Seasonal Synchronization of ENSO Events in a Linear Stochastic Model*

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ABSTRACT

A simple model of ENSO is developed to examine the effects of the seasonally varying background state of the equatorial Pacific on the seasonal synchronization of ENSO event peaks. The model is based on the stochastically forced recharge oscillator, extended to include periodic variations of the two main model parameters, which represent ENSO’s growth rate and angular frequency. Idealized experiments show that the seasonal cycle of the growth rate parameter sets the seasonal cycle of ENSO variance; the inclusion of the time dependence of the angular frequency parameter has a negligible effect. Event peaks occur toward the end of the season with the most unstable growth rate.

Realistic values of the parameters are estimated from a linearized upper-ocean heat budget with output from a high-resolution general circulation model hindcast. Analysis of the hindcast output suggests that the damping by the mean flow field dominates the seasonal cycle of ENSO’s growth rate and, thereby, seasonal ENSO variance. The combination of advective, Ekman pumping, and thermocline feedbacks plays a secondary role and acts to enhance the seasonal cycle of the ENSO growth rate.

1. Introduction

The El Niño–Southern Oscillation (ENSO) is a basin-wide phenomenon of the tropical Pacific that dominates climate variability on interannual time scales. ENSO variability is distinguished by coherent, large-scale patterns of anomalies in the ocean and atmosphere, including sea surface temperature (SST), thermocline depth, winds, currents, precipitation, and atmospheric pressure. ENSO events occur irregularly, approximately every 2–7 yr, yet the events display a robust seasonal synchronization, with event peaks tending to occur in boreal winter (Rasmusson and Carpenter 1982). This feature of ENSO can be seen by overlaying individual El Niño events for the past 50 yr according to calendar month (Fig. 1, top), and by examining the seasonal variance of eastern equatorial Pacific SST anomalies (Fig. 1, bottom). The seasonal synchronization of ENSO events suggests a strong dynamical link between ENSO and the annual cycle. In this paper, we propose a simple theoretical framework to explain the seasonal synchronization of ENSO events in terms of the effects of the eastern equatorial Pacific annual cycle on the stability of the equatorial Pacific coupled ocean–atmosphere system.

The annual cycle of the eastern tropical Pacific can be well characterized by the seasonal movement of the intertropical convergence zone (ITCZ), which resides north of the equator and stretches across the Pacific basin. This
is because the large-scale atmospheric motion of the tropical Pacific corresponds to a thermally driven circulation, with surface-level winds converging into areas of deep convection that have overly high SST (Philander 1990). In turn, the winds influence SST through their effects on upper-ocean currents, upwelling, latent heat flux, and mixing, leading to a coupling between the surface winds and SST. During boreal summer, the ITCZ is strongly developed and is located at its northernmost extent during the year, at approximately 12°N. The associated southeasterly trade winds are strong near the equator, and therefore so too are the wind-driven surface currents, upwelling, wind-forced mixing, and latent heat flux, leading to a well-established cold tongue. Because SST in the western Pacific is much less variable than in the east, the cold SST in the eastern Pacific implies a strong zonal temperature gradient along the equator. Between boreal summer and boreal winter, the ITCZ weakens and moves equatorward, and by early boreal spring it is located near the equator at its southernmost position. The trade winds virtually disappear near the equator during this time, and so the currents, upwelling, latent heat flux, and mixing are weak, leading to a retreat of the cold tongue. From April onward, the trade winds return, the cold tongue reemerges, and the ITCZ rapidly moves northward toward its summer position (Horel 1982; Mitchell and Wallace 1992).

Philander et al. (1984) suggested that the seasonal movement of the ITCZ has a strong effect on the coupled instability of the equatorial Pacific ocean–atmosphere system that is responsible for the onset of ENSO events. Analytical results based on linearized coupled models support this suggestion and indicate that the time-averaged background state of the equatorial Pacific is too stable to allow for the growth of ENSO events (Hirst 1986). Variations in the background state are therefore essential for ENSO events to initiate through coupled instability. Free-mode analysis of linearized coupled models has shown that strong zonal winds, a shallow thermocline, a strong zonal SST gradient, and high SST could all act to increase the coupled instability of the system (Hirst 1986). Numerical experiments with an intermediate coupled model highlighted the role of upwelling in the eastern Pacific in linking subsurface temperature anomalies to SST, leading Battisti (1988) to propose a “basic state potential instability index” based upon the seasonal upwelling and depth of the pycnocline. Experiments with the Zebiak and Cane intermediate model of ENSO (ZC model; Cane and Zebiak 1985), which involved removing the seasonal cycles from individual climatological fields, showed that the seasonal wind divergence field has a dominant effect in the model, with seasonal SST and upwelling playing secondary roles (Tziperman et al. 1997). Sensitivity studies of a hybrid coupled model using the adjoint method suggest that the seasonal outcropping of the thermocline from July to December enhances the instability of the coupled system by effectively linking thermocline depth anomalies with SST anomalies (Galanti et al. 2002). The role of seasonal mixing was emphasized over the role of upwelling in establishing this link. Finally, Harrison and Vecchi (1999) noted that western Pacific wind anomalies shift abruptly at the end of the calendar year from symmetric about the equator to confined to the Southern Hemisphere, which has been associated with an anomalous surface anticyclone (cyclone) that develops over the Philippine Sea prior to the peak of warm (cold) ENSO events (Wang et al. 1999). The shift in the wind anomalies forces oceanic equatorial upwelling (downwelling) Kelvin waves that act to reduce or reverse the eastern equatorial Pacific SST anomalies. It is suggested that the air–sea interaction involved in maintaining the Philippine Sea (anti)cyclone depends on the boreal winter mean atmospheric circulation (Wang et al. 1999). The plethora of theories regarding the dynamical links between the annual cycle and ENSO...
indicates the need for a unifying theoretical framework within which many (if not all) of these mechanisms can be examined simultaneously.

In this study, we propose an extension of the conceptual recharge oscillator model of ENSO (Jin 1997) that includes a statistical–dynamical representation of the seasonally varying background state. We refer to the model as the seasonal stochastic recharge model (SSRM). The SSRM is derived based on a seasonally varying formulation of the Bjerknes coupled stability index, developed by Jin et al. (2006). The Bjerknes index explicitly includes the seasonally varying surface currents, upwelling, and horizontal and vertical temperature gradients, while parameterizing other seasonal effects in terms of the seasonally varying atmospheric wind response and thermal damping of upper-ocean temperature anomalies. The effects of these seasonal fields combine to the time dependence of two of ENSO’s most essential characteristics within the SSRM: its growth rate and angular frequency. Model experiments allow for the description of ENSO’s seasonal variance in terms of these two parameters. The model incorporates a relatively broad physical foundation into a simple framework, making it useful for conceptualizing the effects of the seasonal cycle on ENSO dynamics, as well as a potentially powerful diagnostic tool for analyzing global circulation model (GCM) output.

The structure of the paper is as follows. Section 2 presents the derivation of the SSRM. Section 3 presents results from idealized model experiments, where the model parameters are either prescribed or statistically determined from a fit to GCM output. The seasonal cycle of ENSO variance is related to the time dependence of the model parameters. In section 4, a statistical–dynamical fit of the model to output from a high-resolution global hindcast is performed in order to quantify the effects of different climatological fields on ENSO’s seasonal variance. A more general discussion of the concept of ENSO stability is presented in section 5, and a summary and concluding remarks are presented in section 6.

2. Model derivation

The conceptual recharge oscillator model describes ENSO in terms of two natural variables: the eastern equatorial Pacific SST, which varies in phase with the zonal wind stress and zonal thermocline tilt, and the zonal mean equatorial Pacific thermocline depth, which varies about 90° out of phase with the zonal wind stress and provides the delayed negative feedback necessary for oscillation (Jin 1997). The model has been shown to capture salient ENSO features in coupled GCMs (Mechoso et al. 2003) and the natural system (Meinen and McPhaden 2000). Burgers et al. (2005) show that, in its simplest form, the recharge model takes the form of the classical damped oscillator, with eastern Pacific SST corresponding to position and mean thermocline depth corresponding to momentum in the oscillator analog. Additionally, they show that the eigenvalues of the system display marked seasonal variability when fitted to observations. However, the original derivation of the recharge oscillator assumed an interannual time scale, neglecting the basin-crossing time of equatorial oceanic Kelvin waves and describing the slow ocean adjustment to anomalous wind stress forcing in terms of a single time scale representing the cumulative effect of Rossby wave transport. Allowing the parameters of the system to vary seasonally thus poses a possible contradiction. It is therefore useful to derive a version of the recharge oscillator that includes the seasonally varying background state in a consistent manner.

The derivation of SSRM follows a method similar to that of Jin et al. (2006) for obtaining the Bjerknes coupled stability index for ENSO. We begin with the linearized equation for SST anomalies in the mixed layer:

\[
\frac{\partial T}{\partial t} = -\left(\frac{\partial T}{\partial x} + \frac{\partial T}{\partial y} + \frac{\partial T}{\partial z} + u \frac{\partial T}{\partial y} + v \frac{\partial T}{\partial y} + w \frac{\partial T}{\partial z}\right) + Q,
\]

where \(T\) is temperature, \((u, v, w)\) are upper-ocean currents, and \(Q\) stands for the divergence of anomalous surface heat flux and diffusion. The overbar indicates a climatological field (e.g., monthly means). Next, we consider a volume average of the above equation, extending horizontally over the area of maximum ENSO-associated SSTA variation and encompassing the mixed layer in depth:

\[
\frac{\partial \langle T \rangle}{\partial t} \approx -\left(\frac{\langle u \rangle}{L_x} + \frac{2\langle y \rangle}{L_y} + \frac{\langle w \rangle}{L_z}\right) \langle T \rangle - \langle u \rangle \frac{\partial \langle T \rangle}{\partial x} + \langle \theta(\langle w \rangle) \frac{H}{L_z} \rangle - \langle w \rangle \langle \theta(\langle w \rangle) \frac{\partial \langle T \rangle}{\partial z} \rangle + \langle Q \rangle,
\]

where the brackets \(\langle \cdots \rangle\) denote the volume average and \(\theta\) is the Heaviside step function, ensuring only upstream vertical advection is included. The small term \(v(\partial T/\partial y)\) has been neglected. Note that \(\langle H \rangle\) represents a volume average of temperature below \(\langle T \rangle\), and that \(\langle Q \rangle\) represents the heat fluxes through the boundaries of the \(\langle T \rangle\) volume average.

The factor \(2\langle y \rangle/L_y^2\) comes from the assumption that the meridional structure of ENSO-associated SST anomalies
is Gaussian, with an e-folding scale of \( L_x \), determined by the equatorial Rossby radius of deformation. The latitudinal extent of the volume average is thus determined by this e-folding scale, which is approximately \( \pm 3^\circ \) from the equator. The zonal and vertical extents of the volume average are not strictly determined, but can bereasonably well constrained by dynamical considerations. The minimum depth for the bottom of the volume average should lie below the mean mixed layer depth of the eastern equatorial Pacific, but should be shallow enough that the volume-average temperature retains a strong correlation with SST. The western edge of the volume average is the dividing line between the eastern and western halves of the basin that best satisfies the equation \( H = (H_E + H_W)/2 \), where \( H \) is the mean thermocline depth, and \( H_E \) and \( H_W \) are the average thermocline depths of the eastern and western halves of the basin, respectively. This relationship is used to derive the simplest form of the recharge oscillator (Burgers et al. 2005) and is an implicit assumption in the formulation of the mean thermocline depth adjustment in the SSRM. Optimization of the volume average and the sensitivity of the results to the chosen vertical extents are discussed in section 4.

Additionally, we note that the magnitude of the climatological mean SST gradient in the cold-tongue region tends to increase toward the coast, and that upwelling velocities in the upper ocean are not homogeneous. Because of these spatial inhomogeneities, the zonal and vertical dimensions of the volume average may not correlate with the values for \( L_x \) and \( L_z \) that best satisfy the equations

\[
\langle \nabla \frac{\partial T}{\partial x} \rangle = \langle \pi \rangle \frac{\langle T \rangle}{L_x}, \quad \langle \nabla \frac{\partial T}{\partial z} \rangle = \langle \omega \rangle \frac{\langle T \rangle}{L_z}.
\]

Instead, the parameters \( L_x \) and \( L_z \) can be determined by regressions based on the above equations, and we refer to them as the effective zonal gradient width and the effective depth of vertical advection, respectively.

The right-hand side of (1) can be approximated as a linear function of eastern Pacific SST anomalies \( T \) and zonally averaged heat content anomalies \( H \) by adopting the approximations used to derive the recharge oscillator (Jin 1997).

First, we approximate \( \langle Q \rangle \) as a Newtonian damping of local temperature anomalies (Barnett et al. 1991):

\[
\langle Q \rangle = -\alpha(t)\langle T \rangle,
\]

where \( \alpha \) is the thermal damping rate. Here, the \( \langle Q \rangle \) time series will be composed of the net surface heat flux anomalies over an area with the same meridional and zonal extent as \( \langle T \rangle \). The net surface heat flux is calculated as the sum of the incoming shortwave radiation, incoming and outgoing longwave radiation, sensible heat flux, and latent heat flux. Regressions from atmospheric GCM output and observed SST data show the \( \alpha \) parameter varies spatially in the equatorial Pacific (Barnett et al. 1991). This spatial variability was attributed primarily to the relative importance of latent heat versus cloud radiative effects, which are dominant in the western and eastern parts of the basin, respectively. It follows that the \( \alpha \) parameter could also vary temporally. In the eastern Pacific, where the cloud radiative effect dominates, one may expect to see the largest damping of equatorial SST anomalies during the summer, when the ITCZ is positioned farthest north.

Second, the anomalies of the zonal wind stress and temperature are linearly related:

\[
\{\tau_x\} = \mu(t)\langle T \rangle,
\]

where \( \{\tau_x\} \) is the central Pacific zonal wind stress anomaly. Here, eastern Pacific SST is a proxy for the zonal temperature gradient, as variations in the warm pool SST are generally much smaller than in the cold tongue. Because the large-scale zonal wind stress anomalies are a response to the anomalous zonal SST gradient, the midbasin wind response is highly correlated with ENSO-associated SST anomalies. Multivariate empirical orthogonal function analysis of observational data indicates that ENSO-associated zonal wind anomalies are largest in the central Pacific (Chiang et al. 2001).

SST variations are considered to affect surface winds through two main mechanisms: by inducing low-level atmospheric pressure gradients that drive surface winds directly (see Lindzen and Nigam 1987) or by affecting the position and intensity of cumulus convection and thereby the elevated atmospheric heating (see Gill 1980). These processes are sensitive to the background wind and moisture fields, the position of the ITCZ, and the background SST field via the Clausius–Clapeyron relationship. There are therefore a variety of processes that can act to seasonally modulate the \( \mu \) parameter.

Third, on interannual time scales, the first-order dynamical balance in the equatorial band is for the zonal pressure gradient to be largely in Sverdrup balance with the zonal wind stress (Jin 1997; Burgers et al. 2005). This quasi-balance, which holds within 1–2 oceanic Rossby radii of deformation from the equator, can be expressed as

\[
\langle H \rangle - [H] = \beta_x \{\tau_x\}.
\]

The square brackets \([\cdot]\) denote a volume average with the same meridional extent as \( \langle \cdot \rangle \), but extended
zonally across the entire basin and ranging vertically from the bottom of the $\langle \cdot \cdot \cdot \rangle$ volume to below the thermocline. Because this quasi-balance only holds on time scales longer than a few months, the parameter $\beta_h$ is constant. To maintain consistency, the other ocean adjustment parameters will be treated as constants as well, though we will discuss the validity of this assumption.

Fourth, zonal current anomalies are expressed as the sum of the geostrophic adjustment to the thermocline depth anomalies and forcing due to zonal wind stress anomalies:

$$\langle u \rangle = \beta_{uh} \{H\} + \beta_u \{\tau_x\}. \quad (5)$$

The first term reflects that fact that a mean thermocline depth anomaly along the equator will set up an off-equatorial meridional pressure gradient anomaly, to which the zonal advection in the equatorial waveguide will adjust geostrophically (Jin and An 1999). The geostrophic adjustment of the ocean is not seasonally dependent, so $\beta_{uh}$ is constant. The second term on the right-hand side captures the direct forcing of zonal currents by zonal wind stress. In principle, the adjustment of the ocean to a particular wind field will be time dependent, due primarily to variations in the mixed layer depth of the ocean and to the dependence of the wind stress drag coefficient on the total wind field and stability of the atmosphere. In the SSRM, the effects of the seasonal dependence of the drag coefficient will be folded into the $\mu$ parameter, as we have formulated our system in terms of the wind stress response to given zonal SST gradient anomalies, rather than the low-level wind response. The effect of the mixed layer depth on $\beta_u$, on the other hand, is a complexity that we do not consider in our formulation.

Finally, upwelling anomalies are assumed to be proportional to anomalous wind stress:

$$\langle w \rangle = -\beta_w \{\tau_x\}. \quad (6)$$

The form of Eq. (6) assumes that equatorial upwelling can be largely accounted for by considering continuity with the divergent meridional Ekman transport and zonal current, which are both dependent on the zonal wind stress. Again, the $\beta_w$ parameter is treated as constant, with similar caveats to those stated for $\beta_u$.

Combining Eqs. (1)–(6), one obtains

$$\frac{\partial \langle T \rangle}{\partial t} = 2\gamma(t)\langle T \rangle + \omega(t)[H], \quad (7)$$

where

$$2\gamma(t) = \left[ \frac{\langle w \rangle}{L_z} + \frac{\langle 2y \rangle}{L_y} + \frac{\langle \theta w \rangle}{L_z} \right] - \alpha(t) + \mu(t)\beta_u \left[ \frac{\partial T}{\partial x} \right] + \mu(t)\beta_h \left[ \frac{\theta (\langle w \rangle)}{L_z} \right] + \mu(t)\beta_w \left[ \frac{\partial T}{\partial z} \theta \langle w \rangle \right].$$

The $\gamma$ parameter is the collective growth rate of the model and is equivalent to the seasonally varying Bjerknes coupled stability index (Jin et al. 2006). The $\gamma$ parameter is made more negative (damped) by the terms on the first line, namely, the collective effects of the flow field divergence and the thermal damping rate $\alpha$. The last three terms represent the zonal advection, thermocline, and Ekman pumping feedbacks, respectively (Jin and An 1999). As these terms all represent positive coupled feedbacks, they act to make the $\gamma$ parameter more positive.

The $\omega$ parameter is a measure of the seasonally varying influence of thermocline anomalies on SST anomalies, which we will term the model’s angular frequency after the classic harmonic oscillator nomenclature. The first term of the $\omega$ parameter represents the effects of thermocline depth anomalies on the anomalous zonal advection of the mean temperature gradient [see Eq. (5)]. The second term of the index represents the mean upwelling of thermocline depth anomalies into the mixed layer.

To complete the coupled system, an equation describing the time evolution of the zonally averaged heat content anomalies is required. Based on the simplest form of the recharge oscillator (Burgers et al. 2005), the following equation is used:

$$\frac{\partial [H]}{\partial t} = -R\langle T \rangle, \quad (8)$$

where the constant $R$ provides the time scale for the slow basin-wide geostrophic adjustment of the mean thermocline depth to the zonal wind stress anomalies. This equation reflects the fact that vertically averaged heat transport into and out of the equatorial band is accomplished primarily via Sverdrup transport. It is assumed that the anomalous off-equatorial wind stress curl responsible for the Sverdrup transport is proportional to the zonal equatorial wind stress anomaly. The form of Eq. (8) will also be justified a posteriori in section 3.
\[ \frac{dT}{dt} = 2\gamma(t) T + \omega(t) H + \xi(t) \]
\[ \frac{dH}{dt} = -RT, \]

where \( \xi \) is the Gaussian white noise forcing and we have dropped the brackets for simplicity. Note that although the atmospheric forcing is uncorrelated in time, there is an implicit assumption that the atmospheric forcing has a coherent spatial structure similar to that of westerly wind bursts (Kessler and Kleeman 2000; Kleeman 2008).

By differentiating Eq. (7), one obtains the time-varying growth rate and frequency of the oscillatory system:

\[ \frac{d^2T}{dt^2} + \left(2\gamma - \frac{1}{\omega} \frac{d\omega}{dt}\right) \frac{dT}{dt} + \left(\omega R + 2 \frac{d\gamma}{dt}\right) T = 0, \]

where all variables except \( R \) are time dependent and we have used Eqs. (7) and (8) to express \( H \) and \( dH/dt \) in terms of \( T \) and \( dT/dt \). The equation shows that in general, the variation of \( \gamma \) changes the frequency of the oscillator, and the variation of \( \omega \) affects the growth rate. However, we will provide evidence in the following section that, for the parameter ranges applicable to ENSO, the \( \gamma \) parameter has a dominant effect on the growth rate of the system, and we will thus refer to it as the “growth parameter.”

The SSRM is the simplest system available to study the effects of the seasonally varying background state on ENSO dynamics. In this paper, we focus on the effects of the annual cycle of the eastern equatorial Pacific on ENSO’s seasonal variance, which is in turn a proxy for the seasonal synchronization of ENSO events. In the next section, we perform a statistical fit of the SSRM to output from a GCM hindcast run to obtain values for the growth and angular frequency parameters. The seasonal variance of the ENSO in the hindcast run is then related to the time dependence of these two parameters.

### 3. Idealized runs

The seasonal cycle’s effect on ENSO variance can be inferred from an examination of the optimal perturbation growth around a seasonally varying background state, based upon the singular-value decomposition of intermediate coupled models (Chen et al. 1997; Xue et al. 1997; Thompson and Battisti 2000), as well as Markov models derived from intermediate model output (Pasmanter and Timmermann 2003), global circulation model output (Kallummal and Kirtman 2008), and observations (Johnson et al. 2000). The singular values obtained from these analyses display a strong seasonal dependence, with growth of the singular vectors tending to peak in boreal winter. For the case of a stochastically perturbed ENSO, the results indicate that the seasonally varying background state of the equatorial Pacific is perhaps sufficient to produce the observed seasonal variance, without the need to invoke either nonlinear dynamics or seasonality in the noise forcing (Thompson and Battisti 2000; Kallummal and Kirtman 2008).

Based on the optimal perturbation studies, it can be inferred that the equatorial annual cycle modifies the coupled stability of the ocean–atmosphere system, which in turn influences the timing of ENSO event peaks. The SSRM is an attempt to capture the first-order, linear dynamics of this process. However, it must first be demonstrated that a simple, linear, stochastically forced model of ENSO is able to reproduce a significant seasonal cycle of variance. Doing so is the first purpose of this section. The second purpose is then to interpret the seasonal variance in terms of the time dependence of the growth and angular frequency parameters.

To that end, a series of experiments are performed to examine the SSRM’s variance response to prescribed seasonal cycles of \( \gamma \) and \( \omega \). We begin with a statistical fit of the SSRM to a high-resolution GCM hindcast, which was used in lieu of observations because of the need for a long-term, comprehensive subsurface dataset to perform the fit. These values for \( \gamma \) and \( \omega \) obtained from the fitting exercise will serve as a template for idealized experiments with the SSRM model.

#### a. Statistical fit to OFES output

In the following sections, we utilize model output from the Ocean GCM for the Earth Simulator (OFES), developed at the Japan Agency for Marine-Earth Science and Technology (JAMSTEC). The OFES model is based on version 3 of the Modular Ocean Model (MOM3), with a computational domain of 75°S–75°N and a horizontal grid spacing of \( 1^\circ \times 1^\circ \). The model has a staggered vertical grid with 54 vertical levels, which is designed to produce realistic ocean circulations above the thermocline (Masumoto et al. 2004; Sasaki et al. 2008). The OFES model was forced with winds from the National Centers for Environmental Prediction and the National Center for Atmospheric Research (NCEP–NCAR) reanalysis dataset, with a time domain of 1900–present (Kalnay et al. 1996). The result is a quasi-global eddy-resolving hindcast from 1960 to the present, excluding a 10-yr “spinup” period.

To perform fits of the SSRM to OFES output, we begin by computing monthly volume averages of temperature for the \( T \) and \( H \) indices:
The monthly values of \( d\langle T \rangle/dt \) and \( d[H]/dt \) were obtained from 12 multilinear fits from yearly time series of \( \langle T \rangle \) and \( [H] \) for each month of the year, and the parameter \( R \) is based on a linear regression of \( d[H]/dt \) onto \( \langle T \rangle \). No smoothing of the time series was performed prior to the regressions. The time series for the growth and angular frequency parameters, as well as the 95% confidence intervals of the regressions, are shown in Fig. 2. The growth parameter is shown to vary significantly over the course of the year; the same cannot be said for the angular frequency parameter, which is not significantly different from a constant value of \( \approx 1.1 \) yr\(^{-1}\).

\[
\frac{d\langle T \rangle}{dt} = -2\gamma_i\langle T \rangle + \omega_i[H_i]
\]  
(9)

\[
\frac{d[H]}{dt} = -R\langle T \rangle,
\]  
(10)

where \( i = 1, \ldots, 12 \), indicating the month of the year. The monthly values of \( \gamma(t) \) and \( \omega(t) \) are obtained from 12 multilinear fits from yearly time series of \( \langle T \rangle \) and \( [H] \) for each month of the year, and the parameter \( R \) is based on a linear regression of \( d[H]/dt \) onto \( \langle T \rangle \). No smoothing of the time series was performed prior to the regressions.

The time series for the growth and angular frequency parameters, as well as the 95% confidence intervals of the regressions, are shown in Fig. 2. The growth parameter is shown to vary significantly over the course of the year; the same cannot be said for the angular frequency parameter, which is not significantly different from a constant value of \( \approx 1.1 \) yr\(^{-1}\).

The assumption that \( dH/dt \) is a function of \( T \) only appears valid, based on OFES model output. Figure 3 shows the scatterplots of \( d[H]/dt \) versus \( \langle T \rangle \) and \( [H] \). The scatterplot of \( d[H]/dt \) versus \( [H] \) shows that the time series have virtually no relationship; the correlation coefficient between the two time series is \(< 0.01\). In contrast, the scatterplot of \( d[H]/dt \) versus \( \langle T \rangle \) shows a robust correlation. A regression of \( d[H]/dt \) onto \( \langle T \rangle \) produces a time scale for the adjustment of the mean thermocline depth of 23 months \( \pm 7\% \). If both \( \gamma(t) \) and \( \omega(t) \) were set to their mean values, the result would be a damped oscillator with a period of \( 2\pi/\omega_n = 2\pi/\sqrt{R - \gamma^2} \approx 3.5 \) yr and a damping rate of \( \gamma \approx 2.5 \) yr\(^{-1}\).
b. Idealized experiments

For all of the model runs presented here, the SSRM was integrated via a centered-difference time-stepping method for 5000 yr to obtain statistically stable results. A time step of 1 day was used, with a year length of 360 days (12 months of 30 days each). Monthly mean values of \( T \) and \( H \) were saved as output. The daily values of \( g(t) \), \( v(t) \) were obtained by linearly interpolating between monthly values. The stochastic forcing of the atmosphere was approximated as Gaussian white noise, applied at each time step. Temperature output was normalized to unit variance, so the amplitude of the white-noise forcing is arbitrary. All runs were initialized with zero anomaly (\( T_0 = H_0 = 0 \)). Sensitivity experiments were performed to rule out model artifacts. Several time-differencing schemes and time steps for the model were tested, with no significant impacts on the results.

The first experiment investigated the effects of the seasonal cycle of \( g \) alone, setting \( v \) to its mean value. The damping rate \( \gamma \) was decomposed into its mean (\( \bar{\gamma} \)) and seasonally varying (\( \gamma_{acy} \)) components, with the parameter \( S \) controlling the strength of seasonal cycle:

\[
\omega = \bar{\omega},
\gamma(t) = \bar{\gamma} + S(\gamma_{acy}).
\]

To examine the effects on the synchronization of ENSO event peaks, successive runs of the SSRM with values of \( S \) increasing from 0 to 1 were performed, and the seasonal variance from each run was calculated. Figure 4 displays the seasonal variance and the monthly values of \( \gamma \) for each of these runs. The seasonal variance of the model temperature increases proportionally to the increase in the amplitude of the \( \gamma \) seasonal cycle, as can be seen in Fig. 5. The point \( \gamma = \bar{\gamma} \) is critical in terms of the timing of event peaks. Model events tend to peak at the mean crossing that follows a period of lower than normal stability (\( \gamma > \bar{\gamma} \)). For our idealized seasonal cycle, the two mean crossings occur in January and July, as do the extrema in seasonal variance.

To more clearly display the relationship between \( \gamma(t) \) and ENSO’s seasonal variance in the SSRM, we repeated the above experiment with a prescribed triangle waveform for \( \gamma(t) \). The results are shown in Fig. 6. For all the runs with this prescribed form, the peak in seasonal variance occurs in the last month that \( \gamma(t) > \bar{\gamma} \), and vice versa for the month of minimum variance. For example, the maximum seasonal variance occurs in December, due to the fact that \( \gamma(t) < \bar{\gamma} \) for part of January. If the maximum variance corresponded to the time when the system was moving from a linearly unstable to a damped state, it would occur in November instead of December. Similarly, the minimum seasonal variance occurs in June rather than July.

For comparison, the seasonal variance of the \( \langle T \rangle \) index from the OFES model output is shown in the top plot of Fig. 4 (black line). The range of the SSRM’s variance response is comparable to that of the OFES output, and the two seasonal cycles of variance have a similar shape. Thus, the time dependence of the growth rate captures a majority of the processes responsible for the seasonal

![Seasonal Variance of (T)](image1)

![Growth Rate (yr⁻¹)](image2)

FIG. 4. (top) The seasonal variance of the SSRM temperature output and (bottom) the seasonal cycle of \( \gamma \), from model runs where \( S \) is increased from 0 to 1 in increments of 0.25. The seasonal cycle of the growth rate parameter (\( \gamma \)) was determined from a statistical fit of the SSRM model to output from the OFES GCM. The seasonal variance of the \( \langle T \rangle \) index from OFES is shown in the top panel for comparison (thick black line).

![Range of Seasonal Variance vs S](image3)

FIG. 5. The range of the seasonal variance of SSRM output vs the strength of the seasonal cycle of the growth rate parameter (\( S \)), for model runs where \( S \) is increased from 0 to 1 in increments of 0.05.
cycle of variance of ENSO in the OFES model, a result that agrees well with previous studies based on optimal perturbation growth within more complex systems (Thompson and Battisti 2000; Kallummal and Kirtman 2008).

Allowing the $\omega$ parameter to vary in time had little effect on the SSRM’s variance response. Figure 7 displays the obtained seasonal variance for two model runs: one with the full seasonal cycle of $g(t)$ but with $\omega(t)$ set to its mean for all months, and one with full seasonal cycles of both parameters. The effect of varying the models’ angular frequency on the seasonal temperature variance are modest, slightly modulating the seasonal variance during the first half of the year. Thus, the seasonal variance of the SSRM is almost entirely determined by the growth rate parameter, and the timing of event peaks in the model is therefore set by the direct suppression of event growth when the system moves from an anomalously unstable into an anomalously damped regime.

Stochastic forcing introduces a degree of irregularity into both the timing and the shape of individual model events. This effect can be seen in Fig. 8, where ensemble diagrams of El Niño events from 55-yr runs of the SSRM with the full seasonal cycles of $\gamma$ and $\omega$ are displayed. El Niño events were defined as periods where $T(t) > 1.2 \times \text{std}(T)$, corresponding to temperature anomalies of 1.2°C. Note that the SSRM is symmetrical in terms of positive and negative temperature anomalies, so the results apply to La Niña events as well. Figure 8 shows four ensemble diagrams from four consecutive runs, with the thick black line representing the composite El Niño event. With a long enough integration time, the shape of the composite event is stable. However, for model runs of several decades, the stochastic forcing causes enough irregularity in the model output to induce significant scatter in the shape of the composite El Niño event for each realization.

The results indicate that for parameter ranges of $\gamma$, $\omega$ applicable to ENSO, the synchronization of model events is determined by the seasonal cycle of the $\gamma$ parameter. The inclusion of the time dependence of the angular frequency parameter has a negligible effect on the simulated seasonal cycle of ENSO variance. Thus, for the SSRM, the effects of the seasonally varying background state of the tropical Pacific on ENSO’s stability are captured by the $\gamma$ parameter, which justifies our denotation of $\gamma$ as the model’s growth rate parameter. Next, we examine the main physical processes responsible for the seasonal variance of this parameter.

### 4. Statistical–dynamical fit to OFES output

In this section, we present a statistical–dynamical fit of OFES model output to the SSRM, using Eqs. (2)–(6) from the derivation of the model. Following Jin et al. (2006), the values for the growth rate and angular frequency obtained from the statistical–dynamical fit will be referred to as the Bjerknes indices, with $\gamma_{BJ}$ referring to the growth parameter and $\omega_{BJ}$ referring to the angular frequency parameter. We will compare the results of the two fits to validate the simplifications used to derive the SSRM, and examine the contributions of the individual terms of the Bjerknes indices to determine to first order the effects of the seasonal cycle on ENSO’s variance.
To obtain the Bjerknes indices, the same zonal, meridional, and depth extents were used for the $\langle \cdots \rangle$ and $[\cdots]$ volume averages as were used for the statistical fit of the SSRM to OFES. The area averaged and used to calculate $\{\tau_z\}$ had the same meridional extent as $\langle \cdots \rangle$, and extended zonally from 110°W to 170°W. These spatial averages were then applied to Eqs. (2)–(6) to obtain the constant $\beta$ parameters and the time-varying $\mu(t)$ and $\alpha(t)$ parameters, and to calculate directly the seasonal fields of currents, as well as upwelling and zonal and vertical temperature gradients. Regressions to determine the values of the effective zonal gradient width and effective depth of vertical advection produced values of $\approx 20^\circ \pm 30\%$ for $L_x$ and 50 m $\pm 10\%$ for $L_z$. The area of maximum upwelling along the equator in OFES occurs between 50 and 60 m, so we consider the value obtained for $L_z$ to be physically reasonable. However, the value for $L_x$ appears to be unreasonably low, and the confidence interval of the regression is large. As such, we choose to set the value of the effective zonal gradient width to 30°, slightly above the upper limit of the confidence interval of the regression.

Bar graphs of the monthly values of the Bjerknes indices for OFES and their individual terms are shown in Fig. 9, and the seasonal cycles of $\gamma$ and $\gamma_{BJ}$ for the OFES model are compared in Fig. 2. The direct fit of the SSRM and the indirect fit via the Bjerknes indices produce similar mean values and seasonal cycles of ENSO’s growth rate. The amplitude of the seasonal cycle of $\gamma_{BJ}$ is larger than that of $\gamma$, but is within the uncertainties produced by the statistical fit for all months except January and February. The same is not true for the angular frequency parameters, as the values of $\omega_{BJ}(t)$ fall outside the 95% confidence intervals of $\omega(t)$ during the spring. We note that it is possible to obtain fits of the Bjerknes indices that fall within the confidence intervals of the statistical fits if the indices are “tuned” by choosing the values for $L_z$ and $L_x$. Because the values obtained for $\omega(t)$ are not statistically different from a constant, it is not clear at this point whether the difference in the shapes of the seasonal cycles of the two angular frequency parameters is significant. In any case, the mismatch between $\omega_{BJ}(t)$ and $\omega(t)$ does not affect the SSRM’s seasonal variance, though it may be important for other aspects of the ENSO dynamics.

The seasonal variance of the SSRM runs utilizing $\gamma(t)$, $\omega(t)$ and $\gamma_{BJ}(t)$, $\omega_{BJ}(t)$ are compared to the seasonal variance of the $\langle T \rangle$ index from OFES in Fig. 10. As can be seen, both runs satisfactorily reproduce the seasonal cycle of the ENSO variance displayed in OFES. The result suggests that the seasonally varying Bjerknes coupled stability index ($\gamma_{BJ}$) incorporates the first-order physical mechanisms whereby the seasonal cycle influences the seasonal synchronization of ENSO events.

Fig. 8. Time series of El Niño events from (clockwise from top left) four consecutive 55-yr SSRM model runs, overlaid based on calendar month and aligned so that the peak of the El Niño event occurs in year 0. Dashed lines are individual events and the solid line is the mean of the individual events. El Niño events were defined based on a temperature anomaly of 1.2 times the standard deviation of the times series ($\approx 1.2^\circ$C).
The statistical–dynamical fit of the SSRM to OFES (Fig. 9) indicates that the growth rate of ENSO in OFES is primarily determined by the mean damping of the flow field in the eastern equatorial Pacific, which is strongly related to the seasonal position of the ITCZ. The mean zonal advection and upwelling terms are minimal during boreal spring when the ITCZ is closest to the equator, and attain their maximum values during July and August, when the ITCZ is farthest poleward. These two terms have magnitudes 2–3 times larger than any of the other terms that contribute to the SSRM growth parameter, with the mean zonal advection displaying the largest seasonal cycle. The mean poleward (as opposed to cross equatorial) advection in the eastern equatorial Pacific, which is largest during June and July, has a much less significant effect on the seasonal growth rate.

The combined effect of the zonal advection, Ekman pumping, and thermocline feedback terms plays a secondary role to that of the mean damping of the flow field, with the thermocline feedback having the largest magnitude. Because all three positive feedbacks attain their maxima in September and their minima in May–June, they act to enhance the seasonal cycle of the growth rate parameter. Figure 11 displays the two time-varying components of each of the feedback terms. The \( \mu(t) \) parameter, which quantifies the anomalous atmospheric zonal wind stress response to eastern equatorial SST anomalies [Eq. (3)], is common to all three feedback terms and is responsible for the three terms all peaking in September. The Ekman pumping feedback displays the largest seasonal cycle because the mean upwelling in the eastern equatorial Pacific tends to vary in phase with \( \gamma(t) \), whereas

![Figure 9](image-url)  
**FIG. 9.** Bar graphs of the (top) \( \gamma_{BJ} \) and (bottom) \( \omega_{BJ} \) indices for the OFES model, and their individual terms obtained from the derivation of the SSRM. The 12 bars for each term represent the values for each month from January on the left to December on the right. The 12 values for the \( \gamma_{BJ} \) and \( \omega_{BJ} \) indices are obtained by summing all of the terms to the right of the vertical hash marks.

![Figure 10](image-url)  
**FIG. 10.** The seasonal variance of \( h_T \) from SSRM runs utilizing \( \gamma(t) \) from the direct fit (light gray, dashed–dotted), and \( \gamma_{BJ}(t) \) from the Bjerknes index (gray, dashed) based on fits of OFES model output. The seasonal variance of the \( h_T \) index from OFES is shown for comparison (solid black).
The mean zonal and vertical temperature gradients do not. The three main coupled feedbacks have a cumulative effect on the SSRM’s seasonal growth rate that is approximately half that of the mean damping of the flow field. These results lead to the following interpretation of ENSO’s seasonal growth rate: during the late spring–early summer, the coupled feedbacks between ocean and atmosphere are weakest and the climatological damping strongest, effectively preventing the growth of perturbations into ENSO events and damping temperature anomalies that developed during the previous year. Over boreal summer, there is an abrupt transition between the period of maximum damping of temperature anomalies and the period of minimum damping of temperature anomalies during the fall. Variations between years as to when exactly this transition occurs should have a strong influence on the onset of ENSO events. Over boreal winter and spring, the stability of the system gradually increases until the system returns to its most damped state. In the SSRM, the synchronization of ENSO event peaks is achieved by the climatological damping of temperature anomalies that occurs at this time.

5. Discussion

Throughout this paper, we have relied on the concept of ENSO stability, which has been the basis for much of the theoretical work done on ENSO over the past few decades. It is this concept of stability that has engendered the debate between those who view ENSO as a self-sustained oscillation versus those who view ENSO as a stable mode that is excited by noise. The implicit assumption of this debate is that the stable and unstable regimes are strictly divided. The analysis of the SSRM in this paper relies on this “absolute” view of ENSO stability: we have described values of $\gamma$ greater than zero as corresponding to an unstable ENSO state, and values of $\gamma$ less than zero as corresponding to a damped ENSO state. However, recent work has called into question the utility of this type of view of ENSO stability (Timmermann and Jin 2007). The concept of ENSO stability relies on two strong assumptions about the coupled ocean–atmosphere system:

- that atmospheric noise forcing is independent of ENSO and
- that the background state of the equatorial Pacific is stable (i.e., the assumption of stationarity of the system).

There is increasing evidence that these assumptions may not be valid for the natural system. For example, westerly wind bursts (WWBs) in the western equatorial Pacific have been linked to the onset of El Niño events through the initiation of downwelling Kelvin waves (Luther et al. 1983). Several studies have indicated that the probability of WWBs depends on the state of ENSO (Kessler et al. 1995; Kessler and Kleeman 2000; Eisenman et al. 2005). Thus, the noise forcing of ENSO may be state...
dependent, which violates the first assumption listed above. Second, long-term temperature trends in the tropical Pacific have been proposed to cause “regime shifts” of the ENSO mode, indicating that the climate system may be nonstationary (An and Jin 2000).

Timmermann and Jin (2007) utilize a low-order ENSO model to analyze the effects of state-dependent noise forcing and nonstationarity on ENSO dynamics. They find that state-dependent noise forcing leads to a shift in the Hopf bifurcation of the system, and that a slowly varying background state leads to “weathering” of the Hopf bifurcation, making it difficult to identify the bifurcation point in parameter space. This raises the question of whether conceptual ENSO models that assume stationarity are useful for understanding the historic ENSO, and whether they will be able to predict ENSO’s behavior under future anthropogenic climate forcing. More generally, the utility of the concept of ENSO stability is called into question.

These considerations can be largely rectified with our analysis of the SSRM if one considers the seasonal cycles of γ to represent a “relative” stability as opposed to an “absolute” stability. Model experiments reveal that changing the mean damping rate of the SSRM (γ) does not alter the seasonal cycle of the temperature variance, as long as the shape of the seasonal cycle of γ is maintained (not shown). This is because there is a balance between the mean damping rate of the SSRM and the variance of the noise forcing. The variance of the noise forcing only sets the overall variance of ENSO in the model, whereas the amplitude and shape of ENSO’s seasonal variance are set by the γ term. As long as nonlinear saturation of the ocean–atmosphere system is not a dominant process, the analysis of the SSRM suggests that the extrema of seasonal variance will correspond to the ends of periods of relatively high–low stability, as opposed to the transitions between linearly unstable and damped states.

Finally, we mention briefly that the results of the experiments with the SSRM support the linear paradigm previously proposed in many studies, which views the ENSO dynamical system as stable, and cites external stochastic forcing as the source of ENSO’s observed variance and irregularity (see, e.g., Penland and Sardeshmukh 1995; Chang et al. 1996; Thompson and Battisti 2000; Kleeman 2008). This view stands in contrast to the nonlinear paradigm, which holds that ENSO variance is a result of the instability of the coupled ocean–atmosphere system of the tropical Pacific, and ENSO’s irregularity is best captured by low-order chaotic processes. Under the nonlinear paradigm, the seasonal synchronization of ENSO events is seen as the result of the frequency locking of ENSO to periodic forcing by the seasonal cycle (Chang et al. 1994; Jin et al. 1994; Tziperman et al. 1995; Jin et al. 1996; Chang et al. 1995; Neelin et al. 2000). Under the linear paradigm, the seasonal synchronization of ENSO events could result from the annual variation of the background state, seasonality in the synoptic-scale atmospheric forcing, or a combination of both. Floquet analysis and singular vector analysis of a linearized version of the ZC model indicates that the annual variation of the background state of the equatorial Pacific alone may be sufficient to produce significant synchronization of ENSO events (Thompson and Battisti 2000). Galanti and Tziperman (2000) also show this is the case within simple models, derived from a two-strip approximation to the ZC model, which fall into the fast-wave, fast-SST, and mixed-mode regimes. They suggest that in the fast-SST and mixed-mode regimes, the physical mechanism responsible for the synchronization of ENSO events is the seasonally varying amplification of Kelvin and Rossby waves, which results in the opposing tendencies of the two waves balancing only during boreal winter (Tziperman et al. 1998). The results of our study support the hypothesis that background-state changes can induce significant ENSO event synchronization, and highlight a number of physical mechanisms through which this process could occur, in addition to the wave-amplification mechanism.

6. Conclusions

To examine the effects of the seasonally varying background state of the equatorial Pacific on ENSO dynamics, we constructed a linear, stochastic oscillator model of ENSO with seasonally varying coefficients, based upon the simplest form of the recharge oscillator model. The model, named the SSRM, reduces the effects of the seasonal cycle to a time dependence of two model parameters: one representing ENSO’s growth rate and the other ENSO’s angular frequency. The SSRM was then used to analyze the seasonal synchronization of ENSO events in terms of variations in these parameters.

It was found that the seasonal synchronization of events in the SSRM is set by ENSO’s growth rate parameter, where event peaks occur as the system moves from an anomalously unstable to an anomalously damped state. The inclusion of the time dependence of the angular frequency parameter had a negligible effect on SSRM’s seasonal variance. Our interpretation of the results is that the timing of event peaks in the SSRM occurs through direct suppression of event growth by the climatological damping.

We then calculated the growth rate and angular frequency parameters of the SSRM based on the background fields of the wind, currents, temperature, and thermal damping fields from the OFES hindcast. It was found that damping by the climatological flow field, which is dominated by the zonal advection term, had a
first-order effect on the SSRM’s seasonal growth rate. The combined effects of three main positive feedbacks involved with ENSO play a secondary role, enhancing the seasonal cycle of the growth parameter.

Overall, our analysis suggests that the linear, stable hypothesis remains a viable explanation for ENSO’s observed variance, irregularity, and seasonal synchronization. Atmospheric forcing at fast time scales provides a source of energy to maintain ENSO’s observed variance, as well as a source of the oscillations irregularity. The variance is stratified seasonally due to the annual cycle’s influence on ENSO’s growth rate, without needing to invoke nonlinear processes or temporal coherence in the noise forcing. Additionally, it was shown that the SSRM provides a useful physical framework for understanding the first-order effects of the background state on ENSO’s stability, as well the potential to diagnose and hopefully improve the simulation of ENSO in coupled global circulation models.

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