Surface Fluxes and Ocean Coupling in the Tropical Intraseasonal Oscillation

ERIC D. MALONEY
College of Oceanic and Atmospheric Sciences, Oregon State University, Corvallis, Oregon

ADAM H. SOBEL
Department of Applied Physics and Applied Mathematics, and Department of Earth and Environmental Sciences, Columbia University, New York, New York

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ABSTRACT

Sensitivity of tropical intraseasonal variability to mixed layer depth is examined in the modified National Center for Atmospheric Research Community Atmosphere Model 2.0.1 (CAM), with relaxed Arakawa–Schubert convection, coupled to a slab ocean model (SOM) whose mixed layer depth is fixed and geographically uniform, but varies from one experiment to the next. Intraseasonal west Pacific precipitation variations during boreal winter are enhanced relative to a fixed-SST (infinite mixed layer depth) simulation for mixed layer depths from 5 to 50 m, with a maximum at 20 m [interestingly, near the observed value in the regions where the Madden–Julian oscillation (MJO) is active], but are strongly diminished in the 2-m depth simulation. This nonmonotonicity of intraseasonal precipitation variance with respect to mixed layer depth was predicted by Sobel and Gildor using a highly idealized model. Further experiments with the same idealized model help to interpret results derived from the modified NCAR CAM.

A sensitivity study shows that the convection–surface flux feedback [wind-induced surface heat exchange (WISHE)] is important to the intraseasonal variability in the CAM. This helps to explain the behavior of the 2-m SOM simulation and the agreement with the idealized model. Although intraseasonal SST variations are stronger in the 2-m SOM simulation than in any of the other simulations, these SST variations are phased in such a way as to diminish the amplitude of equatorial latent heat flux variations. Reducing the mixed layer depth is thus nearly equivalent to eliminating WISHE, which in this model reduces intraseasonal variability. The WISHE mechanism in the model is nonlinear and occurs in a region of mean low-level westerlies.

Since a very shallow mixed layer is effectively similar to wet land, it is suggested that the mechanism described here may explain the local minimum in MJO amplitude observed over the Maritime Continent region.

1. Introduction

In this study, we examine the sensitivity of the Madden–Julian oscillation (MJO; Madden and Julian 1994), in an atmospheric general circulation model (GCM) coupled to a slab ocean model, to the depth of the ocean mixed layer. We are able to explain some interesting qualitative features of the simulated MJO’s amplitude dependence on mixed layer depth using additional GCM sensitivity studies and comparisons with a much simpler model. These results shed some light on the basic dynamics of the MJO in this GCM.

Significant intraseasonal variations of sea surface temperature (SST) accompany the MJO, forced by ocean–atmosphere heat exchange variations (e.g., Kawamura 1988; Krishnamurti et al. 1988). Intraseasonal SST variations greater than 1°C have been observed over the western Pacific Ocean in association with the strongest MJO events (Weller and Anderson 1996). Such intraseasonal SST variations may then feedback on the atmosphere, playing a significant role in MJO variability. Many previous studies have noted at least a modest improvement in the simulation of intraseasonal variability, compared to fixed-SST simulations, when an atmospheric GCM is coupled to an interactive ocean (Flatau et al. 1997; Waliser et al. 1999; Gualdi et al. 1999; Maloney and Kiehl 2002; Kembal-Cook et al. 2002; Inness and Slingo 2003, among others). Several studies using models of intermediate or lower complexity have attempted to explain the role of ocean coupling on intraseasonal time scales (e.g., Wang and Xie 1998; Sobel and Gildor 2003).

Watterson (2002) found that when the Commonwealth Scientific and Industrial Research Organisation atmospheric GCM was coupled to mixed layer oceans of varying depth, both the amplitude and eastward propagation speed of intraseasonal variability in velocity potential at 200 hPa monotonically increased as mixed
layer depth decreased. A simulation with a 10-m deep mixed layer—the shallowest used in the study—produced the most realistic phase speeds, but larger than observed variance at intraseasonal time scales. Watterson attributed the increase in phase speed with decreasing mixed layer depth to the reduced thermal inertia of the ocean and consequently the tendency for positive SST anomalies to develop rapidly to the east of enhanced intraseasonal convection. Watterson also suggested that these SST anomalies force increased surface convergence within regions of positive MJO convective anomalies via the mechanism of Lindzen and Nigam (1987), thereby strengthening MJO convection and amplifying the model MJO signal.

Sobel and Gildor (2003, hereafter SG03) proposed a simple zero-dimensional model in order to understand some aspects of coupled intraseasonal variability. Their model consists of an atmospheric model, based on the Neelin–Zeng quasi-equilibrium tropical circulation model (QTCM; Neelin and Zeng 2000), but with several additional strong simplifications (most notably, the restriction to a single horizontal location and neglect of all horizontal advection terms). This simple atmosphere was coupled to a slab ocean model (SOM). In certain parameter regimes, the steady solutions of this model are linearly unstable, leading to spontaneous coupled oscillations on intraseasonal time scales. In isolation (i.e., in the absence of an MJO) these oscillations can be thought of as single-point SST “hot spots” that develop during periods of clear skies, strong surface shortwave radiative heating, and low surface latent heat flux and are then shut down by the high surface latent heat flux and reduced shortwave radiation associated with the deep convection, which eventually develops in response to the high SST, as observed (e.g., Waliser 1996; Sud et al. 1999). The growth rate of these oscillations in the SG03 model actually increases as the mixed layer depth increases. However, when the model is put in a stable part of parameter space (arguably the appropriate regime to represent observations) and forced with an imposed intraseasonal oscillation in atmospheric heating—representing the MJO, which we expect to organize the intraseasonal variability in reality (Lau and Sui 1997; Hendon and Glick 1997; Jones et al. 1998; Fasullo and Webster 1999, 2000)—the amplitude of the model response is a nonmonotonic function of mixed layer depth. A monotonic increase in intraseasonal variance with decreasing mixed layer depth [as found by Watterson (2002)] occurs down to depths of 10–20 m in their model, but the variance reaches a maximum at that value and then decreases as mixed layer depth decreases. We will show that nonmonotonic behavior also occurs in an atmospheric GCM coupled to an SOM, with the amplitude maximum occurring near the 10–20-m predicted value.

The coupled variability in the SG03 model is due to a combination of radiative–convective feedbacks (e.g., Lee et al. 2001; Raymond 2001; Bretherton and Sobel 2002; Lin and Mapes 2004, hereafter LMJAS) and surface flux–convective feedbacks (Neelin et al. 1987; Emanuel 1987). We expect the GCM to reproduce the nonmonotonic behavior only if at least one of these feedbacks is important in the simulated MJO. The surface flux feedback [wind-induced surface heat exchange (WISHE), Emanuel 1987] turns out to be important in the GCM that we use, as is verified by a sensitivity study in which we turn off WISHE. The WISHE mechanism in the model appears to be nonlinear and occurs in a region of mean low-level westerlies.

Section 2 will describe the modified version of the National Center for Atmospheric Research (NCAR) Community Atmospheric Model 2.0.1 (CAM2.0.1) and the slab ocean model used in this study and will briefly describe the zero-dimensional model developed by SG03. The limited observational datasets used in this study will also be described. Section 3 will describe equatorial precipitation, surface flux, and SST variability in coupled model sensitivity experiments in which SOMs of depths of 50 m, 20 m, 10 m, 5 m, and 2 m are coupled to the modified NCAR CAM2.0.1. These results will also be compared to a climatological SST simulation with latent heat fluxes set at climatological values, elucidating the effects of WISHE on the simulation of intraseasonal convective variability. Results using the zero-dimensional model of SG03 will also be presented and compared to those from the GCM. Section 4 describes zonal wind variability and the horizontal structure of the model MJO. Section 5 presents a summary of major conclusions and some plans for future work.

2. Model and data description

a. The NCAR CAM2.0.1

The atmospheric GCM that we use in this study is a modified version of the NCAR CAM2.0.1 (Kiehl and Gent 2004). The CAM2.0.1 is the atmosphere component of the NCAR Community Climate System Model 2, a stable non-flux-corrected earth system model that provides state-of-the-art climate simulations. The deep convection parameterization of Zhang and McFarlane (1995) used in the standard version of CAM2.0.1 produces very weak tropical intraseasonal variability, as has been documented in previous versions of the NCAR CAM (e.g., Maloney and Hartmann 2001). We have replaced the Zhang and McFarlane convection scheme with the relaxed Arakawa–Schubert (RAS) convection scheme of Moorthi and Suarez (1992). The RAS parameterization produces more realistic intraseasonal variability in previous versions of the NCAR CAM than the standard deep convection scheme (e.g., Maloney and Kiehl 2002). This improvement of intraseasonal variability by changing convection parameterization demonstrates that factors other than ocean coupling are also important for producing realistic intraseasonal variabil-
ity in atmospheric models (e.g., Grabowski 2003; Randall et al. 2003).

The version of RAS that we use allows deep convective rainfall to evaporate into the environment as described in Sud and Molod (1988). The cooling caused by this rainfall evaporation does not, however, explicitly drive parameterized dynamic downwinds. The Hack (1994) convection parameterization is retained to simulate shallow convection as in the standard version of CAM2.0.1.

We integrate CAM2.0.1 at T42 horizontal resolution during all experiments, which approximately corresponds to a grid resolution of 2.8° latitude by 2.8° longitude. Twenty-six levels in the vertical are resolved, and the model time step is 20 minutes.

b. The slab ocean model

We use a simple SOM based on the formulation of Hansen et al. (1984):

$$\rho_o C_o h \frac{dT}{dt} = F + Q,$$

(1)

where $T$ is the slab ocean temperature, $\rho_o$ is the density of seawater (constant), $C_o$ is the heat capacity of seawater (constant), $h$ is the slab ocean depth, $F$ is the net atmosphere to ocean heat flux, and $Q$ is the oceanic mixed layer heat flux (the “$Q$ flux”) and is used to account for processes such as ocean mixing and advection that cannot be simulated by the simple thermodynamic SOM. Here $h$ is prescribed to be horizontally invariant within the domain of the SOM (the manner in which $h$ varies among experiments is described below); $F$ includes surface latent heat, sensible heat, shortwave radiative, and longwave radiative fluxes; and $Q$ is calculated as the residual oceanic heat flux needed to satisfy the heat balance in (1) using climatological monthly surface heat fluxes derived from a control simulation forced by observed climatological SSTs. This model is nearly identical to that used in Maloney and Kiehl (2002), except that their model prescribed spatially varying mixed layer depth.

The SOM is fully applied from 30°N to 30°S, and climatological SSTs are used poleward of 40°. The influence of the slab ocean model is tapered exponentially between 30° and 40°, ensuring that no strong SST gradients are artificially created by the model near 30°N and 30°S. An examination of SST climatologies and instantaneous values verifies this (not shown).

The design of $Q$ is such that the SST climatology in the SOM simulations remains similar to that in the control simulation. Deviations of the SST climatology from the control simulation tend to be most pronounced for shallow mixed layer depths. For example, a SOM simulation using 2-m $h$ is described below. This simulation is characterized by climatological wintertime SSTs that are more than 1°C cooler than the control over parts of the tropical Indian Ocean. To ensure that these SST biases are not responsible for the changes in intraseasonal variability described in this paper, we conducted two additional 2-m $h$ SOM simulations with an added term on the right-hand side of (1) that damps back to the control simulation SST climatology. These runs were conducted with damping time scales of 10 and 20 days, harder adjustments than the 50-day damping time scale applied in Waliser et al. (1999). Biases in the SST climatology were substantially reduced in these simulations as compared to the undamped 2-m SOM simulation, although the character of intraseasonal variability did not substantially change from the undamped simulation. We are therefore confident that variations in intraseasonal variability among the SOM simulations described below are not due to variations in the mean climate. This will be discussed further in section 4.

c. Description of GCM simulations

A 15-yr CAM2.0.1 control simulation forced by observed climatological seasonal cycle SSTs was conducted. We hereafter refer to this simulation as the “control” simulation. The climatological surface fluxes from this simulation were used to determine the oceanic $Q$ flux in simulations in which the CAM2.0.1 is coupled to SOMs of different depths as in (1). SOM simulations using ocean depths of 50 m, 20 m, 10 m, 5 m, and 2 m were conducted. Each SOM simulation was initiated with a 5-year spinup to ensure that the model attained a stable climate. The SOM simulations were then integrated an additional 15 years, the period for which results are presented in this paper.

An additional 15-yr CAM2.0.1 simulation was conducted that used observed seasonal cycle SSTs but in which, over the oceans, surface latent heat fluxes were set to their seasonally varying climatological values from the control simulation (over land, fluxes were computed interactively in the normal way). We refer to this simulation as the No-WISHE simulation, although technically more than just the influence of wind speed variations on surface latent heat flux is removed (in the control simulation, the influence of low-level specific humidity variations on tropical intraseasonal surface latent heat flux variations is small). GCM simulations are summarized in Table 1.

Table 1. Descriptions of CAM2.0.1 simulations.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Description</th>
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<tr>
<td>Control</td>
<td>Climatological SST</td>
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<tr>
<td>SOM.50m</td>
<td>50-m slab ocean</td>
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<tr>
<td>SOM.20m</td>
<td>20-m slab ocean</td>
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<tr>
<td>SOM.10m</td>
<td>10-m slab ocean</td>
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<tr>
<td>SOM.5m</td>
<td>5-m slab ocean</td>
</tr>
<tr>
<td>SOM.2m</td>
<td>2-m slab ocean</td>
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<tr>
<td>No-WISHE</td>
<td>Climatological SST and latent heat fluxes</td>
</tr>
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d. Sobel and Gildor model

The simple model of SG03 is based on the quasi-equilibrium tropical circulation model (QTCM) of Nee lin and Zeng (2000) but makes a number of additional simplifying assumptions. Only a single horizontal location is represented, making the model a single-column model. As the vertical structure of all variables is fixed, essentially a “first baroclinic mode” in the case of velocity and temperature, the model is really zero-dimensional. Horizontal gradients of both temperature and moisture are neglected, so there are no horizontal advection terms. Additionally, temperature is assumed constant in time. The temperature is thus a given constant in the model, consistent with the “weak temperature gradient” (WTG) approximation (e.g., Sobel and Bretherton 2000; Sobel et al. 2001; Majda and Klein 2003). The model equations are

\[ M_s \delta = P - R, \]

\[ b \frac{\partial q}{\partial t} - M_s \delta = E - P, \quad \text{and} \]

\[ C \frac{\partial T_s}{\partial t} = S - E. \]

Equation (2) is for the atmospheric temperature \( T \), but \( T \) does not appear because of the WTG approximation; \( q \) is the specific humidity times the latent heat of vaporization of water (assumed constant) and divided by the heat capacity for air so that \( q \) has units of degrees. Both represent deviations from fixed reference profiles. Here \( P, R, \) and \( E \) are precipitation, radiative cooling, and evaporation from the sea surface, respectively; \( M_s \) and \( M_s \) are the dry static stability and gross moisture stratification, both of which are taken as constant. Keeping \( M_s \) fixed is consistent with WTG, while SG03 argued that keeping \( M_s \) fixed is appropriate because it suppresses an artificial positive feedback resulting from the neglect of horizontal moisture advection: \( b \) is a constant of order unity; \( \delta \) is the upper-level divergence, which by the fixed vertical structure of all variables is proportional to the vertical velocity; \( T_s \) is the SST and \( C \) is a bulk heat capacity proportional to the mixed layer depth; and \( S \) is the surface forcing, including ocean heat transport and the net surface energy flux excluding the surface latent heat flux.

Equation (2) states that adiabatic cooling (warming) balances the net diabatic heating (cooling) given by the net residual of convective heating and radiative cooling, (3) states that the vertically integrated specific humidity tendency plus moisture convergence equals surface evaporation minus precipitation, and (4) states that the SST tendency is proportional to the difference between the net surface forcing (ocean heat transport plus surface radiation) and the surface evaporation. Surface sensible heat flux variations are neglected in (2) and (4).

Precipitation, or equivalently convective heating, is parameterized by the simplified Betts–Miller scheme:

\[ P = H(q - T) \frac{q - T}{\tau_e}, \]

where \( H \) is the Heaviside function and \( \tau_e \) is a specified convective time scale. Evaporation is parameterized by a bulk formula,

\[ E = \frac{\hat{q}_s^b}{\tau_e} \]

in which \( \hat{q}_s^b \) is the saturation specific humidity at \( T_c \); \( b \) is the value of the moisture basis function at the surface pressure (which happens to be exactly 1 in the model we use here); and \( \tau_e \) is an exchange time scale, in principle a function of the surface wind speed and exchange coefficient: \( \tau_e \) was kept constant by SG03 but is allowed to vary below to represent forcing by variable surface winds associated with the MJO.

The radiative cooling is parameterized by

\[ R = R^{\text{clr}} - rP. \]

The clear-sky radiative cooling, \( R^{\text{clr}} \), is constant. The second term models the greenhouse effect of high clouds as proportional to the precipitation with a coefficient \( r \). The surface forcing is modeled by

\[ S = S^{\text{clr}} - rP. \]

in which \( S^{\text{clr}} \) is the clear-sky value and the term \( rP \) models the shortwave cloud–radiative feedback; ocean heat transport and the surface longwave flux are assumed constant. Use of the same coefficient \( r \) in (7) and (8) assumes that longwave and shortwave effects of high clouds cancel at the top of the atmosphere, as is approximately observed in an averaged sense (Ramanathan et al. 1989; Harrison et al. 1990; Kiehl 1994; Hartmann et al. 2001). Lin and Mapes (LMJAS) have recently found that at the intraseasonal time scales the cancellation is less complete, with shortwave perturbations being somewhat larger than longwave ones. We do not incorporate this new finding into the model.

SG03 argued that \( r \) could be considered to represent the effects of both cloud–radiative and surface flux feedbacks since perturbations in surface fluxes are nearly in phase with those in convection on intraseasonal time scales. As long as the coefficient \( r \) is equal in (7) and (8), cloud–radiative perturbations function like surface flux perturbations, exchanging energy between the ocean and atmosphere with no net flux at the top of the atmosphere. Since \( \tau_e \) was kept fixed in SG03, the wind-induced surface flux variations were not included in \( E \), so it was consistent to lump them into the \( rP \) terms in (7) and (8). In this study, we consider \( r \) to represent cloud–radiative effects only, allow \( \tau_e \) to vary, and thus use the value \( r = 0.15 \), roughly consistent with the range 0.1–0.15 found by LMJAS, as opposed to the larger control value of 0.25 used by SG03 to represent both effects.

SG03 showed that the stability of this model is highly sensitive to \( r \) and \( \tau_e \), with instability to intraseasonal
oscillations occurring for large $r$ and small $\tau_c$. The period is much less sensitive to parameters and tends to remain in the intraseasonal range (tens of days) for all plausible parameter choices. SG03 argued that observations suggest parameter values near the stability boundary, perhaps marginally stable. In the present study, we only consider the model in the stable regime since $r$ represents only radiation as described above.

e. Observed data

A limited comparison of model fields to observed data is made in this study. Observed daily 850-hPa vector wind components during 1979–99 are from the National Centers for Environmental Prediction (NCEP)–NCAR gridded ($2.5^\circ \times 2.5^\circ$) reanalysis dataset (Kalnay et al. 1996). Climate Prediction Center Merged Analysis of Precipitation (CMAP) gridded ($2.5^\circ \times 2.5^\circ$) precipitation fields during 1979–99 are used (Xie and Arkin 1996). These data are interpolated from pentad means to daily values.

3. Results: Amplitude of variability and comparison of GCM and simple model

We will here compare December–May intraseasonal variability among the seven 15-yr simulations of the NCAR CAM2.0.1. A limited comparison to observations will also be presented. The dependence of the variability amplitude on mixed layer depth will be compared to that in the simple model.

a. GCM results

Figure 1 shows December–May equatorial ($10^\circ N$–$10^\circ S$ averaged) bandpass-filtered (30–90 day) 850-hPa zonal wind and precipitation anomalies during an observed MJO life cycle. Fields displayed are calculated by regression onto the principal component (PC) of the leading extended empirical orthogonal function (EEOF) (Weare and Nasstrom 1982) of the December–May 30–90-day equatorial 850-hPa zonal wind. The observation vector used to form the covariance matrix for eigenvector computation is constructed by padding together five consecutive observation times at lags of $-10, -5, 0, +5,$ and $+10$ days. The first two EEOFs form a quadrature pair that describes eastward propagating MJO zonal wind anomalies across the Indian and Pacific Oceans. We choose to regress upon the first PC, although regression onto a combined index of the leading PCs produces very similar results (e.g., Maloney and Hartmann 1998; Bond and Vecchi 2003). Regressed values correspond to a $1 \sigma$ value of the first PC. Intraseasonal oscillations in the simulations described below are analyzed using EEOF analysis in a manner identical to that used for the observations. The longitudes of maximum zonal wind variance may shift slightly among the different realizations (observations and different model simulations), leading to slightly different structures for the leading EEOFs. These variations are not large enough to invalidate comparisons of observations and simulations using the same EEOF technique. We have also regressed all observed and modeled fields onto local indices, including time series of 30–90-day west Pacific equatorial zonal winds and precipitation. None of the conclusions of this paper change by using these alternate analysis techniques.

We show the observed regressions in Fig. 1 as a benchmark to compare against subsequent model results. Regressed anomalies here, and throughout the remainder of this paper, are derived using 30–90-day bandpass-filtered fields. As has been extensively documented (e.g., Hendon and Salby 1994; Maloney and
Hartmann 1998), observed MJO-related zonal wind anomalies propagate slowly eastward across the Indian and west Pacific Oceans, with a change in propagation speed near the date line (Fig. 1). These wind anomalies are associated with precipitation variations that propagate slowly eastward across the Indian and west Pacific Oceans. The propagation speed of precipitation anomalies is slightly slower than that of the wind anomalies (see Figs. 3 and 11 below). Equatorial precipitation anomalies have double maxima in the Indian and west Pacific Oceans with a relative minimum in the Maritime Continent region. Further analysis of observed MJO propagation characteristics, amplitude, and structure is described below.

Figures 2a–e show December–May regressed equatorial precipitation anomalies for the five SOM simulations. Results for the climatological SST control simulation are qualitatively similar to that of the 50-m SOM
Simulation, although slightly weaker in terms of precipitation variance (as shown in Fig. 3 below). We will therefore, in the interest of symmetry, not show the control simulation in this plot. All SOM simulations show eastward propagation of precipitation anomalies across the western Pacific Ocean. SOM simulations of 5-m to 50-m depth all have west Pacific precipitation variance that is larger than in the control simulation (not shown). Although not shown, precipitation variance in the 5-m to 50-m SOM simulations maximizes in a similar eastward wavenumber and intraseasonal frequency range to observations. The largest west Pacific precipitation amplitude occurs in the 20-m SOM. To the extent that intraseasonal precipitation anomalies increase in amplitude as SOM depths decrease down to 20 m, our results are consistent with those of Watterson (2002). However, as the mixed layer depth is decreased further, the nonmonotonic behavior predicted by SG03 is evident. The amplitude of intraseasonal precipitation anomalies slightly weakens in the 10-m and 5-m SOM simulations as compared to the 20-m simulation and then strongly declines in the 2-m SOM simulation. The amplitude and propagation characteristics of the 2-m SOM simulation are more similar to those of the fixed-SST No-WISHE simulation (Fig. 2f) than to those of the other SOM simulations and the control simulation. Model intraseasonal precipitation variability over the Indian Ocean is relatively weak in all simulations compared to observations, consistent with that found in previous versions of the NCAR CAM with RAS convection (Maloney and Kiehl 2002).

A more quantitative analysis of Fig. 2 is displayed in Fig. 3, which shows the root-mean-square amplitude and average eastward propagation speed of regressed equatorial precipitation anomalies over the equatorial west Pacific. Amplitudes are displayed as a fraction of the control simulation and are computed as the quadratic mean over the domain 105°–165°E and over lags = 30 days to 30 days. The propagation speed is simply calculated from the time required for anomaly maxima to traverse the west Pacific from 105° to 165°E, although results are very similar using other criteria.

As expected based on Fig. 2, the amplitude of precipitation anomalies increases from the control simulation to the 20-m SOM simulation (Fig. 3a), declines modestly as SOM depth decreases to 5 m, and then drops sharply in the 2-m SOM simulation as compared to the 5-m SOM simulation, attaining an amplitude about 30%–40% lower than that of the control. The precipitation amplitude of the 2-m SOM simulation is quite similar to that of the No-WISHE simulation. The observed amplitude is about 10% lower than that of the control simulation.

The propagation speed of precipitation anomalies is eastward from 3 to 6 m s⁻¹ in the control and 5–50-m depth SOM simulations (Fig. 3b). These speeds are generally consistent with the observed MJO propagation speed of around 4–5 m s⁻¹ for precipitation anomalies.

The propagation speeds of precipitation anomalies in the 2-m SOM and No-WISHE simulations are eastward at about 13 m s⁻¹, a speed more consistent with that of convectively coupled Kelvin waves than the MJO (Wheeler and Kiladis 1999). However, it should be noted that precipitation amplitude is much weaker for the No-WISHE and 2-m SOM simulations than for the other simulations, so the propagation speed is more uncertain.
Figure 4 shows that, although intraseasonal precipitation variance is smallest at a mixed layer depth of 20 m, intraseasonal SST variance is largest at 2 m. (Since 2 m is the smallest mixed layer depth used, it is likely that still larger SST variance would occur for mixed layer depths below 2 m.) Maximum local west Pacific SST variations of 0.6°C (in the regressed fields) occur during an intraseasonal oscillation life cycle in the 2-m simulation, as opposed to about 0.2°C in the 20-m simulation (not shown). These SST variations in the 20-m simulation are of comparable or slightly greater magnitude to those derived from observations using compositing or regression techniques (e.g., Waliser et al. 1999); larger variations are, of course, observed at single stations during individual events (e.g., Lin and Johnson 1996). Variations in equatorial mixed layer heat content, on the other hand, maximize in the 20-m SOM simulation (Fig. 4). The larger thermal inertia of the ocean in the 20-m SOM versus the 2-m SOM allows a much larger transfer of energy (heat content, on the other hand, maximize in the 20-m SOM simulation (Fig. 4). The larger thermal inertia of the ocean in the 20-m SOM versus the 2-m SOM allows a much larger transfer of energy between the ocean and atmosphere during an intraseasonal oscillation. These results suggest that this larger exchange of energy in the 20-m SOM simulation supports stronger convective heating anomalies in this simulation than in the other runs. This is consistent with the notion that the ocean can amplify atmospheric intraseasonal variability via a recharge–discharge mechanism. The larger the amount of energy stored in the “capacitor” (the ocean mixed layer), the larger the amplification of the intraseasonal oscillation.

By design of the SOM, (1), anomalous variations in mixed layer heat content are controlled solely by the flow of energy through the air–sea interface. The two dominant terms in the intraseasonal SOM heat budget are latent heat flux and shortwave radiation. Latent heat flux variations maximize in the 20-m SOM simulation with maximum equatorial west Pacific anomalies of greater than 11 W m⁻² during a model intraseasonal oscillation life cycle (Fig. 5). Maximum latent heat flux anomalies slightly lag precipitation anomalies. These latent heat flux anomalies in the 20-m simulation are of comparable or slightly greater magnitude to those derived from observations using compositing or regression techniques (e.g., Jones et al. 1998; Woolnough et al. 2000). [As in the case of SST, individual realizations observed at single stations have produced latent heat flux anomalies that are almost an order of magnitude larger (e.g., Lin and Johnson 1996).] Latent heat flux variations in the 20-m SOM simulation are rather weak, with maximum equatorial west Pacific anomalies on the order of 3 W m⁻². Obviously, oceanic latent heat flux anomalies in the No-WISHE simulation are zero, although some weak flux anomalies still occur over land (where the fluxes are computed interactively) in the Maritime Continent and Africa. The relative amplitudes of west Pacific latent heat flux anomalies among the runs are generally similar to those of precipitation (Figs. 2 and 3). Although large enough to be important, anomalies in surface shortwave radiation (not shown) are generally weaker than those of latent heat flux during model intraseasonal oscillation events. For example, shortwave radiation flux anomalies are approximately a third as large as the latent heat flux anomalies in the 20-m SOM simulation. Shortwave radiation variations tend to be of comparable magnitude to latent heat flux variations in observations (e.g., Shinoda et al. 1998; Woolnough et al. 2000). The underestimation of shortwave variations in this model is not surprising, given previous studies. Kiehl et al. (1998b) showed that equatorial Pacific shortwave cloud forcing was poorly simulated in a previous version of the NCAR CAM. Although the simulation of shortwave cloud forcing has been improved in the CAM2.0.1, deficiencies nevertheless remain.

Shinoda et al. (1998) note that intraseasonal SST variations act to damp the amplitude of west Pacific intraseasonal latent heat fluxes during an MJO life cycle over what they would have been for the same meteorological conditions but with SST fixed at its average value over an MJO life cycle. This feedback seems to be particularly influential in our simulations with shallow mixed layer depth. The NCAR CAM2.0.1 computes turbulent fluxes of latent heat based on a bulk formula that is a function of the lowest model level wind speed, the specific humidity difference between the ocean surface (QDIFF) and lowest model level, and a stability-dependent transfer coefficient (e.g., Kiehl et al. 1998a). We do not consider stability influences on the transfer coefficient here, expecting such variations to be small for the purposes of our analysis. Figure 6 shows regressed anomalies of surface wind speed, the specific humidity difference between the surface and lowest model level, and latent heat flux at 140°E for the control simulation.
Latent heat flux anomalies are in phase with wind speed variations in the control simulation; QDIFF anomalies are approximately in quadrature. Because the control simulation uses climatological SSTs, QDIFF variations are controlled by variations in specific humidity of the lowest model level. Due to strong variations of SST in the 2-m SOM simulation, QDIFF anomalies tend to oppose wind speed anomalies, decreasing the amplitude of latent heat flux anomalies. SST anomalies peak near day 0 in the 2-m SOM simulation (not shown). As in Shinoda et al. (1998), positive (negative) wind speed anomalies are shifted toward negative (positive) SST anomalies (not shown). This shift is most pronounced in the 2-m SOM simulation. Notice that the magnitude of wind speed variations does not change as strongly as does the magnitude of latent heat flux variations.

Surface saturation specific humidity variations caused
by increased variance in intraseasonal west Pacific SST begin to dominate the signal in QDIFF for shallow mixed layer depths, as is implied by Fig. 7, which shows the rms amplitude of west Pacific surface saturation specific humidity anomalies and lowest atmosphere level specific humidity anomalies as a function of mixed layer depth. For the deeper mixed layer depth simulations, anomalies in the lowest atmosphere level specific humidity exceed surface specific humidity variations, whereas anomalies in surface specific humidity dominate for shallower mixed layer depths.

b. Simple model results

We first briefly consider the linearized versions of (2)–(4) as shown in Eqs. (11)–(13) of SG03. SG03 impose the forcing as an atmospheric heating; that is, they placed the forcing on the rhs of the linear version of the atmospheric temperature equation (2). Below we will force the nonlinear model with imposed intraseasonal variations in wind speed in (3) for greater fidelity with the GCM simulations (e.g., Fig. 6). This difference in forcing does not qualitatively influence the linear solution, so we briefly retain the temperature forcing for the linear solution.

Here, we wish to clarify one aspect of the linear calculation presented by SG03. SG03 showed that the divergence field, \( \delta \), had a maximum in the forced response amplitude at a mixed layer depth of 10–20 m for forcing of intraseasonal periods. They did not show the amplitude of SST and precipitation and simply stated these other fields were proportional to \( \delta \). This is somewhat misleading because the proportionality factor in the case of SST depends on the mixed layer depth. Here \( T_s \) is given by the relation

\[
T_s = \frac{(\sigma C_p - \gamma)}{(1 + \sigma C - \gamma \tau_e)} M \delta, \tag{9}
\]

where \( \sigma \) is the frequency and \( \gamma \) is the coefficient relating perturbations in saturation specific humidity (converted into temperature units) and temperature from their reference values. This relationship results from a linearization of the Clausius–Clapeyron equation. Other variables and parameters are as defined above.

Equation (9) shows that the SST amplitude increases monotonically as the mixed layer depth approaches zero, consistent with the GCM. Figure 8 shows results from a set of linear calculations with forcing frequencies of 0.1 and 0.2 day\(^{-1}\), corresponding to forcing periods of approximately 60 and 30 days (here the time dependence is described using the convention \( \cos(\omega t) \), so the period

\[
T = 2\pi/\omega.
\]

These calculations are similar to those pre-
Fig. 8. Forced linear calculations using the simple model. Amplitudes of (a) SST in °C and (b) precipitation in mm day^{-1} are shown as a function of mixed layer depth, for forcing frequencies of 0.2 and 0.1 d^{-1} (corresponding to periods of approximately 30 and 60 days, since here the period \( T = 2\pi/\omega \), with \( \omega \) the frequency). Absolute amplitude is arbitrary since the calculations are linear, but relative amplitude is meaningful since the forcing amplitude is the same for all calculations.

Fig. 9. Peak-to-peak amplitude of variability for nonlinear calculations with the simple model, forced by imposed oscillations in surface wind speed with a period of 50 d^{-1} showing (a) SST in °C and (b) precipitation in mm day^{-1} as a function of mixed layer depth.

Presented by SG03, but use the smaller value \( r = 0.15 \) as described in section 2d above, and we show \( T_s \) and \( P \) rather than \( \delta \). \( P \) and \( \delta \) are proportional to one another in the linear calculation,

\[ P = \frac{M \delta}{(1 + r)}, \]

but Fig. 8b shows much less pronounced peaks in \( P \) than did the plots \( \delta \) shown by SG03 because of the smaller value of \( r \) used. The behavior here is best described as a gradual rise in amplitude with decreasing mixed layer depth at deeper depths, followed by a dramatic decrease at shallow mixed layer depths. As in the GCM simulations, \( T_s \) increases monotonically as mixed layer depth decreases, eventually leveling off at very small mixed layer depths due to the constant factor \( \gamma / \tau_p \) in the denominator on the rhs of (9).

Next, we consider a nonlinear calculation in which the forcing is placed in the “surface wind speed” in (5), for most appropriate comparison to the GCM. That is, we model the surface flux time scale by

\[ \tau_E^{-1} = \tau_{E0}^{-1}(1 + a \cos \omega t), \]

where \( \tau_{E0} \) is the control value of 12 days and \( a \) controls the magnitude of the forcing. In the simple model, the frequency \( \omega \) corresponds to a period of 50 days, and the magnitude \( a = 0.4 \). Figure 9 shows the peak-to-peak amplitude of the resulting nonlinear oscillations in SST and precipitation. Again, the dependence on mixed layer depth is qualitatively similar to that seen in the
GCM simulations, as well as the linear calculations above.

Figures 10a,b show temporal traces of a number of quantities from nonlinear simulations at mixed layer depths of 10 and 1 m, respectively. From these we can form a physical interpretation of the rapid drop in precipitation amplitude at the shallow mixed layer depths. For sufficiently large mixed layer depth (in this particular model, ~2 m or greater), the wind forcing drives a recharge–discharge oscillation in the oceanic mixed layer as described by SG03. For shallower mixed layers, the storage term in the SST equation (4) becomes small even though the SST is varying quite strongly. At this point, (4) effectively reduces to the steady-state balance $S = E$; we see in Fig. 10b that variations in $E$ are much smaller than those in Fig. 10a. This in turn causes a drop in the variability of precipitation. We can see this if we form the moist static energy equation by adding (2) and (3):

$$ \frac{\partial q}{\partial t} + M \delta = E - R, $$

where $M = M_s - M_c$ is the gross moist stability (Neelin and Held 1987; Neelin and Zeng 2000). Because the time scale is intraseasonal, and for an additional reason to be discussed momentarily, the moisture storage term is small compared to the others and can be neglected. Solving for $\delta$ and substituting back into (2) to obtain an expression for $P$, assuming $S = E$ and using (6) for $S$ and (7) for $R$, we find that

$$ P = [S^{\text{in}} - (M_s/M - 1)R^{\text{in}}]/(1 + r), $$

where $S^{\text{in}}$ and $R^{\text{in}}$ are the incoming solar and cloud fluxes, respectively.
which shows that precipitation is constant in this limit. Accordingly, we see that the precipitation varies much less for a 1-m SOM than for a 10-m SOM. In fact, the 10-m SOM has periods of zero precipitation, but the 1-m SOM does not. If precipitation is nonzero at all times, a strong constraint is placed on the moisture field, \( q \). During periods when \( P > 0 \), the Betts–Miller scheme (5) relaxes \( q \) strongly toward \( T \), which is constant by WTG. If there are periods of zero precipitation, then during those periods \( q \) does not feel this constraint, and can vary more. Thus, we see much smaller \( q \) variations in Fig. 10b than in 10a. This helps to justify our neglect of the tendency term in the above discussion.

The end result of this argument is that, in the shallow mixed layer case, \( q \) and \( E \) are both approximately held to constant values while the wind speed varies in a prescribed way. The only possibility then is for \( q^s \) to vary by changing SST within the constraints provided by the other three variables in (6). In other words, SST must vary in such a way as to reduce surface latent heat flux variations.

The GCM results are qualitatively consistent with these simple model results. The essential mechanism of the precipitation variance reduction at small mixed layer depth is the same in both models. We see the strong reduction in surface evaporation variations in the 2-m GCM simulation in Fig. 5. On the other hand, the mixed layer depth dependence of the surface air humidity in the GCM (Fig. 7) is not entirely consistent with the simple model’s behavior. The variance in surface air humidity increases monotonically as mixed layer depth decreases, whereas in the simple model the former decreases as the latter reaches very small values. Nonetheless, the surface air humidity variance increases more slowly than does the variance saturation humidity of the sea surface in the GCM. This presumably indicates some regulation of the surface air humidity by deep convection (despite the lack of parameterized downdrafts in the convection scheme), as in the simple model. In both models, the SST responds to keep surface evaporation variations small in the face of large surface wind variations and constrained surface air humidity variations.

To some degree, the reduction in amplitude (both in the GCM and simple model) as the mixed layer becomes very shallow should be expected, given that the variability depends on energy exchange between the atmosphere and ocean. In the “swamp” limit (zero mixed layer depth), there can be no energy exchange. Neelin et al. (1987) showed in a GCM simulation that the WISHE mechanism was rendered inoperative in the swamp limit. The most important new result here, perhaps, is the explicit demonstration that neither the fixed-SST nor the swamp limits yields the maximum amplitude, but rather that the maximum occurs near the observed mixed layer depth in the regions where the MJO is active.

c. Discussion: Relevance to observations

Our simple SOM with fixed, uniform mixed layer depth is a primitive substitute for the real ocean. We view our sensitivity tests with this model, in which the fixed mixed layer depth is varied, as valuable primarily for the insight they give us into the coupled MJO dynamics in the GCM. It is difficult to imagine a fully convincing observational test of the above results since the dramatic dependence of precipitation variability on mixed layer depth only occurs at mixed layer depths of a few meters or less, smaller than those ever (to our knowledge) observed in the ocean regions where the MJO is active. However, wet land is somewhat like a very shallow ocean mixed layer in that it has minimal heat capacity and a small Bowen ratio. The dependence on mixed layer depth found here may help explain the local minimum in MJO amplitude that is observed in the Maritime Continent. During austral summer when the MJO is most active, it is the rainy season over the Maritime Continent and the landmasses are presumably fairly wet. The land may be considered comparable to a very shallow mixed layer, which our simulations suggest should lead to a drop in MJO amplitude.

This does not preclude that other factors may contribute to the local amplitude minimum, such as the topography associated with the Indonesian mountain ranges or the strong diurnal component of convection over land (e.g., Zhang and Hendon 1997). (The strong diurnal cycle over land is actually closely related to the mechanism that we described for the weakening of the MJO. The diurnal cycle is also a forced recharge–discharge oscillation. Land has small heat capacity, so the high-frequency diurnal cycle is strong while the low-frequency MJO is weak.) We would like to test these ideas in future work, for example, by performing GCM simulations in which the Indonesian islands are retained, but with their surface elevations set to zero. Unfortunately, the GCM used here is not ideal for these studies; its amplitude minimum is not particularly well defined due to unrealistically weak MJO variability in the Indian Ocean (e.g., Fig. 2).

4. Results: Zonal wind and horizontal structure in the GCM simulations

Interestingly, equatorial zonal wind variability exhibits somewhat different behavior than precipitation variability among the model simulations. Figure 11 shows the same quantitative analysis of equatorial amplitude and propagation speed as in Fig. 3 except for 850-hPa zonal wind. Zonal wind anomalies in the SOM simulation and No-WISHE simulations are either slightly larger or similar to those in the control simulation. Although precipitation anomalies in the 2-m SOM and No-WISHE simulations are much weaker than the control (Fig. 3), the same is not true of zonal wind anomalies. All simulations have stronger than observed zonal wind
variance. Propagation speed remains roughly constant, at about 5 m s\(^{-1}\), over most of the simulations, although the No-WISHE simulation propagation speed is 7 m s\(^{-1}\) (which happens to be approximately the observed value). Recall that the propagation speed of precipitation anomalies in the 2-m SOM and No-WISHE simulations was 13 m s\(^{-1}\).

The disparity in the behavior of equatorial precipitation and wind anomalies, particularly for the 2-m SOM and No-WISHE simulations, is somewhat difficult to explain. One possible explanation for the amplitude behavior might be that equatorial convective heating feeds back more efficiently onto the large-scale circulation in the 2-m SOM and No-WISHE simulations than in the control (implying a shift in the structure of such heating). A calculation of the covariance between regressed equatorial tropospheric diabatic heating and temperature anomalies appears to lend some support to this possibility (not shown). Although convective heating anomalies are weaker in the 2-m SOM and No-WISHE simulations than in the others, heating is better correlated with temperature in these simulations than in the control simulation. Another possibility is that a coupling between convection and the large-scale circulation outside of the equatorial waveguide sets the slow eastward propagation and the amplitude of the MJO (e.g., Raymond 2001; Straub and Kiladis 2003). Such ideas will be explored in future work.

Some clues to the role that wind–evaporation feedback plays in forcing model equatorial precipitation anomalies can be gained by examining anomaly maps from the 20-m SOM simulation (Fig. 12). Displayed are December–May 30–90-day 850-hPa wind and precipitation anomalies from the 20-m SOM simulation and observations (Figs. 12a,b), and latent heat flux and wind anomalies from the 20-m SOM simulation (Fig. 12c). Fields are derived by regression at zero lag onto the intraseasonal zonal-wind time series at 140\(^{\circ}\)E. Values shown correspond to a 1\(\sigma\) value of the reference zonal wind time series. We could have regressed onto the PC of the leading EEOF as in earlier figures and produced very similar results. However, we wanted to ensure that we are analyzing the same zonal wind phase in longitude between the observations and simulation in this plot since the structure of the leading EEOFs shifts slightly among the realizations.

The 20-m SOM simulation shows maximum latent heat flux anomalies within and to the west of the region of strongest precipitation anomalies, as has been previously documented in observations (e.g., Zhang and McPhaden 2000). Positive (negative) west Pacific latent heat flux anomalies in the 20-m SOM simulation are generated by the coincidence of low-level westerly (easterly) anomalies and mean westerly December–May winds (particularly between the equator and 10\(^{\circ}\)S). Although different than the WISHE mechanism originally proposed by Neelin et al. (1987) and Emanuel (1987) that required enhanced fluxes in regions of low-level easterly perturbations, this dependence of latent heat flux on wind anomaly direction represents a form of wind–evaporation feedback. The mechanism in these simulations appears to be nonlinear: the maximum positive latent heat flux anomalies slightly lag the maximum precipitation anomalies, but the total eastward wind (to which the mean and perturbation contribute comparably) exceeds the phase speed of the model MJO so that positive moist static energy anomalies generated by the latent heat flux anomalies can be advected ahead of the precipitation anomalies. These modeling results suggest the WISHE may help produce the observed distribution...
of precipitation associated with the observed MJO. Of course, moisture convergence anomalies also likely occur within the convective region and are important at least in a diagnostic sense for balancing precipitation in the moisture budget. Nonetheless the No-WISHE results suggest that, in this model, surface flux anomalies play a large role—presumably disproportionate to their relative magnitude in the moisture budget—in the MJO instability mechanism.

Our results are consistent with the finding that the linear version of the WISHE mechanism, which requires a mean easterly flow for the essential instability, is inconsistent with observations (e.g., Hendon and Salby 1994; Lin and Johnson 1996; Jones and Weare 1996; Zhang 1996; Cronin and McPhaden 1997; Shinoda et al. 1998). Some observational evidence exists in favor of a more generalized, nonlinear WISHE, however. A number of observational studies have shown positive covariability of surface latent heat flux and deep convection (Zhang 1996; Zhang and McPhaden 2000; Shi-
noda et al. 1998; Maloney and Esbensen 2003). This is also consistent with some modeling studies (Lin et al. 2000; Raymond 2001). Inness and Slingo (2003) found that a proper simulation of wintertime low-level mean westerlies in the west Pacific is important for realistically simulating intraseasonal variability. Other observational studies suggest that maximum latent heat fluxes lag maximum convection more distinctly (e.g., Jones and Weare 1996; Jones et al. 1998; Woolnough et al. 2000; Weare 2003), although it is not clear that the local correlation between west Pacific latent heat fluxes and precipitation is zero in these studies. Numerical modeling studies by Xie et al. (1993a,b) showed that in a “quasi-linear” (positive-only precipitation, other dynamics linear) as well as a fully nonlinear model, unstable WISHE modes could occur on resting basic states. Their WISHE modes are somewhat different from the simulated MJO here, however; in Xie et al. (1993a,b) the maximum surface fluxes occurred in the easterlies ahead of the precipitation maximum, whereas in our simulations the maximum fluxes occur in the westerlies behind and collocated with the precipitation maximum.

Clearly, differences in the structure of subseasonal precipitation and wind variability do exist between the 20-m SOM simulation and observations. The 20-m SOM simulation tends to have stronger off-equatorial precipitation anomalies and circulation anomalies than observed (Fig. 12), particularly over the Northern Hemisphere. However, the 20-m SOM simulation is characterized by precipitation and wind variations that much more resemble observations than those associated with No-WISHE and 2-m SOM simulations (not shown).

We now comment on the December–May mean state. An examination of Fig. 13 shows that variations in mean December–May west Pacific surface winds among the model simulations appear unlikely to be responsible for variations in latent heat flux and precipitation variability among the model simulations. No systematic changes in the model mean states occur in the west Pacific and Indian Oceans among the simulations. Mean west Pacific surface westerlies are slightly stronger in the 2-m SOM simulation than the other simulations, implying that, if west Pacific intraseasonal latent heat flux anomalies were to show any mean state dependence, they would be biased high. This is clearly not the case in the 2-m SOM simulation. As mentioned above, several 2-m SOM simulations were conducted in which SSTs were damped back to climatology. These simulations are characterized by reductions in the mean-state biases from the undamped simulation when compared to the control, although they exhibit little change in intraseasonal variability from the undamped simulation. We should also note that the mean December–May distribution of precipitation is qualitatively similar among the model simulations (not shown). The simulations all show somewhat of a bias relative to observations with a tendency to have a more pronounced minimum of precipitation on the equator.

**5. Conclusions**

We have found that tropical intraseasonal variability in the modified National Center for Atmospheric Research Community Atmosphere Model 2.0.1 (NCAR CAM2.0.1) with relaxed Arakawa–Schubert convection is sensitive to mixed layer depth when coupled to a slab ocean model (SOM). Mixed layer depths of 50 m, 20 m, 10 m, 5 m, and 2 m were employed as well as a control simulation with prescribed climatological SSTs. The amplitude of December–May equatorial-averaged west Pacific precipitation variations at 30–90-day time scales was found to be a nonmonotonic function of mixed layer depth. Intraseasonal precipitation variability is enhanced relative to the fixed-SST (infinite mixed layer depth) simulation for mixed layer depths from 5 to 50 m, with a maximum at 20 m, but strongly diminished relative to the fixed-SST simulation in the 2-m depth simulation.

A simulation was also performed in which SST was fixed, but latent heat fluxes were set to their climatological values from the control simulation, suppressing the wind–evaporation or WISHE feedback (No-WISHE simulation). The amplitude of intraseasonal precipitation variations in the No-WISHE simulation was greatly reduced from the fixed-SST control simulation, showing that WISHE is important to the intraseasonal variability in this model. This also explains the reduction in precipitation variability in the 2-m SOM simulation. Although intraseasonal SST variations are stronger in the
2-m SOM simulation than in any of the other simulations, so the surface flux variations are smaller in the 2-m SOM simulations than in any of the others. For intraseasonal variations, 2 m is close to the “swamp” limit in which WISHE is eliminated, which in this model has the effect of weakening equatorial convective variability. The control simulation and the SOM coupled simulations with mixed layer depths greater than 2 m produce near-equatorial intraseasonal precipitation variations that more closely resemble observations than the 2-m or No-WISHE simulations.

The nonmonotonic dependence of precipitation variability on mixed layer depth was predicted by SG03 using a highly idealized model. Further experiments are described here with the same idealized model, which help to interpret results derived from the modified NCAR CAM2.0.1. When the nonlinear SG03 model is placed in a stable regime and forced with intraseasonal surface wind speed variations, changing the mixed layer depth has an effect very similar to that in the GCM with regard to both the amplitude and the structure of the variability.

This study has been an exercise in understanding the dynamics of the simulated MJO more than an attempt to prove any particular point about the real MJO. Doing the latter is difficult in GCM studies since different models may (and do) lead to different results. However, we can make a few suggestions about observed variability:

1) To the extent that exchange of energy between ocean and atmosphere is important to the MJO (whether via surface fluxes or cloud–radiative effects), the enhancement to the MJO resulting from ocean coupling can be expected to maximize at a particular mixed layer depth. Our results (and those of SG03) suggest that this depth is close to the observed value in the active MJO regions, so the real system is close to optimally tuned for this coupled enhancement to the MJO.

2) We hypothesize that the MJO amplitude minimum in the Maritime Continent region may result from the inhibition of the coupled recharge–discharge oscillation there due to the presence of land, which, if it is wet, is approximately equivalent to an ocean of zero depth.

3) A nonlinear version of the WISHE mechanism, occurring on a westerly mean state, is important to the simulated MJO in at least one reasonably state-of-the-art GCM, suggesting that a similar mechanism may operate in reality.

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