the future. This recent decline in ENSO prediction skill is demonstrated by comparing
4 hindcast predictions (referred to as control forecasts) of surface temperature in the equatorial
5 eastern Pacific during 2000-2013 and 1981-1999 using the Australian Bureau of
6 Meteorology operational seasonal forecast system⁴ (Fig. 1d): the level of skill that was
7 achievable to 9 months lead time in the late 20th century is only be attained to 3 month lead
8 in the early 21st century. The further drop in skill when 2000-2013 is compared to 2000-
9 2010 indicates that the previously reported decline in skill for the early 2000's is ongoing.

10 This dramatic drop in forecast skill in the recent two decades coincides with a marked
11 reduction in ENSO activity⁶ as indicated by reduced temperature variability in the Niño3
12 region (Fig. 1a). The drop in forecast skill thus can be understood as resulting from decreased
13 signal-to-noise: big events are easier to predict than weak events^{1,15,16}. This impact of
14 variability on predictive skill is demonstrated by a decrease in forecast skill when the two
15 large El Niño episodes in 1982/83 and 1997/98 are excluded from the assessment of skill in
16 the earlier epoch by comparing 1981-1999 to 1985-1995 (Fig. 1d).

17 The reduction of ENSO activity, which can explain the drop in forecast skill in the
18 early 21st century, has been postulated to result from a random reduction in ENSO events¹⁷.
19 However, the recharge-discharge mechanism that provides the long lead predictability of
20 ENSO¹⁴ also weakened in the recent epoch¹⁸, which indicates that there have been changes in
21 the primary mechanism causing ENSO that might have contributed to the decline in forecast
22 skill.

23 Concurrent with the decline in ENSO variability and predictive skill, the climate of the
24 Pacific varied decadal as manifest by a swing in the Interdecadal Pacific Oscillation (IPO)
25 to its cold phase after the strong El Niño 1997-98^{7,8,8,10,11,17}. The key changes in background

1 climate are captured by the epochal mean differences shown in Figs. 1a,b,c. The recent epoch
2 is characterized by stronger trade winds in the central and western Pacific, a strengthened
3 east-west surface temperature gradient, westward displaced equatorial upwelling, and a more
4 steeply tilted thermocline⁶. The upwelling change reflects the local response to changes in
5 surface stress, whereas the steepened thermocline stems from the integrated effect of
6 increased trade winds across the basin. The increased trade winds are reflective of a stronger
7 Walker Circulation^{97,8,9,10,11} with increased rainfall and lower surface pressure over a warmer
8 western Pacific and Indian Oceans and reduced rainfall, higher pressure and stronger
9 subsidence over a colder eastern Pacific (Supplementary Fig. 1). This shift in background
10 climate is counter to that anticipated by anthropogenic climate change¹² and has been
11 associated with the recent hiatus in global warming^{10,11}, but here we will show it has also
12 acted to reduce ENSO variability and predictability and so results in lower predictive skill.

13 We demonstrate this with a forecast sensitivity experiment, whereby we re-run the
14 seasonal hindcasts in the later epoch but initialized with the background climate from the
15 earlier epoch, and vice versa for the hindcasts in the earlier epoch (see Methods). We then
16 compare ENSO prediction between pairs of control and experiment hindcasts. The strength
17 of this approach is that rather than assessing impacts of projected or idealized variations of
18 background climate on ENSO evolution^{162,13,19,20}, observed background changes are imposed
19 onto observed initial anomalies using a forecast model whose past performance for predicting
20 the observed ENSO is established⁴. Any detected changes in ENSO predictability thus should
21 reflect impacts of the observed changes in background climate. This approach also removes
22 the ambiguity of whether the enhanced predictability in the earlier epoch was simply due to
23 the random occurrence of stronger ENSO events then because by design we assess the impact
24 of the mean state change on the events that did occur in each epoch.

1 Initializing the forecasts in the later epoch with the background climate from the earlier
2 epoch results in increased ENSO amplitude (Fig. 2a) and predictability (Fig. 2b), and vice
3 versa for the forecasts in the earlier epoch. The differences grow with lead time, and by 6
4 months the changes in amplitude are comparable to the observed differences between the two
5 epochs (compare Supplementary Figs. 4c,f to Fig. 1a). Predictability differences are
6 comparable to the epochal differences in the control forecasts (Fig. 2b), with the biggest
7 changes occurring for forecasts initialized in the first half of the year (Supplementary Fig. 5)
8 when ENSO is most rapidly growing. Importantly, the initial mean state changes are largely
9 maintained through the first few months of the experiment similar to the epochal differences
10 in the control forecasts (Supplementary Figs. 2a-c), so we are confident that detected changes
11 in ENSO behaviour stem from the imposed initial differences in background climate.

12 The impact of the background climate change on individual El Nino and La Nina
13 events is demonstrated by the scatter of the differences in predicted Niño3 index at 1 month
14 lead versus the observed Niño3 index anomaly at the initial time (Figs. 3 c and d), recalling
15 that the control and experiment forecasts are initialized with the same observed Nino3
16 anomaly. Importantly, El Niños get warmer and La Niñas get colder in the presence of the
17 background climate from the earlier epoch (and vice versa in response to background climate
18 in the later epoch), confirming that the mechanisms causing ENSO are altered by the change
19 in background climate. The slope of the regression in Figs. 3c,d, which has nearly identical
20 magnitude but opposite sign in the two epochs, is interpreted as the difference in growth rate
21 of an ENSO anomaly in response to the change in background climate (see Methods) and has
22 magnitude of about 15% of the typical ENSO growth rate. This regression is also computed
23 at every model grid point (Fig, 3 a,b) and shows that the difference in growth rate has
24 largest amplitude in the equatorial eastern Pacific where ENSO variability is strongest and

1 the pattern is similar to the observed epochal changes in variability (Fig. 1a) and predicted
2 differences in amplitude (Supplementary Fig. 4).

3 Positive feedbacks involving the atmosphere and ocean are fundamental to
4 development of ENSO^{14,21}: the ENSO ocean surface temperature anomaly drives rainfall and
5 zonal wind variations that act to strengthen the ocean temperature anomaly²¹. The strength of
6 these feedbacks depends on the background climate¹⁴. The difference (experiment minus
7 control) heat budget in the upper ocean (Supplementary Information) reveals how these
8 feedbacks respond to changes in the background climate (Supplementary Fig. 6). Reduced
9 ENSO variability during the recent epoch results from a roughly equal contribution of
10 weakened "thermocline feedback" (i.e., the growth of a temperature anomaly due to
11 advection of thermocline perturbations by mean upwelling) because of reduced mean
12 upwelling east of the dateline (Fig. 1c), and weakened "zonal advective feedback" (ie growth
13 of temperature anomaly due to advection of the mean zonal SST gradient by anomalous
14 zonal currents; Supplementary Fig. 6d) because of weaker generated zonal current anomalies
15 in the central Pacific^{7,9}. An increase of zonal advective feedback in the far western Pacific,
16 due to the intensified surface temperature gradient in the recent epoch (Fig. 1a), is also
17 detected (Supplementary Fig. 6c) and has been attributed to be the cause of the recent
18 increase of surface temperature variability in the western Pacific^{7,9,20}.

19 Weakened zonal advective feedback in the central Pacific during the recent epoch
20 stems from weakened atmosphere-ocean coupling^{7,9,20}: based on observed data, the westerly
21 (easterly) wind response to an El Niño (La Niña) surface temperature anomaly is shifted
22 west in the recent epoch (Supplementary Fig. 7), which results in a weaker ocean response to
23 the east^{7,9}. This change in the zonal wind response comes about because a) a surface
24 temperature anomaly developing in the colder eastern Pacific during the recent epoch will
25 produce a weaker and westward shifted rainfall response^{7,9,19,20} and b) stronger mean

1 subsidence in the eastern Pacific in the recent epoch due to the strengthened Walker
2 circulation acts to suppress the rainfall/wind response to a surface temperature anomaly^{7,9}.

3 These findings shed light onto the challenges of predicting development of El Niño in
4 early 2014, which stalled during boreal summer after strong development during spring²².
5 Forecasts from initial conditions on 1 April 2014 (Fig. 4a) predicted continued development
6 of El Niño but underestimated the decay around July, which has been attributed to the lack
7 of an accompanying sustained response in the atmosphere as embodied by a negative swing
8 in the Southern Oscillation²². Forecasts from 1 May 2014 (Fig. 4b) well captured the demise
9 in July but now predict near-neutral conditions by year's end. In contrast, if these forecasts
10 are remade using the background climate from the late 20th century, a much stronger, more
11 predictable El Niño develops from 1 April, while little decay is predicted from 1 May,
12 suggesting that the fickle nature of El Niño 2014 reflects weakened atmosphere-ocean
13 coupling as a result of the ongoing shift in background climate.

14 The robust impact of variations in background Pacific climate on ENSO activity and
15 predictability suggest the potential for prediction of decadal variations in ENSO activity.
16 However, we have not provided insight as to what caused the recent intensification of the
17 Walker circulation. It might stem from natural, yet largely unpredictable, decadal variations
18 of Pacific climate^{13,19,20,23}, or it may be a response to forced climate change such that the
19 eastern Pacific warms more slowly than the other oceans^{24,25}. Furthermore, although a
20 consensus is emerging about expected changes of ENSO impacts in a warming climate²⁶,
21 there is as yet little insight or as to how ENSO predictability might change because there is
22 little agreement as to how ENSO activity might change¹². The recent shift in Pacific climate
23 appears to be not well simulated with contemporary climate models¹¹, suggesting model
24 errors are limiting the capability to simulate and predict variations of Pacific climate that are
25 relevant to future variations of ENSO activity. We suggest that our approach of evaluating

1 ensembles of short-lead seasonal predictions, initialized from observed states at multiple start
2 times from different climate epochs could be an efficient manner to reveal the source of error
3 in the representation of climate variations such as those discussed here, and so lead to
4 improved climate models that are of more utility for predicting future climate.

5 **Methods**

6 **Coupled Model Seasonal Hindcasts**

7 A 10-member ensemble of 9-month control hindcasts (re-forecasts) using the
8 Australian Bureau of Meteorology seasonal prediction system POAMA24.c are initialized on
9 the first of each month for January 1981 to December 2013 from observed atmosphere-
10 ocean states⁴. Ocean initial conditions are provided by the PEOODAS reanalysis²⁷. The quality
11 of the PEOODAS reanalyses is comparable to other operational ocean re-analyses²⁸. Ensemble
12 mean forecasts are obtained by averaging the 10 members. We refer to these hindcasts as the
13 control forecasts. Prediction skill of ENSO using the control hindcasts is on par with other
14 state-of-the-art coupled model seasonal forecast systems^{1,4}.

15 ENSO forecast skill is assessed using correlation of the Niño3 Index (ocean surface
16 temperature averaged 5°N-5°S, 90°W-150°W), which captures the maximum surface
17 temperature variability associated with ENSO. For assessment of the forecasts in 2014 we
18 also use the Niño3.4 Index (5°N-5°S, 120°W-170°W). Forecasts are verified using the
19 Reynolds OI-v2 surface temperature analyses²⁹.

20 **Forecast Experiment**

21 We conduct a forecast experiment by swapping the mean states of the initial conditions
22 defined over the 2 epochs (1985-1995) and (2000-2010). Note that we have excluded the two
23 big El Niño events (1982/83 and 1997/98) from the definition of the mean state in the earlier
24 epoch in order to not bias the results due to the occurrence of these big events, however there
25 is little difference in the mean state or in the impact on the forecast experiment if these two

1 events are included in the definition of the earlier epoch mean. The mean state changes in
 2 the initial conditions are applied to the full 3-dimensional atmosphere (u, v, T, moisture,
 3 surface pressure, soil temperature and moisture) and ocean (u, v, T, and salinity) fields.
 4 These mean state differences are nearly identical to those derived from 2000-2013 minus
 5 1981-1999 as depicted in Figs. 1a,b,c and Supplementary Fig. 1.

6 Let $X_c(0)$ represent an initial atmosphere-ocean state during the earlier epoch (1985-
 7 1995). Let $Y_c(0)$ similarly describe an observed state during the later epoch (2000-2010). The
 8 subscript c , for control, indicates that observed initial states are used for the control forecasts.
 9 With an overbar representing the time average over the respective epoch and a prime
 10 indicating a deviation from that mean, the initial conditions for the control forecasts in the
 11 two epochs are

$$X_c(0) = X'(0) + \bar{X}_c(0)$$

12 And

$$Y_c(0) = Y'(0) + \bar{Y}_c(0).$$

14

15

16 The initial conditions in the experiments with the swapped background climates are
 17 then

$$18 \quad X_e(0) = X'(0) + \bar{Y}_c(0) = X_c(0) + \Delta$$

19

$$20 \quad Y_e(0) = Y'(0) + \bar{X}_c(0) = Y_c(0) - \Delta$$

21

22 Here $\Delta = \bar{Y}_c - \bar{X}_c$, and noting that $\bar{X}_e = \bar{Y}_c$ and $\bar{Y}_e = \bar{X}_c$.

23 After swapping the initial mean states, we rerun the forecasts for the two periods and
 24 examine the experiment minus control differences. We define the forecast anomalies relative

1 to the lead-time dependent climatology for that epoch, and we do this for control and
2 experiment forecasts for each epoch separately.

3

4 **Predictability**

5 We assess *prediction* skill, which is the capability of the forecast system to predict
6 observed events, by verifying forecasts against observations. We assess *predictability*, which
7 is an inherent characteristic of the climate, using a perfect model assumption. Here we use
8 the method of analysis of variance³⁰, which assumes that the predictable fraction of the total
9 variance of the ensemble is given by

$$10 \quad Var_{pred} = Var_{ensm}^* / (Var_{ensm}^* + Var_{sprd})$$

11 where

$$12 \quad Var_{ensm}^* = Var_{ensm} - \frac{1}{N} Var_{sprd}$$

13 is a non-biased estimate of the variance of the ensemble mean. The variance of the
14 ensemble spread Var_{sprd} is computed using the deviation of each of the ten members about
15 the ensemble mean.⁶

16 **Statistical Significance**

17 Significance of the difference in means is assessed using a standard t-test, the
18 difference in standard deviations using an f-test, and the differences in correlation using a t-
19 test after applying Fischer's transform. Our null hypothesis is no difference. For the observed
20 behavior we use a 2-sided test, but use a one sided test for the experiment-control
21 differences. For the two 11-year epochs (1985-1995 and 2000-2010) there are 132 forecast
22 start times. There are 228 forecast start times for 1981-1999 and 168 for 2000-2013.

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- 23
- 24 **Supplementary Information** is linked to the online version of the paper at
25 www.nature.com/nature.

1

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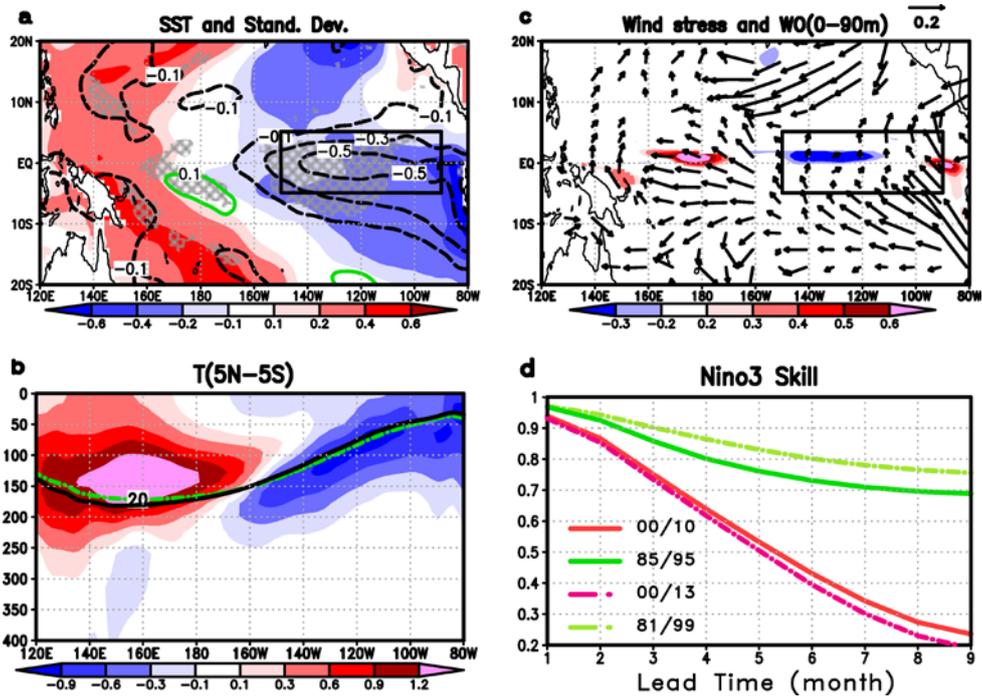
7 **Author Contributions** O. A., H. H., and M.Z. conceived and designed the experiments. G.L.
8 created the initial conditions and ran the experiments. M. Z., H. H. and G.W. conducted the
9 analysis. H.H. wrote the first draft of the paper and all authors contributed to the revisions.

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2 **Figures**

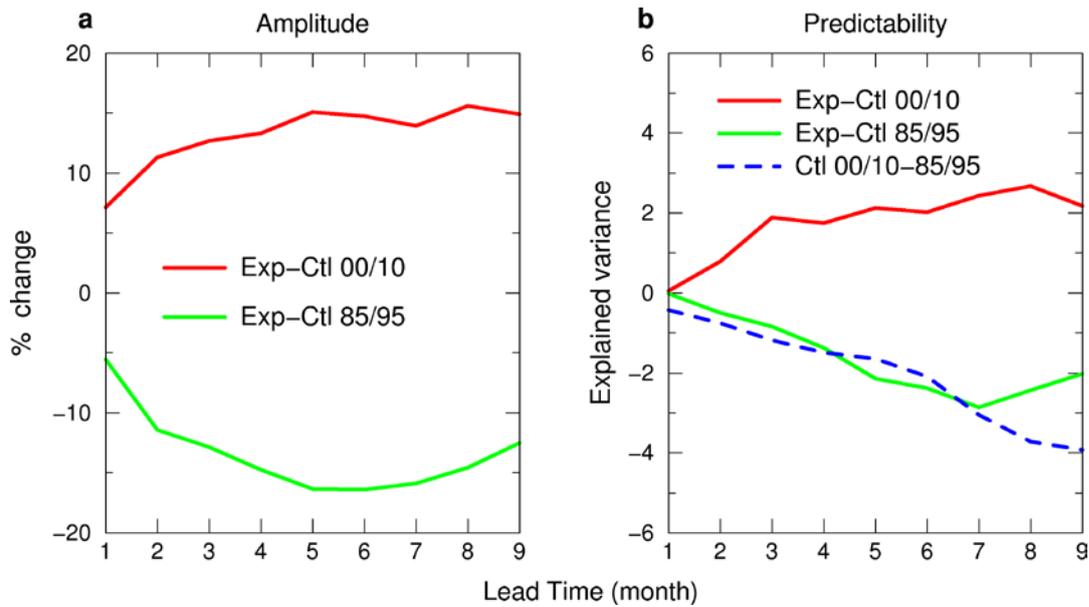


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Figure 1 Epochal mean differences (2000-2013 minus 1981-1999). **a:** Surface temperature (shaded °C) and its monthly standard deviation (contour interval 0.2 °C with first contour at +/- 0.1, solid green for positive differences and dashed black for negative differences); **b:** temperature along equator (5°N-5°S) versus depth (shaded °C) with thermocline indicated by 20°C isotherm for later epoch (black solid) and earlier epoch (green dashed); **c:** upwelling velocity averaged 0-90 m, (shaded, units 10^{-5} m s^{-1}) and surface stress (maximum displayed vector 0.2 Nm^{-1}). **d:** prediction skill (correlation versus lead time in months) of the Niño3 index from control hindcasts initialized every month during 2000-2010 (red solid curve), 2000-2013 (red dashed curve), 1985-1995 (solid green curve) and 1981-1999 (dotted green curve). The solid black box in **a** and **c** depicts the Niño3 Index region. Mean differences in **a**), **b**) and **c**) are shaded and vector differences are plotted where significant for ($p < 0.1$).

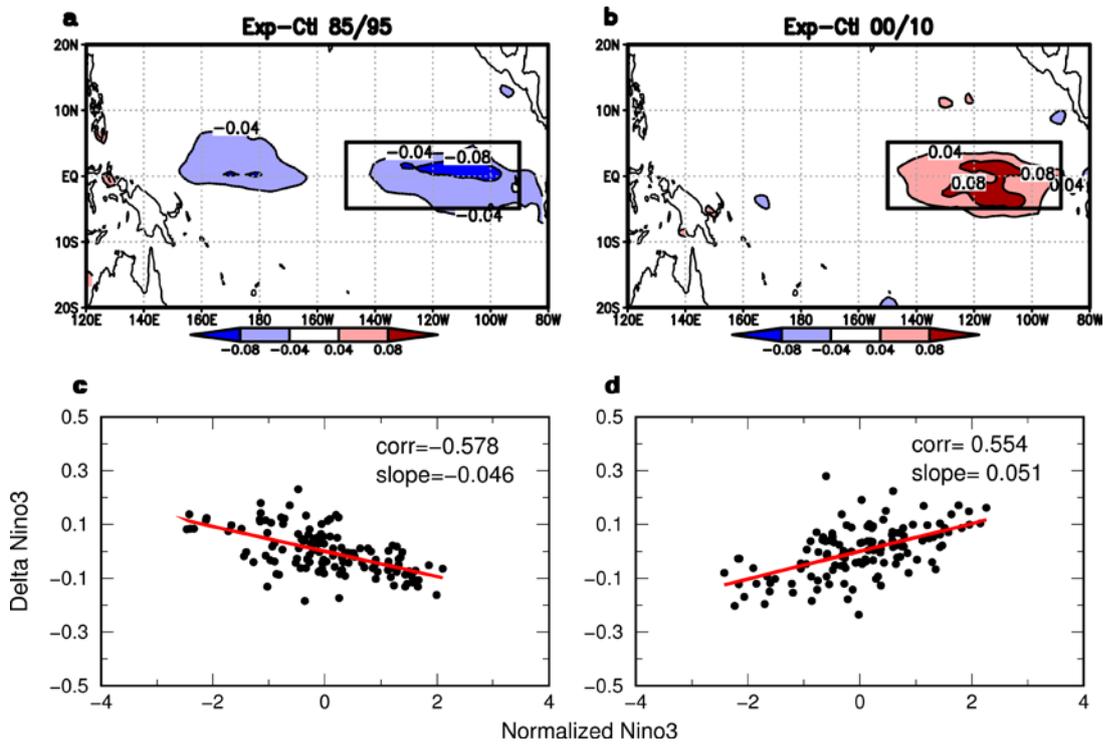
1 Significant differences ($p < 0.1$) in standard deviation in a) are hatched. Epochal differences in
 2 correlation in d) are significant ($p < 0.1$) at every lead time.

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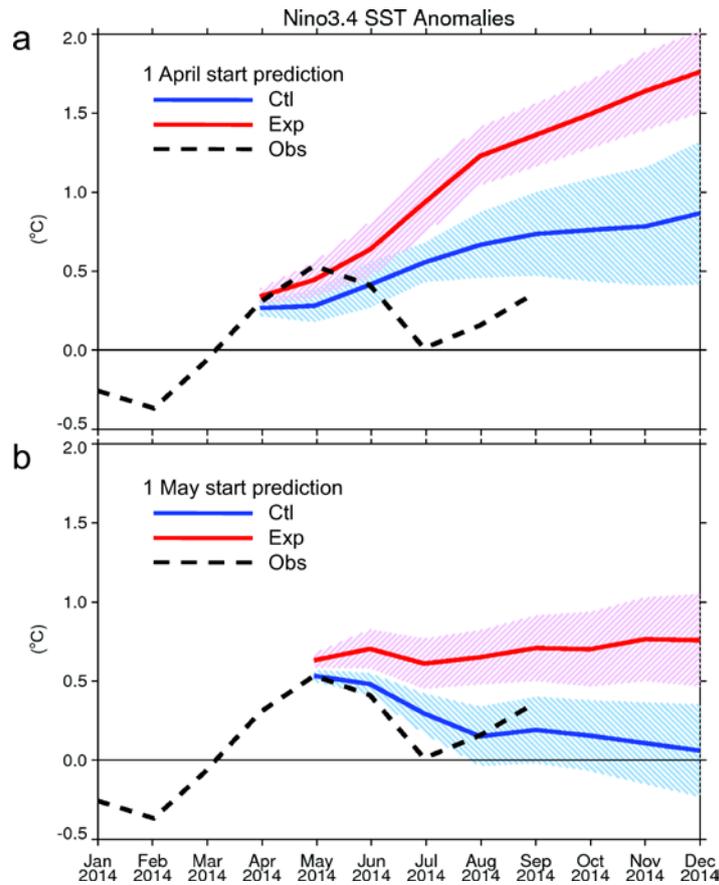
Figure 2 Changes in predicted Niño3 amplitude and predictability. a: Percentage change
 amplitude for the forecast experiment compared to the control for 2000-2010 period (red
 curve), for 1985-1995 period (solid green curve), and for 1981-1999 period (dashed-dot
 green curve); **b:** Differences of potential predictability (experiment minus control) for 2000-
 2010 (red curve) and 1985-1995 (solid green curve). Blue-dash curve denotes the difference
 of potential predictability for control forecasts 2000-2010 minus 1985-1995. Differences in
 amplitude and predictability are significant ($p < 0.1$) for all lead times after month 1.



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Figure 3 Experiment minus control differences in ENSO growth rate. Differences in growth rate of ENSO surface temperature anomalies computed by the regression of the difference in predicted surface temperature (experiment minus control) after 1 month onto the observed Niño3 anomaly at the initial time for **a**: 1985-1995 and **b**: 2000-2010. Differences in growth rate are shaded (unit C month⁻¹) where significant ($p < 0.05$, $n = 132$). The scatter of the differences in predicted surface temperature in the Niño3 region versus the observed Niño3 anomaly at the initial time are shown for **c**: 1985-1995 and **d**: 2000-2010. The red lines in **c** and **d** are the least squares regressions onto the Niño3 Index and the slope (growth rate) has unit °C mnth⁻¹. The negative slope in **c** shows that 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 **d** shows that El Niño and La Niña during the later epoch both strengthen in response to the background climate from the earlier epoch. The fits (correlation) in **c**) and **d**) are significant ($p < 0.001$, $n = 132$). The solid black box in (a) and (b) highlights the Niño3 region.

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4 **Figure 4 Predictions for El Niño 2014.** Observed (dashed curve) and predicted Niño3.4

5 Index (5°N-5°S, 120°W-170°W) initialized on **a:** 1 April 2014 and **b:** 1 May 2014. Blue

6 curves are operational predictions initialized with observed states and red curves are

7 experiment predictions initialized with the 1985-1995 background climate. To be consistent

8 with the experimental protocol, observed and predicted anomalies are formed relative to their

9 respective 2000-2010 climatologies. Hatching is the standard deviation of the 10 member

10 ensemble about the ensemble mean and shows that the experiment prediction from 1 April

11 has lower spread than the operational forecast so indicating higher predictability.

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1 **Supplementary Information**

2 **Upper Ocean Heat Budget**

3 To reveal how the atmosphere-ocean coupled processes that influence the amplitude of
4 ENSO are affected by the changes in background climate, we consider the mixed layer heat
5 budget (averaged 0-90 m) along the equator (averaged 5°N-5°S). To good approximation the
6 growth of an ENSO temperature anomaly is given by¹

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$$8 \quad \frac{\partial T'}{\partial t} \approx -\bar{w} \frac{\partial T'}{\partial z} - u' \frac{\partial \bar{T}}{\partial x}$$

9 Overbars denote epochal means and primes are perturbations from those means. T is
10 the temperature averaged over the mixed layer of depth $H = 90$ m. w is the vertical velocity
11 (upwelling) at base of mixed layer H and u is the zonal current averaged over depth H . The
12 vertical temperature gradient is computed at depth H . The first term on the right hand side is
13 referred to as the thermocline and the second term is referred to as the zonal advective
14 feedback. We have neglected a) nonlinear terms, b) advection of the mean vertical
15 temperature gradient by anomalous vertical velocity (the Ekman feedback term which is
16 typically large only in the far eastern Pacific), c) advection of anomalous zonal temperature
17 gradient by mean zonal currents, d) meridional advection, and e) surface heat fluxes and the
18 residual terms, all of which appear to not contribute to differences in ENSO behaviour under
19 investigation here.

20 We form the difference heat budget¹ for the initial month of the forecast (time 1), and
21 use the fact that both the experiment and control forecasts start off from the same observed
22 anomaly at time 0:

$$23 \quad \Delta \frac{\partial T'}{\partial t} = \frac{T'_e(1) - T'_c(1)}{\Delta t} =$$
$$- \left[\Delta \bar{w}(1) \frac{\partial T'_c(1)}{\partial z} + \bar{w}_e(1) \Delta \frac{\partial T'(1)}{\partial z} \right] - \left[u'_c(1) \Delta \frac{\partial \bar{T}(1)}{\partial x} + \Delta u'(1) \frac{\partial \bar{T}_e(1)}{\partial x} \right] \quad (1)$$

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The delta operator for means and perturbations is defined, for example, as

$$\Delta \bar{w}(1) = \bar{w}_e(1) - \bar{w}_c(1)$$

and

$$\Delta \frac{\partial T'(1)}{\partial z} = \frac{\partial T'_e(1)}{\partial z} - \frac{\partial T'_c(1)}{\partial z}$$

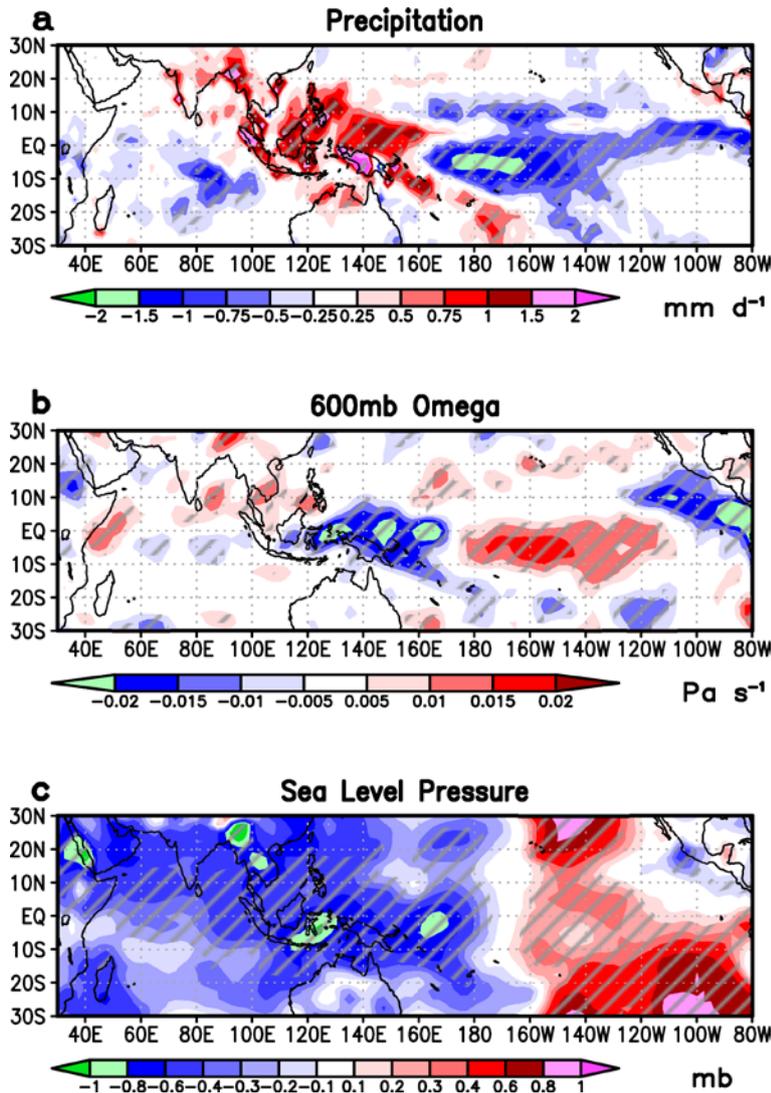
The left hand side of (1) is the total difference in tendency in month 1 as a result of imposing the change in mean state at the initial time. The thermocline feedback (first set of brackets on the right hand side of (1)) is composed of the difference in mean vertical velocity acting on the perturbation vertical temperature gradient and the mean vertical velocity acting on the induced change in perturbation vertical temperature gradient. The zonal advective feedback (second set of brackets on right hand side of (1)) is composed of the anomalous zonal current acting on the difference in mean zonal temperature gradient, and the induced change in anomalous zonal current acting on the mean zonal gradient.

To highlight how ENSO anomalies react to the imposed change in mean state, we form a composite difference heat budget by regressing all terms in (1) onto the normalized observed Niño3 anomaly at the initial forecast time, recognizing that both the control and experiment forecasts are initialized with the same anomalies. The regression of the first term in each bracket of (1) reveals the direct response due to the imposed change in the background climate, while the second term reveals the result of a change in the anomaly during the forecast due to the imposed change in background climate.

Supplementary References

- 1 1. DiNezio, P.N., Kirtman, B.P., Clement, A.C., Lee, S.K., Vecchi, G.A. & Wittenberg,
2 A. Mean climate controls on the simulated response of ENSO to increasing
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- 4 2. Kalnay, E. *et al.* The NCEP/NCAR Reanalysis 40-year Project. *Bull. Amer. Meteor.*
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- 6 3. Xie, P., & Arkin, P.A. Global precipitation: A 17-year monthly analysis based on
7 gauge observations, satellite estimates, and numerical model outputs. *Bull. Amer.*
8 *Meteor. Soc.*, **78**, 2539 - 2558 (1997).
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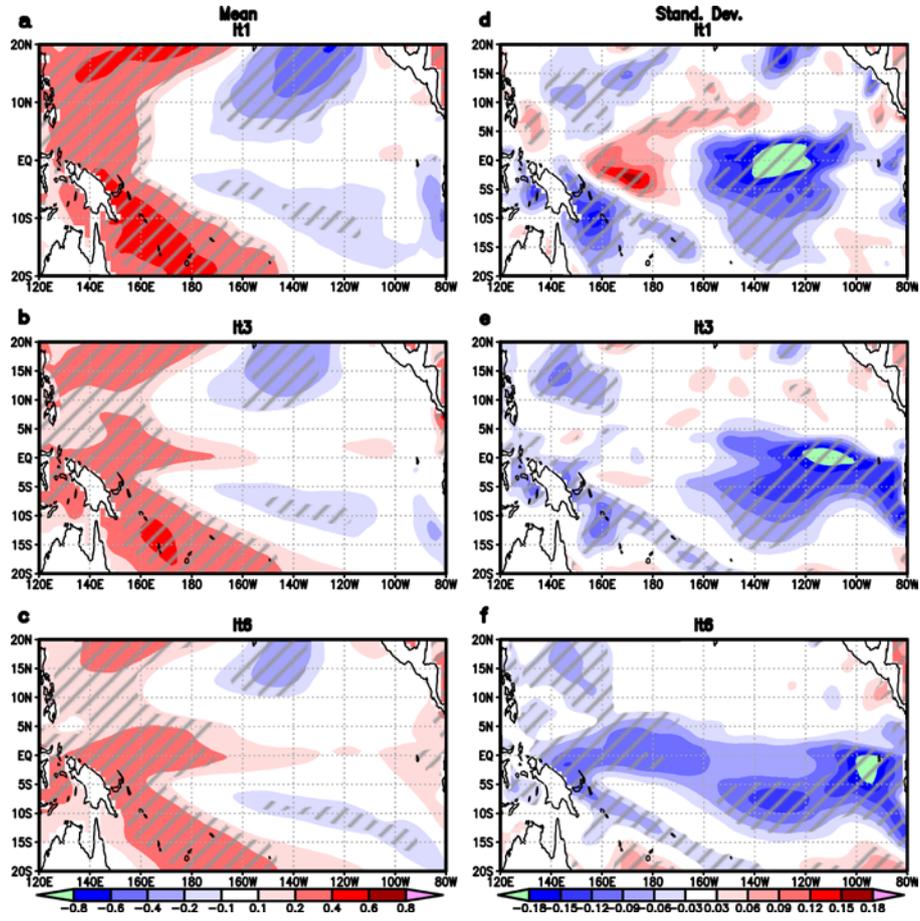
1 **Supplementary Figures**



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Supplementary Fig. 1: Epochal mean differences (2000-2013) minus (1981-1999) for **a:** CMAP rainfall³⁷, and **b:** pressure vertical velocity at 600 hPa and **c:** sea level pressure from NCEP reanalyses³³. Significant difference are hatched ($p < 0.1$). Data acquired from NOAA/ESRL Physical Sciences Division, Boulder Colorado <http://www.esrl.noaa.gov/psd>

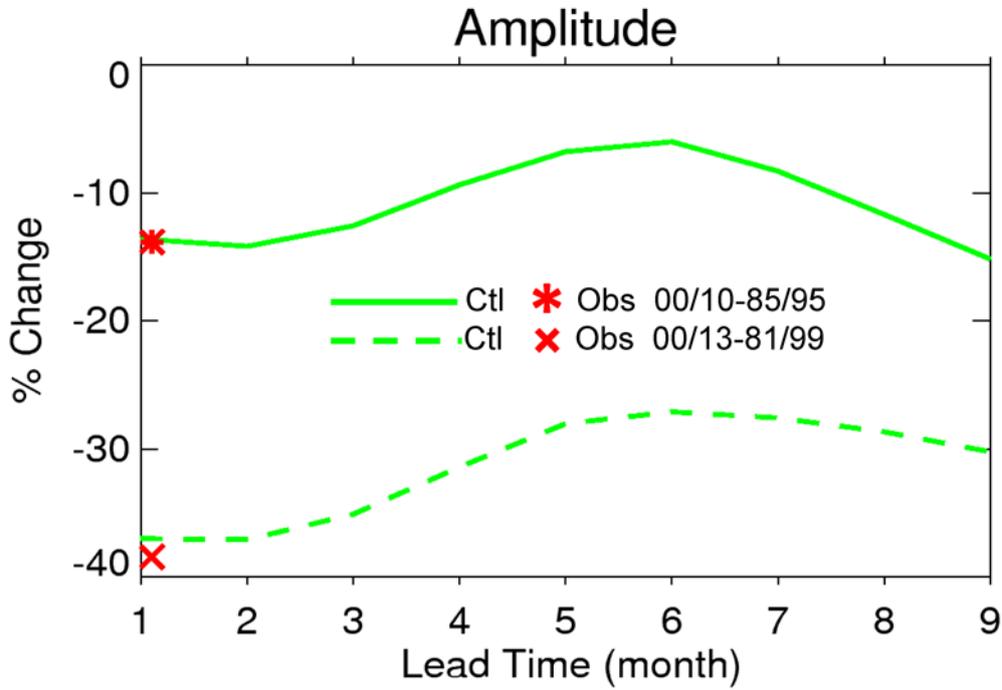
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Supplementary Figure 2: Difference in mean SST from control forecasts (2000-2010 minus 1985-1995) at lead time **a**: 1, **b**: 3 and **c**: 6 months. (**d-f**) As is (**a-c**) except for difference in standard deviation. Units are °C. Significant differences ($p < 0.1$) are hatched.

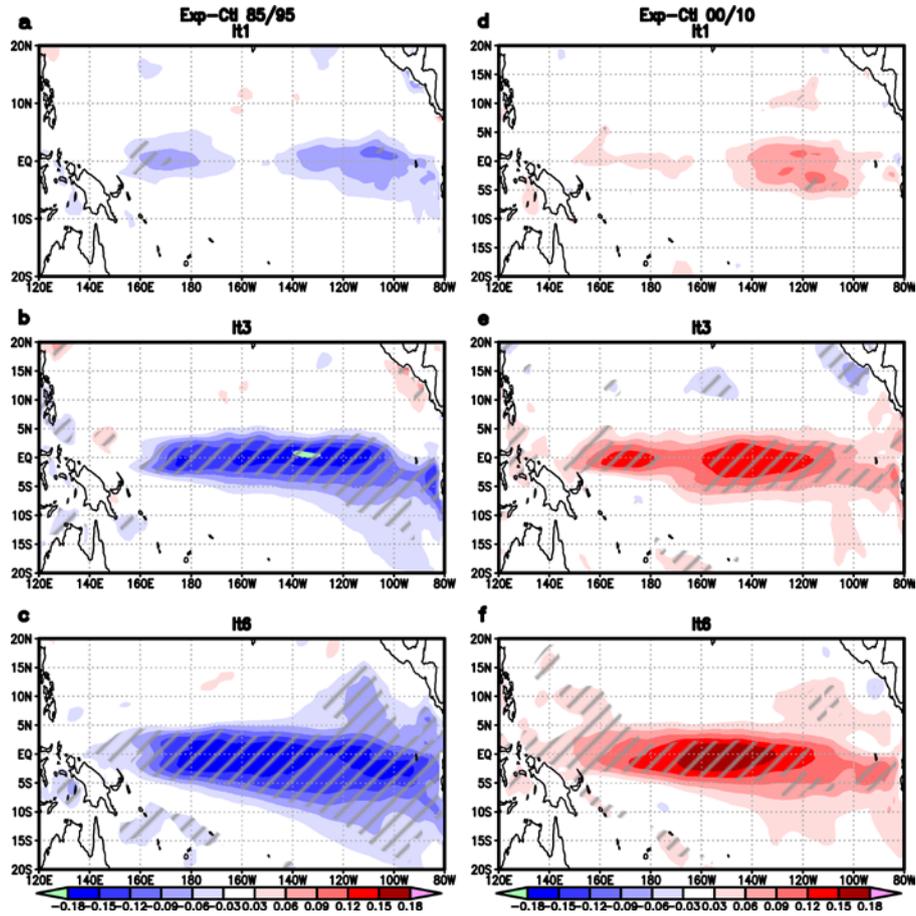
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Supplementary Fig. 3: Percentage change in predicted amplitude of Niño3 Index in control forecasts 2000-2010 compared to 1985-1995 (solid green curve) and 2000-2013 compared to 1981-1999 (dash green curve). Asterisks indicate the percentage change of observed Niño3 amplitude for 2000-2010 compared to 1985-1995 (bold asterisk) and 2000-2013 compared to 1981-1999 (light asterisk). Observed and forecast difference in amplitude are all significant ($p < 0.1$, $n = 132$)

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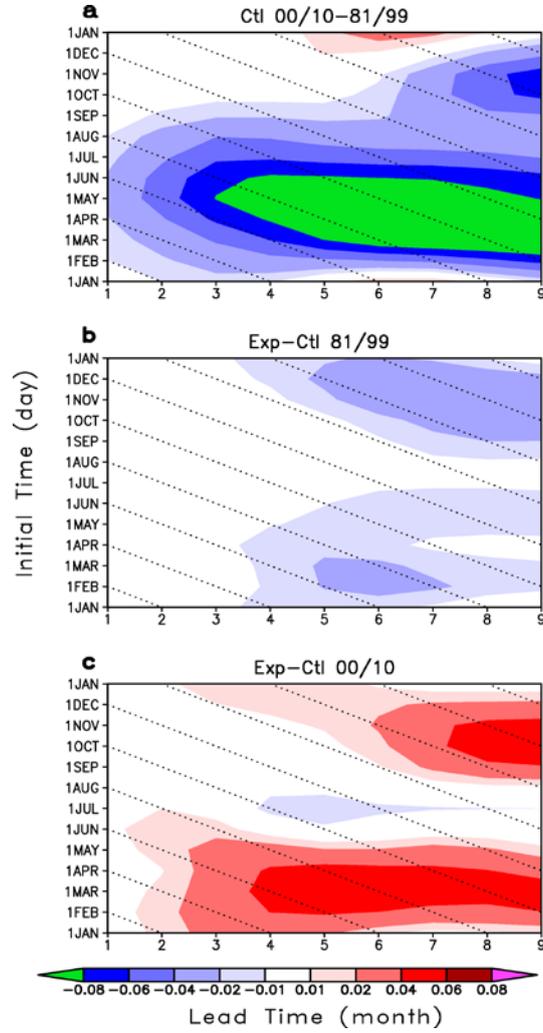


Supplementary Fig. 4: Differences in standard deviation of SST (experiment minus control) for (left) 1985-1995, and (right) 2000-2010 for lead times 1 month (a,d), 3 month (b,e) and 6 months (c,f). Significant differences ($p < 0.1$, $n=132$) are hatched.

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6 **Supplementary Fig. 5:** Differences in potential predictability (explained variance) of Niño3

7 Index for **a:** control forecasts 2000-2010 minus 1981-1999; **b:** experiment minus control

8 forecasts for 1981-1999 and **c:** experiment minus control forecasts for 2000-2010. Difference

9 in predictability is shown as a function of forecast start month (y-axis) and lead time (x axis).

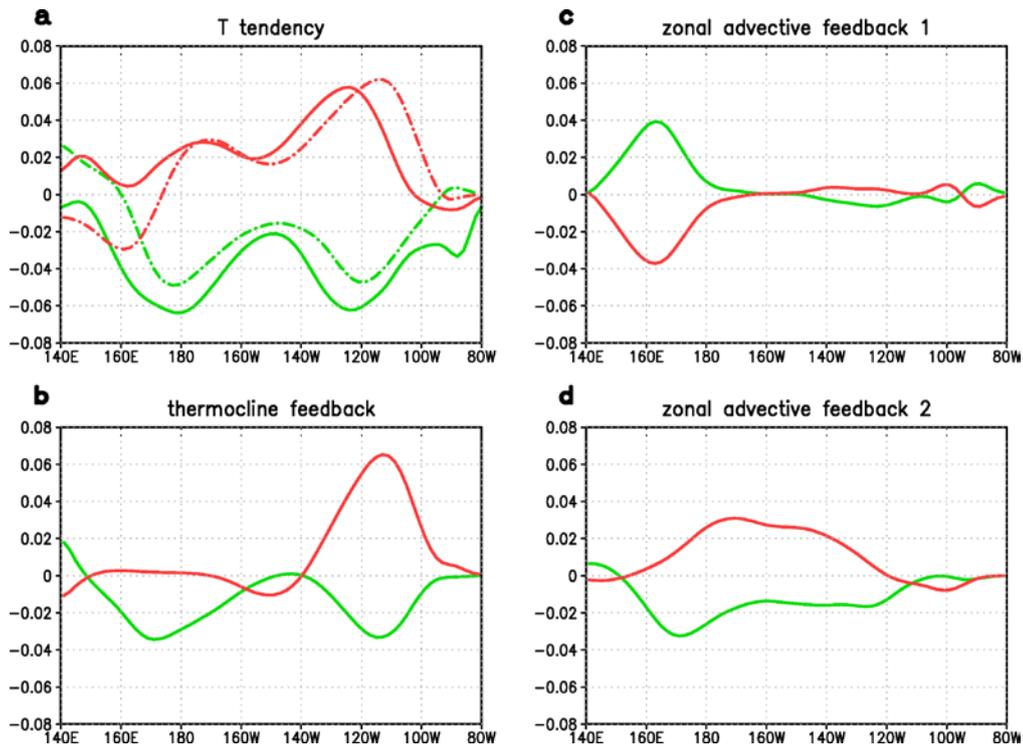
10 Dotted sloping lines indicate a constant verification month but at varying lead time.

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4 **Supplementary Fig. 6:** Differences in predicted upper ocean temperature tendency

5 (experiment minus control) at month 1 averaged in latitude (5°N - 5°S) and over depth (0-90

6 m). **a:** Differences in total temperature tendency (solid curves) and tendency approximated

7 by the sum of the three components shown in panels (**b,c,d**) (dot-dashed curves); **b:**

8 Difference in thermocline feedback tendency due to mean change in background upwelling;

9 **c:** Difference in zonal advective tendency due to mean change in background zonal

10 temperature gradient; and **d:** Difference in zonal advective tendency due to the induced

11 change in zonal current anomalies during forecast. The tendency differences (experiment

12 minus control) are computed as the respective tendency differences from month 1 of the

13 experiment and control forecasts regressed onto the observed normalized Niño3 Index

14 anomaly at the initial time. Scale for tendency differences has units $^{\circ}\text{C mnth}^{-1}$. Red curves

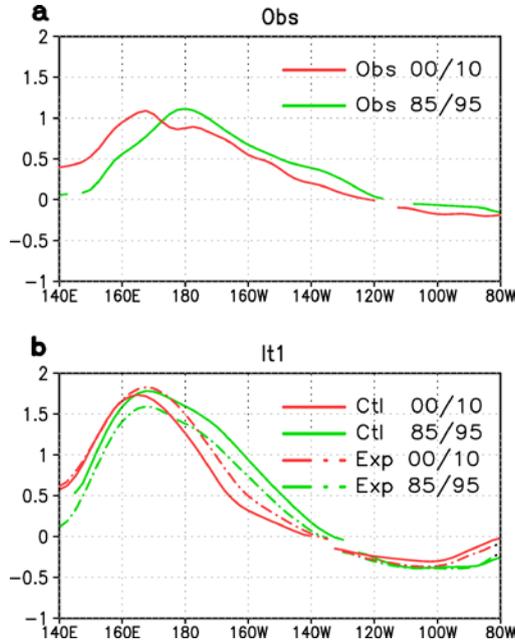
15 are experiment minus control forecasts for 2000-2010 and green curves for 1985-1995.

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6 **Supplementary Fig. 7:** Regression of normalized Niño3 index onto zonal surface wind
 7 anomalies (5°N-5°S) **a:** for observations, and **b:** for control (solid curves) and experiment
 8 (dot-dash curves) forecasts at lead time 1 month. The red curves denote 2000-2010 period
 9 and green curves denote 1985-1995 period. Curves are only plotted where regression is
 10 significant ($p < 0.1$).

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