Revisiting ENSO Coupled Instability Theory and SST Error Growth in a Fully Coupled Model

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ABSTRACT

A coupled model framework is presented to isolate coupled instability induced SST error growth in the ENSO region. The modeling framework using CCSM4 allows for seasonal ensembles of initialized simulations that are utilized to quantify the spatial and temporal behavior of coupled instabilities and the associated implications for ENSO predictability. The experimental design allows for unstable growth of initial perturbations that are not prescribed, and several cases exhibit sufficiently rapid growth to produce ENSO events that do not require a previous ENSO event, large-scale wind trigger, or subsurface heat content precursor. Without these precursors, however, ENSO amplitude is reduced.

The initial error growth exhibits strong seasonality with fastest growth during spring and summer and also dependence on the initialization month with the fastest growth occurring in the July ensemble. Peak growth precedes the peak error, and evidence suggests that the final state error may be sensitive to a slight temperature bias in the initialized SST. The error growth displays a well-defined seasonal limit, with ensembles initialized prior to fall exhibiting a clear seasonal halt in error growth around September, consistent with increased background stability typical during fall. Overall, coupled instability error growth in CCSM4 is deemed best characterized by strong seasonality, dependence on the initialization month, and nonlinearity.

The results pose real implications for predictability because the final error structure is ENSO-like and occurs without a subsurface precursor, which studies have shown to be essential to ENSO predictability. Despite the large error growth induced by coupled instabilities, analysis reveals that ENSO predictability is retained for most seasonal ensembles.

1. Introduction

Unlocking the primary mechanism responsible for the initiation of ENSO events and the associated uncertainty has proven exceptionally challenging, especially from the dynamical and prediction standpoints. Often, the inherent complexities of the coupled system prove a substantial hurdle in determining why, on a mechanistic level, certain ENSO events are initiated. This is true for both observations and dynamical forecasts, where the latter of which is subject to potentially large uncertainty because of errors in the initial conditions.

Since the development of general circulation models (GCMs) and enhanced observational methods (McPhaden et al. 2001), many studies examining ENSO initiation have turned toward identifying deterministic “trigger patterns” in the atmospheric winds and many patterns have proven effective in triggering certain ENSO events in observations and models (e.g., Kessler et al. 1995; Kirtman and Shukla 2000; Clarke and Van Gorder 2001; Zhang and Gottschalk 2002; Chang et al. 2007; Zhang et al. 2009; Larson and Kirtman 2013). That being said, attempting to identify specific deterministic trigger patterns to solely explain ENSO initiation may be underestimating the role that coupled instabilities play in the initiation process. This point is raised because the possibility exists that an event may be initiated in the absence of a clear wind stress trigger, for instance, westerly wind bursts (WWBs), which can reduce ENSO predictability in certain coupled models (Lopez and Kirtman 2014). Another possibility is that an event may be initiated in the absence of a “subsurface precursor,” often described as the slow buildup of upper-ocean heat content along the equatorial Pacific prior to ENSO events (Jin 1997) that is essential to the predictability of ENSO (Meinen and McPhaden 2000; McPhaden 2003). As such, quantifying the error growth induced by
coupled instabilities, assumed to be a leading mechanism capable of explaining the physics of ENSO initiation that does not require a subsurface precursor or large-scale deterministic wind stress trigger (Lau 1981; McCreary 1983, 1985; Philander et al. 1984; Anderson and McCreary 1985; Gill 1985; Yamagata 1985; Hirst 1986, 1988; Battisti 1988; Battisti and Hirst 1989; Wakata and Sarachik 1991), is essential to understanding the fidelity of models and their forecasts.

Because some ENSO events appear to spontaneously arise in the absence of a subsurface precursor (Philander 1983), the notion that ENSO events can be triggered without the presence of a subsurface precursor seems plausible (Penland and Sardeshmukh 1995; Kleeman and Moore 1997; Moore and Kleeman 1999; Kessler 2002; Moore et al. 2006). That is not to say that coupled modes (Anderson 2007; Deser et al. 2012; Larson and Kirtman 2013) and heat content precursors (Wyrtki 1975, 1985; Cane et al. 1986; Zebiak 1989; Jin 1997; Guilyardi et al. 2003; McPhaden 2003; Zebiak and Cane 1987; Meinen and McPhaden 2000) do not prime the coupled system for an event and that the presence of triggers do not enhance confidence in forecasts (Larson and Kirtman 2014) or augment ENSO predictability in models (Lopez and Kirtman 2014).

Many ENSO studies determine how one component of the climate system responds to alterations in another; however, the assumption that one component forces the other is not necessarily ideal along the equatorial region, where the atmosphere–ocean coupling is strong (Bjerknes 1969; Neelin and Dijkstra 1995; Wu and Kirtman 2005). This is important because coupled feedbacks are considered necessary to catalyze SST growth characteristic to ENSO (Bjerknes 1969; Lau 1981; McCreary 1983, 1985; Philander et al. 1984; Anderson and McCreary 1985; Gill 1985; Yamagata 1985; Hirst 1986, 1988; Battisti 1988; Battisti and Hirst 1989; Wakata and Sarachik 1991). Philander et al. (1984) argue that, while many studies reveal how the atmosphere responds to a particular ocean state (Bjerknes 1969; Shukla and Wallace 1983; Neelin et al. 1994; Trenberth et al. 1998) or vice versa (Wyrtki 1975; McCreary 1976; Philander 1981), neither of these pathways ultimately can explain why small initial perturbations exhibit unstable growth and result in ENSO events. For this reason and the particularly unexpected 1982/83 El Niño event that exhibited rapid growth much later in the seasonal cycle than traditional theory would predict (Gill and Rasmusson 1983; Philander 1983), the popularity of coupled instability theory increased rapidly, much like the basis of the theory itself. Coupled instability theory flourished out of pioneering work in the 1980s with the implementation of simple and intermediate coupled models and what would now be considered fairly crude representation of coupling processes compared to current-day, complex coupled models (Lau 1981; Anderson and McCreary 1985; Battisti 1988; Battisti and Hirst 1989; Gill 1985; Hirst 1986, 1988; McCreary 1983, 1985; Philander et al. 1984; Yamagata 1985; Wakata and Sarachik 1991). The central idea is the incorporation of air–sea coupling into the model equations. The resulting behavior includes the potential destabilization of equatorial ocean waves, given that the coupling is sufficiently strong to induce the instability.

Coupled instability theory was initially introduced and applied to coupled models of simple and intermediate complexities; however, there has yet to be rigorous current-day application using state-of-the-art coupled GCMs that resolve more complex coupled processes and include the full nonlinear system of equations. It is necessary that we reintroduce coupled instability theory in fully coupled models to better understand mechanisms that promote rapid perturbation growth in the types of models that are used in current-day dynamical prediction systems. The goal being that we can create a framework to confront the hypotheses of previous coupled instability work and gain insight into the relative role of the subsurface precursor in the initiation process. Hereafter, the terms “anomaly” and “error” can be considered synonymous because we are discussing initial perturbations (or errors in the initial conditions) in the context that they have the capacity to grow into anomalously warm or cold ENSO events.

The overarching goal of this paper is to identify the temporal and spatial behavior of coupled instabilities and how they contribute to SST error growth that may affect the predictability of ENSO in CCSM4. This paper is organized as follows: First, a two-step coupled model framework is presented to isolate coupled instability growth. Second, each step of the framework is discussed individually, including model behavior and key results. Third, the main conclusions are discussed in the context of error growth and ENSO predictability. Last, a summary and discussion conclude the presented work.

2. Experimental design

a. Overview

The type of initial conditions necessary to isolate coupled instability growth in a fully coupled model is outlined in this section. The objective is to not add variability to the system by prescribing a heat flux or wind stress ($\tau_{x,y}$) refers to both zonal and meridional wind stresses discussed in tandem) perturbation to induce coupled instabilities but
instead to allow intrinsic atmospheric and oceanic perturbations the opportunity to interact and grow with time. By not prescribing the perturbations, the coupled system presents the opportunity for warm, cold, and neutral ENSO events as determined solely by the initialized state. We hypothesize that initial ocean conditions that are close to climatology, particularly along the equatorial waveguide, are essential to minimize large state-dependent responses by the atmosphere that can, in turn, affect the interannual evolution of the ocean (Eisenman et al. 2005; Gebbie et al. 2007; Lopez et al. 2013) as well as remove the subsurface preconditioning often seen with ENSO precursors (Anderson 2007; Deser et al. 2012; Larson and Kirtman 2013). The motivation against using climatological ocean initial conditions is to allow intrinsic variability to always be present, thus ensuring the presence of random perturbations and the associated uncertainty in the initial state.

Removing subsurface precursors and minimizing large-scale $\tau_{x,y}$ triggers from the tropical Pacific is essential to isolate coupled instability growth for several reasons. First, low-frequency coupled modes can precondition the coupled state by inducing the buildup of anomalous heat content in the equatorial region and bias the system toward the initiation of an event (Anderson 2007; Deser et al. 2012; Larson and Kirtman 2013). Westerly wind bursts perhaps generated by the Madden–Julian oscillation can produce similar effects (McPhaden 2004) and a previous ENSO event can provide the slow ocean thermal inertia that allows for much of the predictability of ENSO (Wyrtki 1975, 1985; Philander 1983; Cane et al. 1986; Neelin et al. 1994; Rosati et al. 1997; Latif 1998; McPhaden 2003). Second, $\tau_{x,y}$ triggers tend to be seasonally dependent, thus potentially affecting the seasonality of ENSO (Lau and Chan 1988; Clarke and Shu 2000; Kirtman and Shukla 2000; Zhang and Gottschalk 2002; Hendon et al. 2007). The amplitude or frequency of the trigger can also depend on the climate state (Eisenman et al. 2005; Gebbie et al. 2007; Jin et al. 2007; Kug et al. 2008; Lopez et al. 2013). If certain precursors or triggers are solely responsible for initiation of events, then the observed false alarms would be markedly less (Larson and Kirtman 2014). As such, in the present study we eliminate the influence of the subsurface precursor, demonstrate that large-scale atmospheric variability is not playing a dominant role in the initiation of events, and show that coupled instabilities alone can be responsible for large error growth.

As outlined below, the coupled model framework allows for initial perturbations determined solely by the model’s atmospheric intrinsic variability to interact with a minimally biased equatorial ocean state that also exhibits intrinsic variability of its own. In the end, we can quantify the error produced by coupled instabilities without manually adding anomalous forcing (i.e., triggering) and determine how coupled instabilities affect ENSO predictability.

b. Coupled model framework

The experimental design is implemented using the National Center for Atmospheric Research (NCAR) Community Climate System Model, version 4 (CCSM4). ENSO in CCSM4 exhibits a spatial structure and 3–6-yr period that compares well with observations but overestimates SST variability in the ENSO region by roughly 30% and exhibits too much regularity. The cold tongue also extends too far west (Deser et al. 2012). The asymmetry between El Niño and La Niña events is generally consistent with observations as is ENSO diversity (Capotondi 2013). The thermocline feedback plays a dominant role in the eastern equatorial Pacific heat budget in CCSM4, whereas the zonal advective feedback dominates in the central Pacific. CCSM4 also simulates a realistic “seasonal footprinting mechanism” (SFM; Vimont et al. 2001, 2003a,b; Anderson 2003, 2004; Alexander et al. 2010), albeit with a weaker than observed linkage between the extratropics and tropics (Deser et al. 2012). Furthermore, the SST anomaly spatial structure and seasonal phase locking of the Pacific meridional mode in a precursor release of CCSM4 also compares well with observations (Larson and Kirtman 2013).

The control simulation is a fully coupled, preindustrial configuration at 1° × 1° horizontal resolution. The experimental design is of a similar configuration and consists of a two-step methodology. The first step is to produce the proper initial atmosphere and ocean states that will allow for the isolation of coupled instability growth for an ensemble of experiments. This step consists of removing ENSO itself, as well as subsurface precursors and large-scale atmospheric triggers that may bias the initial state toward a specific ENSO phase. As much of the aforementioned variability is characterized by anomalous winds or generated via dynamic air–sea feedbacks, the most direct way to dampen such types of variability is to disengage the mechanical coupling between the atmosphere and ocean. Doing so hinders the amplification of such types of variability and dampens its possible influence on the ocean surface.

In the coupled model framework, mechanical coupling is the anomalous wind-driven forcing that generates momentum transfers between the atmosphere and ocean. Mechanically decoupling the ocean is achieved here by forcing the ocean with the model’s daily climatological (determined from a free-running control
simulation) \( \tau_{x,y} \) while allowing the atmosphere to respond freely to the ocean state without constraint. This way, the ocean component does not respond to the atmosphere interactively in terms of anomalous momentum transfer, but the components remain thermally coupled via heat and freshwater fluxes. As we show here, allowing the buoyancy coupling to remain interactive does not produce substantial equatorial SST variability in the model.

In the model code, the atmosphere and ocean components exchange fields via the flux coupler once per model day. Accordingly, the atmospheric \( \tau_{x,y} \) is passed through the coupler to the ocean and, at this time, we override the \( \tau_{x,y} \) with daily climatological values determined from the unconstrained control simulation. CCSM4 model climatological \( \tau_{x,y} \) are used to achieve a dynamically consistent ocean at the model’s approximate mean state. Otherwise, if forced with observed winds, the model’s initial response when the constrained forcing is released (discussed below) is dominated by drift because of the differences in \( \tau_{x,y} \) climatologies (Jin et al. 2008). The simulation is integrated for 90 years and named the climatological wind experiment (CWE).

Step two of the methodology includes a “releasing” of the constraints to allow perturbations to grow under the fully coupled configuration. In CWE, coupled instabilities are essentially prohibited because coupled feedbacks instigated by atmospheric perturbations are unsupported by a complementary ocean response and vice versa, although ocean dynamics are technically unconstrained. Unlike in the CWE, when the atmosphere and ocean are dynamically coupled and \( \tau_{x} \) and zonal ocean current perturbations are in phase, the atmosphere can transfer momentum to the ocean, reinforcing unstable growth by increasing the local ocean kinetic energy (Hirst 1986). This type of momentum transfer is unsupported in the CWE.

It should be noted that subtropical SST variability produced by the SFM (Vimont et al. 2001, 2003a,b) is not necessarily removed in CWE. However, the CWE methodology prohibits 1) SST variability produced by the SFM to induce coupled instabilities and 2) sufficient dynamic support for the buildup of a subsurface heat content precursor often accompanying the Pacific meridional mode (Chiang and Vimont 2004; Anderson 2007; Deser et al. 2012; Larson and Kirtman 2013) SST pattern, a pattern generated by several processes including the SFM. As a result, effects from extratropical variability on the equatorial region are possible, albeit they are likely confined to earlier calendar months, when the SFM peaks. In a later section, we demonstrate that large-scale atmospheric variability that is often linked to off-equatorial SST patterns is likely not the dominant initiator of error growth in the simulations.

Before introducing step two of the experimental design, we must first verify the hypothesis that disengaging the mechanical coupling eliminates ENSO and minimizes other SST and \( \tau_{x,y} \) variability. Note that the CWE is distinctly different from studies that show ENSO-like variability without a dynamic ocean (Dommenget and Latif 2008; Clement et al. 2011). The CWE has an unconstrained dynamic ocean but does not allow for anomalous \( \tau_{x,y} \) to act on the sea surface, thus prohibiting variability of equatorial trade wind strength that can support large SST variability via thermal fluxes (e.g., Drushka et al. 2015). Accordingly, ENSO-like variability that can arise in the absence of mechanical coupling like the thermally coupled Walker mode found in Clement et al. (2011) is unsupported by the imposed \( \tau_{x,y} \) constraint in the CWE.

c. The climatological wind experiment

In the tropics, where wind-driven forcing largely influences interannual SST variability, the CWE substantially dampens SST variability. Essentially all interannual SST variability in the tropics (10°S–10°N) is removed in CWE (Fig. 1b), particularly that in the eastern Pacific associated with ENSO, as seen in the control (Fig. 1a). Although this response is anticipated, it is striking how comprehensively the SST damping is throughout the equatorial Pacific. Similar results are seen in sea surface height (SSH) variance (contours in Figs. 1a,b), indicating that variations in ocean heat content are also substantially damped in CWE. Figure 2 reveals that the zonally averaged temperature anomaly variance in the Pacific basin as a function of latitude and depth shows no clear subsurface precursor signatures or interannual equatorial thermocline variability as well, confirming that all aspects of ENSO and the subsurface precursor are minimized in CWE. Figure 1d confirms that the CWE Niño-3 index (SST anomalies averaged over 5°S–5°N, 150°–90°W) shows no clear ENSO characteristics compared to the large interannual variability in the control. Although the domain shown is restricted to the tropical Pacific, overall, less variable SST anomalies are seen globally; however, more variability is maintained in the extratropics where thermal fluxes are an important driver of SST variability (Alexander 1992; Neelin et al. 1994; Kushnir et al. 2002).

In theory, because the tropical atmosphere–ocean system is strongly coupled (Bjerknes 1969; Neelin and Dijkstra 1995; Wu and Kirtman 2005), reduction in SST variability should reduce the overlying atmospheric wind variability. This effect is desirable such that only small wind perturbations are present when the \( \tau_{x,y} \)
constraint is released. Figure 1c shows the variance ratio of the zonal wind stress ($\tau_x$) anomalies zonally averaged over the date line (160°E–160°W) of CWE and the control. A ratio of 1.0 (dotted line) indicates that 100% of the variance in the control is reproduced in CWE and a ratio less than 1.0 indicates that CWE variability is reduced. For CWE, the $\tau_x$ used in the calculation is that which the ocean would have felt had the field not been overwritten with climatology. Since the atmospheric component responds freely to the ocean, this particular $\tau_x$ is obtained from the atmospheric component output. In the tropical atmosphere, less variable SST has an anticipated “back interaction” on zonal surface winds in the central Pacific, causing substantial damping of surface winds by as much as 80% (ratio of 0.2), as seen between 5°S and 5°N. Generally, poleward from the equatorial region, the damping of zonal surface winds varies between 0% and 20%. The only substantial exception is in the North Pacific, where $\tau_x$ variability is damped by nearly 50%.

d. The release experiment

Now that tropical SST, subsurface temperature, and $\tau_x$ variability are dampened, we have essentially generated a suite of initial conditions from which to branch ensembles of coupled instability experiments. The first 30 years of the CWE are discounted to reduce effects from model spinup. Note that, during integration, CWE initial conditions are archived every other month. Beginning at year 30, for every set of archived January, March, May, July, and September initial conditions, an additional simulation is branched with the $\tau_{x,y}$ constraint lifted (i.e., integrated under the fully coupled configuration). Since the wind constraint is released, the simulations are referred to as the release experiment (RE).
Figure 3 depicts a schematic of the March ensemble model framework. A total of 60 cases compose the March ensemble, one case for each set of March initial conditions spanning CWE years 30–90. All cases are integrated through the first December of year(0) but only cases branched from CWE years 60–90 are integrated an additional year through the next December of year(1). The process is repeated for January, May, July, and September for a total of 300 members that comprise the RE.

Note that the control mean state and seasonality in the equatorial Pacific is reproduced fairly well by the CWE, indicating that minimal biases in the region of interest are produced in the CWE framework. Figure 4 shows the December, February, April, June, and August mean SST (averaged over 5°S–5°N) as a function of longitude for the control and CWE. These are considered the month(0) for each of the RE ensembles as the initial conditions originate from the previous month of CWE integration. There is a slight warm (cold) bias in the eastern (central) Pacific of no more than 0.5°C for any months shown here, although small biases can have a large atmospheric response in the warm pool region.

The average bias in the Pacific basin of the zonally averaged mean temperature from the surface to 250 m between 20°S and 20°N is −0.39°C. The bias is most likely a result of model spinup in CWE, although the effects from lacking higher-frequency atmospheric variability that may contribute to the mean state SST cannot be fully ruled out. Error calculations for each ensemble are computed separately and by integration month; therefore, all errors shown hereafter are calculated from the specific reference cycle of the ensemble, not the control. As a result, small biases in the mean state do not affect the main conclusions presented here.

We are aware that the month(0) monthly mean SST fields treated here as the initial condition are not necessarily representative of the instantaneous field at initialization. However, the month(0) SST gives a good indication of any prevalent sign biases likely present in the initial conditions. SST anomalies exhibit reasonable persistence: for instance, SST persistence in March–May is 1–2 months, which is the season with the least SST persistence in the tropical Pacific (McPhaden 2003) and well within the range for application here. Visual comparison of the day(0) initialized and month(0) SST confirms that distinct perturbations in month(0) are similarly present at day(0) (not shown). This is not a fair assumption for, say, atmospheric winds, which can have much shorter decorrelation time scales (Blanke et al. 1997). To address the $\tau_{x,y}$ structures at initialization, the first five days of daily mean $\tau_{x,y}$ are obtained from the March ensemble only. An analysis of the day(0), which corresponds to 1 March, $\tau_{x,y}$ is included in the following section.

3. The March ensemble

To exemplify the performance of the RE without being overly exhaustive, the March ensemble is chosen to highlight the general ENSO behavior and confirm the coupled instability growth of ENSO events produced within the model framework. Figure 5 provides a summary of the March ensemble. March is chosen because the equatorial Pacific is often saturated with subsurface precursors and triggers during the spring (McPhaden 2003; Chiang and Vimont 2004; Anderson 2007; Larson and Kirtman 2013), thus masking the effects of coupled instability growth. The spring season is also when much of the predictability of ENSO is lost (i.e., the “spring predictability barrier”; Webster and Yang 1992; Kirtman et al. 2002; Mu et al. 2007) and is a prominent source of uncertainty in ENSO forecasts (Goswami and Shukla 1991; Samelson and Tziperman 2001).

Figure 5e shows the Niño-3 error for the first December of each case, organized by the year of the CWE initial conditions from which the case is branched. El Niño and La Niña events are defined as any event that
exceeds one standard deviation (0.75°C) in December of the respective sign and both types as well as neutral events all occur. This is a good indication that the climatological winds used in CWE are an accurate representation of the actual mean state winds of the model. Otherwise, a bias toward one phase of ENSO events could occur because of the systematic adjustment of the ocean toward the proper mean state and possible effects on the stability of the background state. The frequency of events also falls in line with the 3–6-yr ENSO period of a multicentury CCSM4 control simulation that exhibits multidecadal modulation of ENSO (Deser et al. 2012). Figure 5a shows the December SST error composite of the 10 El Niño events, and Fig. 5b is similar but for the 13 La Niña events. Both exhibit the expected spatial distribution of SST anomalies for ENSO in CCSM4 (Deser et al. 2012).

Although it is difficult to completely rule out the possibility that deterministic atmospheric variability is playing a role in initiating ENSO events in the RE, we will demonstrate that coherent trigger patterns cannot be assumed a dominant factor in the initiation of events. The regressions of December Niño-3 error with day(0) $\tau_{x,y}$ and SST perturbations are shown in Fig. 6. At first glance, there appears weak evidence of a small day(0) Northern Hemisphere $\tau_x$ signal in the central Pacific in the $\tau_x$ regression. However, the day(0), day(2), and day(4) $\tau_x$ perturbation composites for El Niño and La Niña events and their difference (Fig. 7) clearly demonstrate that there is no discernable trigger pattern in the initial conditions that dictates whether an event will evolve into an El Niño or La Niña event. Furthermore, there appears no discernable pattern in the meridional wind stress or SST perturbation regressions as well. We can also confirm that daily $\tau_x$ variability, in addition to monthly means shown in Fig. 1c, is also limited in the equatorial region. Overall, Figs. 6 and 7 demonstrate that large-scale wind patterns in the initial conditions are likely not playing a primary role in the triggering of events in the RE, thus suggesting that coupled instabilities are the dominant mechanism for the initiation of events in the simulations. Note that tropical instability waves (TIWs) are present in the CWE; thus, we cannot rule out the possibility that TIWs are influencing the initiation in some way.

Figure 5c shows a fairly symmetric spread (skewness of 0.21 in December) of the Niño-3 error evolution for each case through the first December, with red (blue) curves indicating El Niño (La Niña) events and neutral

![Diagram](image-url)

**FIG. 3.** Schematic depicting the RE modeling framework for the March ensemble. Beginning at year 30, initial conditions from CWE of each March are used to branch an additional simulation with the CWE wind stress constraints lifted. This procedure is repeated for each January, May, July, and September between years 30 and 90 of the CWE for a total of 60 cases per seasonal ensemble.

![Graph](image-url)

**FIG. 4.** Control (dashed) and CWE (solid) mean SST (°C; averaged over 5°S–5°N) as a function of longitude for December, February, April, June, and August. These months correspond to month(0) initial conditions from which the January, March, May, July, and September RE ensembles are branched, respectively.
in gray. The Niño-3 root-mean-square error (RMSE) in March is 0.19°C and saturates at about 0.75°C in September (Fig. 5d). The most striking aspect of Fig. 5d is how closely the error curve mimics ENSO forecast skill for typical boreal winter and spring initialized forecasts (Jin et al. 2008), which implies that coupled instability growth from initial perturbations may be a large contributor to the limit of ENSO predictability in this model. Typically, idealized predictability studies boast a longer period, often over one year, of error growth prior to error saturation (i.e., forecast skill), as in Cane et al. (1986). However, here the skill saturates around six months, similar to the e-folding time scale of the fast error growth in the Zebiak–Cane model that is suspected to be associated with coupled instabilities (Goswami and Shukla 1991). Error growth of all RE ensembles is discussed in a later section.

So far, the geographical location of the perturbation growth has not been discussed. Suarez and Schopf (1988) argue that coupled feedbacks along the equatorial Pacific are strongest in the central Pacific. In fact, the relative ease for the destabilization of oceanic waves in this region is the basis of the wave delay term in delayed-oscillator theory (Suarez and Schopf 1988; Battisti and Hirst 1989). Figure 8 shows the regression of December Niño-3 error with the previous December–April equatorial temperature perturbations with depth. For the control, 60 years of continuous data are analyzed to compare with the 60 cases from the CWE–RE framework. For the March ensemble, December Niño-3 error is regressed onto March and April from the RE and the preceding December–February from the CWE. Essentially, Fig. 8 shows where the ENSO signal originates and how it evolves by month. For the control, heat content buildup in the western Pacific during the
previous December shows mainly subsurface signals. The signal propagates eastward with time via an equatorial Kelvin wave packet, amplifies, and eventually produces eastern Pacific SST anomalies. For the March ensemble, the signal is not visible in the CWE from December to February, verifying that events are not initiated until dynamic coupling is permitted in the RE. The perturbation grows rapidly throughout March, with both surface and subsurface signals in the central Pacific, in agreement with theory from Suarez and Schopf (1988), although the cold tongue bias may shift the region of strongest coupling slightly toward the west. The perturbation continues rapid growth and eastward propagation, and both the control and RE subsurface structures are remarkably similar by April. Wyrtki (1975) proposes that western Pacific preconditioning is a necessary condition for ENSO, whereas Zebiak and Cane (1987), Schneider et al. (1995), and Kirtman (1997) show that basinwide preconditioning is a necessary condition. The March ensemble is intriguing because neither condition is necessarily realized and subsurface heat content buildup is zonally confined to the central Pacific, where coupled feedbacks are strongest.

A point that must be emphasized is that generally ENSO theory, including the recharge oscillator paradigm (Jin 1997), argues that ENSO events are connected and that the turnabout plays a key role in the initiation of subsequent events. However, the RE shows that rapid SST growth in the ENSO region can occur in the absence of a previous ENSO event or subsurface precursor. Kessler (2002) points out that observed weak El Niño events have occurred without a recharge and, in the present work, not only weak El Niño events but also El Niño and La Niña events of magnitudes greater than 1.0°C yet less than the approximate 3.0°C peak events produced in a multicentury CCSM4 control simulation (Deser et al. 2012) are initiated without a recharge/discharge. This may suggest that the recharge is merely remnant of the previous event and may serve to prime or amplify the oncoming event similar to preconditioning, thus enhancing predictability, but is not fundamentally essential for ENSO initiation.

An alternative interpretation includes that, without the subsurface precursor, the predictability of ENSO is essentially lost (e.g., the symmetric spread in Fig. 5c). Hence, the RE shows that, without a largely biased initial state, initial perturbations can induce rapid growth that appears unpredictable and may result in large errors in a prediction setting. The results are consistent with the idea that the presence of an ENSO cycle reduces the tropical system’s sensitivity to perturbations (Chen et al. 1997). As shown here, the absence of an ENSO cycle in the initial conditions results in a tropical system that is very sensitive to initial perturbations and teasing out any predictability may prove a difficult task.

4. Growth rate seasonality

Previous studies utilizing simple and intermediate coupled models argue that unstable air–sea interactions are seasonally dependent (Philander et al. 1984; Tziperman et al. 1997) and that SST anomaly growth rates in the ENSO region are largest during July–August (Battisti and Hirst 1989; Zebiak and Cane 1987). Growth rates of SST in the ENSO region are also sensitive to the initialization month as discussed in the context of intermediate models (Battisti and Hirst 1989; Xue et al. 1997) and similarly with forecast errors in coupled GCMs (Jin et al. 2008). The model framework presented in the previous section provides a sound
platform to confront earlier findings given that CCSM4 incorporates complex coupled processes similar to models in Jin et al. (2008) but with fewer simplifications in the model physics compared to intermediate models.

First we consider the Niño-3 SST RMSE or equivalently the standard deviation of the error since the reference case is climatology, as a function of integration month, specific to each RE ensemble. We first focus on the dynamically driven initial error growth during year(0). Since the initial equatorial oceanic conditions are close to climatology, the magnitude of the error in the ENSO region greatly depends on the length of time that coupled interactions and feedbacks have been engaged in the model. For this reason, considering the March ensemble, the reference cycle from which errors are computed consists of the full 22-month cycle calculated as the ensemble mean of all 60 March cases. Figure 9a shows the Niño-3 RMSE for the five RE ensembles (solid lines). Month(1) is defined as the initialization month. The dotted lines show the month(0) RMSE that is defined from the prior month CWE SST. The error bars indicate the upper and lower 5% bounds as computed using the Monte Carlo method with 10000 iterations of 30 random samples taken from the 60 cases. The upper (lower) 5% is deemed the average of the 500 cases that are farthest from the RMSE curve in the positive (negative) direction by month, thus showing maximum (minimum) error possible due to the relatively small sample size. The thick dashed line indicates the annual cycle of the Niño-3 anomaly standard deviation from the control. It follows that, if the error is equal to or surpasses the control annual cycle, the error has saturated the Niño-3 signal and predictability is lost. The December(0) RMSE is 0.90, 0.75, 0.51, 0.53, and 0.30, compared to the January, March, May, July, and September ensembles, respectively, compared to the control that surpasses 1.0°C. The error for each ensemble does not fully saturate the Niño-3 signal during September–December, although the January ensemble error upper bound closely approaches the signal from May to August. Predictability during the
peak ENSO months is retained for most initialization months yet minimal for the January ensemble. The error saturation for January initialized cases could be linked to the spring predictability barrier (Webster and Yang 1992; Kirtman et al. 2002; Mu et al. 2007).

The month(0) initial error is small for all ensembles, although, once mechanical coupling is engaged in month(1), the error grows quickly for all ensembles yet the growth rate shows dependence on the initialization month. For instance, initial error for July is the smallest of all ensembles but the July ensemble month-to-month growth from month(0) to month(1) shown in Fig. 9c is clearly the largest of all ensembles. This means that initial errors in the July cases grow the fastest and have doubled by month(1), as shown in Fig. 9b. In contrast, the error doubling time for the remaining ensembles is closer to two months. Results show that in this model, initial error growth in the ENSO region largely depends on the initialization month and error can grow rapidly for all initialization months, especially for summer initializations. The fast month-to-month growth for the July ensemble continues from month(1) to month(2) as error doubles between these months as well. This may, in part, be due to the fact that initial errors in July are a minimum; however, the July ensemble grows rapidly enough to overtake the May ensemble error by September along with attaining the largest month(1) error of all five ensembles (Fig. 9a). These findings follow the work of Battisti and Hirst (1989) and Chen et al. (1997) in which the authors argue that the tropical Pacific background state is most unstable to coupled instabilities in boreal summer, thus promoting fast growth of small perturbations similar to those shown above. Specific to CCSM4, the Bjerknes feedback is strongest in boreal summer (DiNezio and Deser 2014), lending a possible mechanism by which the initial error growth is dynamically accelerated for the July cases.

In addition to dependence on initialization month, initial error growth also exhibits strong seasonality. Consistent with seasonal background stability studies (e.g., Chen et al. 1997; Xue et al. 1997), initial error growth is largest in spring and summer months during year(0). Tziperman et al. (1997) argue that background wind divergence, largely influenced by the ITCZ seasonal migration, is a likely candidate to explain why the background instability is seasonal. For instance, wind convergence is strongest in spring, when the ITCZ approaches the equator, which acts to enhance the air–sea coupling by reinforcing atmospheric heating. Based on findings in Tziperman et al. (1997), Xue et al. (1997) suggest that
initializations that start prior to fall include the months with the most unstable background states that can support rapid perturbation growth. This includes spring, as mentioned above, and summer, when the mean zonal SST gradient along the equator is large and mean upwelling plays a more dominant role in enhancing coupling.

Furthermore, Fig. 9 shows a well-defined seasonal limit to initial error growth in CCSM4. In particular, growth saturates around September–October for all ensembles that are initialized prior to September. All ensembles except September show a month-to-month error growth rate of around 1.0 at this time, indicating no growth (Fig. 9c). The plateau in Niño-3 error beginning in September (Fig. 9a) is also indicative of a halt in growth and error saturation. Goswami and Shukla (1991) show similar characteristics in a prediction error study. The waning of growth is consistent with work by Tziperman et al. (1997) and Xue et al. (1997) in which the authors find a lack of instability in the background state during the fall season due primarily to the placement of the ITCZ and subsequent lack of moisture convergence as well as secondary effects including the background SST and ocean upwelling.

A seasonal limit to growth implies that events in CCSM4 with later onset cannot grow as large in the absence of subsurface precursors and, since growth terminates in September–October, peak growth does not necessarily coincide with the peak event, typically from November to January for ENSO. In reality, El Niño events have been initiated later in the calendar year and still exhibit large amplitude by December (e.g., 1982/83; Gill and Rasmusson 1983; Philander 1983), thus suggesting that subsurface precursors can have an impact on the amplitude of events and, as previously mentioned, enhance predictability. Here we are showing that initial errors induced by coupled instabilities alone can also grow upward of 1.0°C but not large enough that they completely saturate the Niño-3 signal such that all ENSO predictability is lost.

Once the initial error growth saturates and the RMSE curves begin to converge in year(1), the error becomes less of a function of initialization month and lead time. This period is no longer considered part of the initial error growth but seasonal modulation of the error. Seasonal characteristics including a decrease in springtime error and increase of error in winter become more pronounced. These results mirror those in Karspeck et al. (2006) in which strong dependence of spread on the verification month in a version of the Zebiak–Cane model is discussed. The smaller springtime error may be attributed to maximum negative feedbacks from net air–sea fluxes and the delayed thermocline feedback during boreal spring in CCSM4 (DiNezio and Deser 2014). This is also reflected in the slowest initial error growth found with the March initialized cases (Fig. 9a). Note that, although the rapid initial error growth is dynamically driven, after the error saturates, the seasonal modulation of the error by uncoupled atmospheric variability and heat fluxes is entirely possible (Sun et al. 2006, 2009; Lloyd et al. 2011, 2012; DiNezio and Deser 2014).
During the initial error growth, the net effect from thermal fluxes acts primarily as a damping term (not shown); therefore, thermal fluxes are important to the initial growth as a means to prevent runaway heating or cooling.

5. Implications for predictability

The spatial structure of the initial error is shown by the RMSE of the month(0) SST field in Fig. 10 (left). The initial error structure is similar for all ensembles, with the smallest error in the equatorial Pacific interior and larger errors moving poleward. The right column in Fig. 10 shows the “potential growth” calculated as the variance of the RE SST error in December scaled by the variance of the control. Values less than 1.0 indicate error variance that has not fully saturated the signal variance, signifying that predictability is retained. The results in Fig. 10 are analogous to those found in Fig. 9a, although by observing the spatial distribution one can see that predictability remains all along the equatorial Pacific and that, even though the January initialized cases integrate fully coupled for an entire year, much of the eastern and central Pacific still has the potential to grow 20%–50% of the control variance. It follows that, although coupled instability induced errors can be large, the errors do not fully saturate the equatorial Pacific signal and, by extension, do not completely exhaust the predictability of ENSO for the initialization months considered here.

As discussed in section 2, subsurface precursors are practically nonexistent in the RE initial conditions; thus, SST errors are assumed to originate at the sea surface.
and then evolve spatially following the dynamics of coupled instability theory. Figure 11 displays scatterplots of the month(0) Niño-3 SST error versus the December Niño-3 SST error of year(0) for the RE ensembles. The September ensemble shows hint of a positive linear relationship between the initial and final sign, although the other ensembles show only a slight indication of a bias for the cases that exceed the RMSE in December. The slope of the best-fit regression line can reveal if a bias in the initial condition sign is present that may predict the final state sign. In other words, a positive regression coefficient suggests that a positive (negative) sign predictor variable yields a positive (negative) sign predictand. As shown in Fig. 12 (top), calculation of the regression line slope (predictor and predictand variables are standardized separately and by lead time) confirms that month(0) is not a good predictor of the final state for all ensembles (i.e., leftmost point of each ensemble curve), excluding September. The exception of September is because the error exhibits only 4 months of growth by December and

FIG. 11. Scatterplots of the month(0) Niño-3 SST error vs the December Niño-3 SST error of year(0) for the RE ensembles. Green lines indicate the month(0) Niño-3 RMSE and orange lines are similarly for December. Each ensemble has 60 members.

FIG. 12. Potential predictability curves defined as the regression coefficient of the initial state [varying from month(0) to November] and December Niño-3 for (top) Niño-3 as the predictor and (bottom) the OHC. Colors are consistent with Fig. 9. All predictor and predictand values are standardized separately and as a function of lead time.
without the faster growth seasons of spring and summer, resulting in initial and final states that are similar and a slope that is closer to 1.0. Most importantly, while the month(0) regression coefficients are small, they are all positive, indicating a general agreement in the initial and final error sign that is otherwise undetectable in the scatterplots.

If we allow the initial state (e.g., \(x\) axis in Fig. 11) to evolve with the RE integration and recalculate the regression slope, “potential predictability” curves can be drawn as in Fig. 12. As the RE ensembles integrate with time, the Ni\(\text{ñ}-3\) error grows and better predicts the final state such that, by month(3), even the longer lead-time predictions of the final state show some predictability of December error. Again, all regression coefficients are positive indicating that same sign initial and final states often occur. The ocean heat content (OHC; defined as depth-averaged temperature perturbations between 0 and 250 m along the equatorial Pacific) shown in the bottom panel of Fig. 12 reveals that smaller standardized errors are found in the initial state subsurface but potential predictability grows more quickly than at the surface, consistent with growing thermocline perturbations associated with the wave dynamics central to coupled instability theory. This is a good indication that the air–sea coupling is allowing for the destabilization of equatorial ocean waves (i.e., initiation). The Ni\(\text{ñ}-3\) error peaks later once the thermocline effects of the equatorial Kelvin wave manifest at the surface.

Composites of the resulting El Ni\(\text{n}o\) and La Ni\(\text{n}a\) events for each ensemble shown in Fig. 13 confirm that coupled instability error growth is indeed ENSO-like in spatial structure for all initialization months. The final growth structure presents a real challenge for forecasters because the large growth is not accompanied by a subsurface precursor.

6. Summary and discussion

The present work focuses on SST error alone, specifically to emphasize the error growth itself and focus on seasonality. Other dynamical factors, like small \(\tau_{x,y}\) perturbations and high-frequency forcing, may be playing a role in the initiation and evolution of the different cases. This is the main focus of our future work. We have already ruled out that large-scale atmospheric variability is initiating the events, although the possibility that the small-scale variability is playing a role

![Figure 13. December(0) composite SST error (°C) for cases that produce (left) El Niño events and (right) La Niña events by December(0) as a function of ensemble.](image-url)
of the interannual SST variability in the ENSO region in this model.

Best characterize coupled instability SST error growth in dependence on the initialization month, and nonlinearity instabilities. A combination of strong seasonality, de-zation months, despite the large error induced by coupled dictability in the ENSO region is retained for all initiali-

The fall season. Furthermore, we find that some pre-

One of the main conclusions of this work is that initial condition errors that grow into ENSO events do not require a previous ENSO event, subsurface precursor, or large-scale $\tau_{x,y}$ trigger, albeit without these features much of the predictability is lost. We quantify the error growth in the ENSO region for different initialization months and find that strong seasonal characteristics are prevalent in CCSM4 and are consistent with previous work that shows faster initial error growth in spring and summer seasons. The error growth rate seasonality is consistent with the seasonal stability of the background state and, once the initial error growth saturates, the seasonal modulation of the error is consistent with the seasonality of air–sea feedbacks in CCSM4 (DiNezio and Deser 2014).

Apart from the seasonality, we also find that the initial error growth induced by coupled instabilities is dependent on the initialization month, with July initialized cases displaying the most rapid initial growth. Another important finding is that coupled instability error growth has a well-defined seasonal limit in CCSM4. In particular, the January, March, May, and July ensembles all show a clear seasonal halt in error growth in September likely because of the increased background stability that occurs during the fall season. Furthermore, we find that some predictability in the ENSO region is retained for all initialization months, despite the large error induced by coupled instabilities. A combination of strong seasonality, dependence on the initialization month, and nonlinearity best characterize coupled instability SST error growth in this model.

A point that should be emphasized is that nearly 70% of the interannual SST variability in the ENSO region in December is reproduced in the absence of a subsurface precursor in CCSM4 for long lead times (Fig. 10, January ensemble). This is particularly important for the prediction community, because it shows that coupled instabilities can instigate seemingly unpredictable ENSO events and the subsequent growth is a dominant component of nonlinear SST growth in the model. This may prove problematic because the final error structure can be large and ENSO-like, potential predictability of these events is low, and subsurface temperatures fail to provide any additional predictability at month(0). Overall, there appears no clear mechanistic precursor common to the initialization months that aids in the predictability of the oncoming ENSO event, although this could be model specific considering that CCSM4 has a weak “seasonal footprinting mechanism” (Deser et al. 2012). We stress that the results in the present study are based on the initiation of events via coupled instabilities; however, this does not mean that air–sea feedbacks and uncoupled atmospheric variability are not playing a role in seasonally modulating the error after the initial error growth saturates. Furthermore, the fact that the growth is seasonally modulated may aid in the predictability once the event is initiated.

The next step is to swap oceanic and atmospheric initial conditions for RE cases that yield different final states to help us understand how the initialized state can affect the evolution of coupled instability error growth and if there are details in the initial state that can predict this type of growth. Previous studies investigate the relative importance of initial perturbations in the atmosphere and ocean (e.g., Carton and Shukla 1991; Moore et al. 2003) and our ongoing work will potentially help tease out details in the initial conditions that are important for predictability.

Finally, the lower amplitude of events in the January ensemble compared to the peak amplitude of approximately 3.0°C in a multicentury CCSM4 control run (Deser et al. 2012) demonstrates that the subsurface precursor is an important contributor to ENSO amplitude. One may infer from Fig. 10 that nearly 30% of ENSO variability in CCSM4 can be attributed to the subsurface precursor, but a more in-depth exploration of this topic is necessary. The presented framework provides a potential platform to systematically confront this topic for future work.

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