GEOPHYSICAL RESEARCH LETTERS, VOL. 27, NO. 22, PAGES 3691-3694, NOVEMBER 15, 2000

Influence of a stochastic moist convective parameterization on tropical climate variability

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Abstract. Convective parameterizations used in general circulation models (GCMs) generally only simulate the mean or first-order moment of convective ensembles and do not explicitly include higher-order moments. The influence of including unresolved higher-order moments is investigated using a simple stochastic convective parameterization that includes a random contribution to the convective available potential energy (CAPE) in the deep convective scheme. Impacts are tested in an tropical atmospheric model of intermediate complexity. Adding convective noise noticeably affects tropical intraseasonal variability, suggesting inclusion of such noise in GCMs might be beneficial. Model response to the noise is sensitive not only to the noise amplitude, but also to such particulars of the stochastic parameterization as autocorrelation time.

Introduction

If the Reynolds average is taken over a very large ensemble of convective elements, then it is reasonable to expect that ensemble means of convective heating, for a given large-scale forcing, will suitably characterize the feedback from the small to large scales. For a smaller ensemble, such as an average over a GCM grid cell and time step, there will be considerable variance about the mean based upon a larger ensemble. For instance, in a cumulus ensemble model (CEM) acting under a prescribed, time-varying large-scale forcing [*Xu et al.*, 1992], the domain-average surface precipitation tends to follow the imposed large scale forcing, leading the authors to conclude that convection is fundamentally parameterizable. However, for a given value of the large scale forcing, the simulated response shows considerable variance. This suggests that in a GCM convective parameterization, for given grid-scale variables, the convective heating may produce a range of responses. The importance of this second-moment in feeding back to the large-scale motions is not currently known, though GCM simulated convective variance can be much less, with a different spatial and frequency distribution, from the observed variance [*Ricciardulli and Garcia*, 2000]. Effects in linearized primitive equation models have suggested the potential importance of a non-interactive stochastic heating term [*Salby and Garcia*, 1987], and of adding a stochastic heating term to parameterized convection [*Yu and Neelin*, 1994].

In this study, we examine the impacts of convective variance arising intrinsically at the unresolved scales by representing such variance as a stochastic component of convection. Like the stochastic point process approach to simulating temporal rainfall [*Eagleson*, 1978; *Rodriguez-Iturbe et al.*, 1987] used in hydrology, the stochastic forcing used in this study aims to reproduce a few statistical features of precipitation, such as the variance and autocorrelation. The aims, however, for the present modeling are different from the hydrology approach; we are not interested in reconstructing sub-grid scale variability for a given mean, but rather we are interested in the variance at the grid-scale arising from sub-grid scale processes. One approach, explored in ongoing work, adapts probability models taken from hydrology.

In the simple approach described in this present study, the CAPE-based framework of the existing convective parameterization is modified by adding a zero mean, red noise forcing term. We expect that a measure of noise amplitude will be an important parameter. We also expect that the effects of stochastic forcing may be sensitive to the autocorrelation timescale of the unresolved features, which include mesoscale motions as well as cloud-scale convective elements. However, we do not know *a priori* which timescale will be the most important. We thus attempt to constrain noise amplitude by some measure derived from observations, and test the impacts of autocorrelation by varying the autocorrelation timescale in a range of plausible values.

The parameterization is implemented in v2.1 of the Quasi-Equilibrium Tropical Circulation Model (QTCM1), an atmospheric model of intermediate complexity [*Neelin and Zeng*, 2000; *Zeng et al.*, 2000]. The QTCM1 makes use of quasi-equilibrium constraints upon the vertical temperature profile in order to reduce computational expense while retaining primitive equation nonlinearity. Results are evaluated by examining impact on model precipitation statistics such as total precipitation variance, zero precipitation frequency and probability distribution function, as well as impact on model tropical intraseasonal variability. Because of the difficulty of estimating precise parameters for the stochastic parameterization, evaluating the potential impacts using an intermediate-level model instead of a full-scale GCM seems prudent.

Description of the Stochastic Parameterization

The QTCM1's default convective parameterization is a simplified Betts-Miller quasi-equilibrium scheme [*Betts and*

Paper number 2000GL011964.
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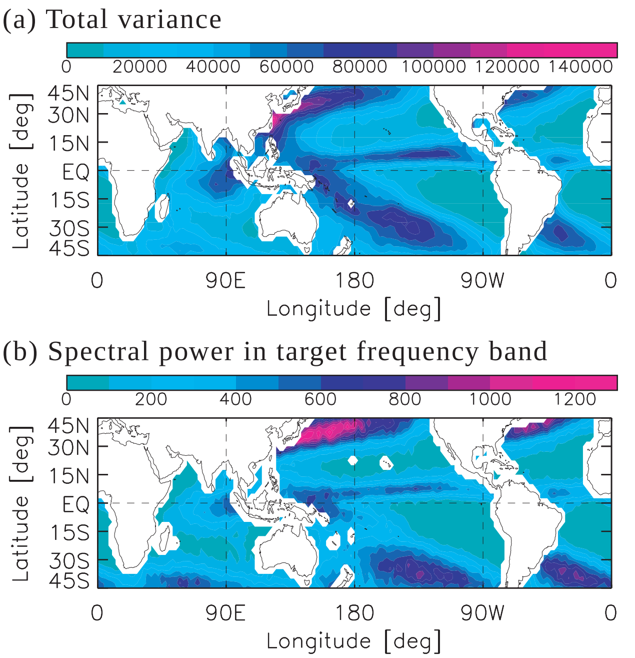

Figure 1. MSU daily mean precipitation (a) total variance (where mean is defined as climatology), in units (W m^{-2})^2, and (b) mean of power spectrum for each grid box (2.5° × 2.5°), in units (W m^{-2})^2, in the target frequency band (+0.4 to +0.5 day^{-1}). Standard deviation of spectra is 10%. See text for details.

Miller, 1986], which is used in some full-scale GCMs. In its simplest form, convective heating Q_c is proportional to C_1, which is a measure of the CAPE (C_1 is in units K). In the stochastic convective formulation, a first-order autoregressive (Markov process) random noise component (ξ) is added to the deterministic C_1 calculated from grid-scale temperature and moisture. Thus, $Q_c \propto \tau_c^{-1}\mathcal{H}(C_1+\xi)(C_1+\xi)$, where ξ at timestep t is given by: $\xi_t = \epsilon_\xi \xi_{t-1} + z_t$, where ϵ_ξ is a coefficient (between 0 and 1), and z_t is a Gaussian random number with mean zero and standard deviation σ_z. The convective relaxation timescale (τ_c) is 2 hrs, and $\mathcal{H}(C_1)$ is zero for $C_1 \leq 0$, and one for $C_1 > 0$.

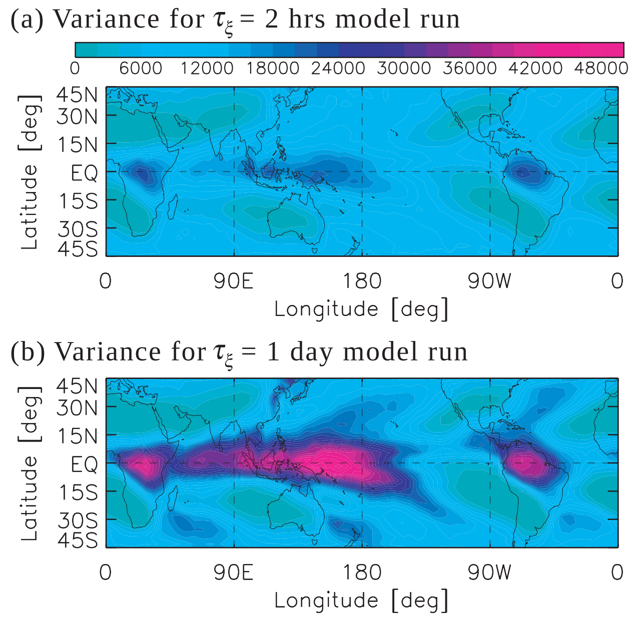

Figure 3. Total variance of model daily mean precipitation (where mean is defined as climatology), in units (W m^{-2})^2. Panels share the same color bar.

The mean of ξ is also zero, and the variance of ξ is [*Chatfield*, 1989]: $\sigma_\xi^2 = \sigma_z^2/(1-\epsilon_\xi^2)$. The autocorrelation function for ξ is $\rho_\xi(k) = \epsilon_\xi^{|k|}$ where k is the lag index. If we define τ_ξ, a characteristic timescale for ξ, as the time for ρ_ξ to fall to e^{-1}, then $\epsilon_\xi = \exp(-\Delta t/\tau_\xi)$ where Δt is the model timestep. Because Q_c is positive-only, an increase in τ_ξ tends to increase the percentage of time daily averaged $Q_c = 0$. The large-scale dynamics will also respond differently to longer τ_ξ. The other important parameter for the large-scale is the spectral power of the noise process, which is related to σ_ξ. Since σ_ξ is affected by τ_ξ and σ_z, we change τ_ξ and σ_z to adjust σ_ξ such that an approximation of a white "noise floor" of Q_c, representing the unresolved convective motions, is roughly constant. The mean of Q_c is not strongly changed by ξ, so the primary effect is to add variance to the system.

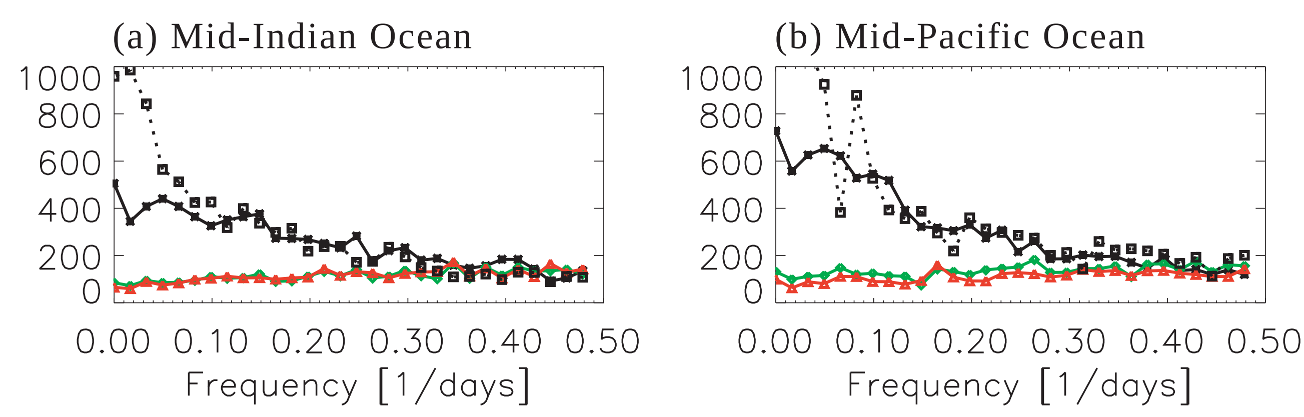

Figure 2. Power spectrum (positive frequencies only shown) of equatorial daily mean precipitation for MSU and model runs at (a) 60°E and (b) the dateline. The $\tau_\xi = 20$ min (red), $\tau_\xi = 2$ hrs (green), $\tau_\xi = 1$ day (black solid) cases, and MSU (black dotted) are shown. The scale in (b) is chosen so high frequencies are visible; the largest values of power are offscale. Units (W m^{-2})^2. Standard deviation of spectra is 10%. In (a), MSU is shown at 60°E, averaged over 2.5°N–2.5°S, and model runs at 61.875°E, averaged over 1.875°N–1.875°S.

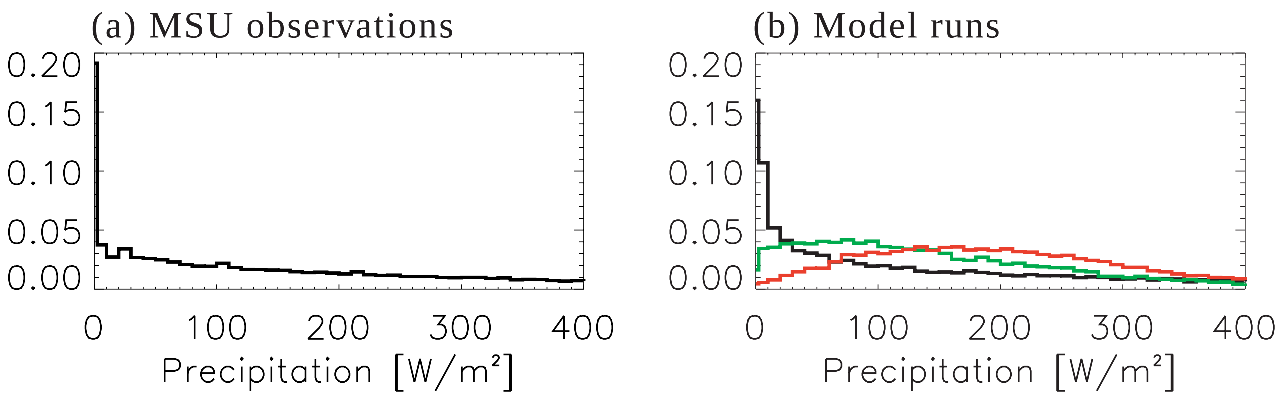

Figure 4. Pseudo-PDF of daily mean precipitation in region of frequent tropical convection for (a) MSU (180–202.5°E, 5°N during the period 1 Jan 1979 to 31 Dec 1995), and (b) model runs (180–202.5°E, 5.625°N for 10 model years). Panel (b) shows $\tau_\xi = 20$ min (red), $\tau_\xi = 2$ hrs (green), and $\tau_\xi = 1$ day (black) model runs. Bin size for both pseudo-PDFs is 10 W m^{-2}.

Data and Model Runs

Three model runs (forced by climatological sea surface temperature at the lower boundary) with different autocorrelation times ($\tau_\xi = 20$ min, 2 hrs, and 1 day) are analyzed to investigate the effects of stochastic convective noise on tropical intraseasonal variability. Model daily precipitation is compared with daily precipitation estimates calculated from satellite microwave sounding unit (MSU) passive radiometer measurements [*Spencer*, 1993]. Although the MSU estimates only include oceanic regions, the dataset is relatively long (1 Jan 1979 to 31 Dec 1995). Where necessary, gaps in the MSU timeseries are filled using spline interpolation. Precipitation in this study is given in energy units (W m^{-2}); divide by 28.2 to convert to mm day^{-1}.

Observed convective variance contains contributions both from large-scale dynamics and from the small-scale dynamics that we hope to parameterize. Unresolved convective motions with short correlation times have a white "noise floor" that affects low frequencies. As an estimate of the portion of power that results from small-scale dynamics, including both local and mesoscale motions, we examine spectral power in a "target" frequency band from +0.4 to +0.5 day^{-1}. This intermediate range is chosen to exclude low-frequency variability that will have a contribution from large-scale dynamics and also to exclude variability within the range strongly affected by autocorrelation of local convective processes. We choose parameters such that the model variance matches observations in this band.

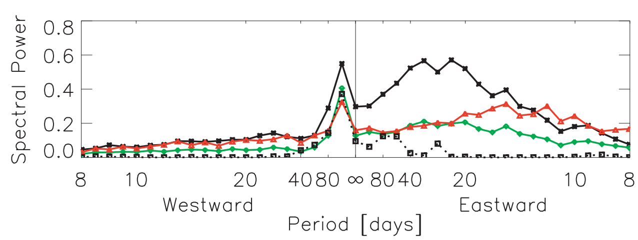

Figure 5. Power spectrum for 850 hPa zonal wind wavenumber 1 of non-areally weighted meridional mean in latitude band from 5.625°N to 5.625°S, for $\tau_\xi = 20$ min (red), $\tau_\xi = 2$ hrs (green), $\tau_\xi = 1$ day (black solid), and control run without stochastic convection (black dotted). Units (m sec^{-1})^2. Standard deviation of spectra is 10%.

The spatial distributions of the observed total variance and gridpoint mean spectral power in the target frequency band (Figure 1) reflect the mean precipitation. In our stochastic parameterization, we need to choose a single parameter (σ_z) to set the random forcing σ_ξ to a level reasonably approximating the observed. We choose σ_z such that the model output roughly approximates the mean of the observed power spectrum in the target frequency band at just two places along the equator: in the Indian Ocean at 60°E and at the dateline. Figure 2 shows the spectral power at these two locations. For frequencies lower than the target frequency band, the larger value of τ_ξ tends to produce a better match to observed, down to about 0.1 day^{-1}. The spatial structures of the mean power in the target frequency band for the model runs (not shown) are have broader spatial scale than observed, and depend upon τ_ξ.

Precipitation and zonal wind spectra are calculated using 6120 and 16200, respectively, days of daily anomalies (climatology removed), detrending with a chi-square minimizing linear regression method, a Hanning window to control frequency leakage, and the "summing" method with a bin group size of $K = 101$, to control the estimate error [*Press et al.*, 1989].

Results

Figure 3 shows total variance from the model for two of the cases with different τ_ξ: (a) $\tau_\xi = 2$ hrs, $\sigma_z = 0.8$ K, and (b) $\tau_\xi = 1$ day, $\sigma_z = 0.1$ K. Total variance for the $\tau_\xi = 20$ min, $\sigma_z = 4.5$ K case (not shown) is similar to the $\tau_\xi = 2$ hrs case, except with weaker variance throughout: over equatorial land regions it is about an order of magnitude less, while over the maritime continent it is about 10% less. We note that the model variance due solely to internal variability (not shown) is roughly an order of magnitude smaller in the tropics than the model runs using the stochastic convective scheme, indicating inclusion of stochastic effects has a large impact on total variance. Although the values of σ_z are tuned so that for each case mean power in the target frequency band roughly matches observations at the equatorial margins of the maritime continent, the effects on total variance are strikingly different, depending on the magnitude of the autocorrelation timescale. Though the total variance simulated by the model for all three values of

τ_ξ is less than observed (Figure 1a), variance for the longer τ_ξ cases are much higher and have a different (and more realistic) spatial distribution than the shorter τ_ξ.

An approximation of the probability distribution function (pseudo-PDF) in a region of frequent tropical convection also shows a strong dependence on autocorrelation time (Figure 4). As autocorrelation time increases, the daily distribution is skewed towards more frequent low precipitation occurrences, resembling more closely the mixed lognormal shape of observed precipitation.

For 850 hPa zonal wind, the inclusion of stochastic convection enhances eastward propagating, low-wavenumber, low-frequency variability. Figure 5 shows the spectra for 850 hPa zonal wind wavenumber 1 in an equatorial band for a control run without stochastic convection (dotted line) as well as with stochastic convection (solid lines). At the shorter τ_ξ, the inclusion of stochastic convection produces a substantial response in the 10–40 day range. At $\tau_\xi = 1$ day, the response occurs at even lower frequencies, with a signal peak in the range of 20–40 days. This is a combination of effects due to dry wave dynamics, moist wave dynamics, and autocorrelation in the stochastic process. Interestingly, precipitation (not shown) does not show a spectral structure with a similar low-wavenumber, low-frequency response.

Discussion and Conclusions

These results suggest a number of implications for climate modeling. First, a stochastic convective parameterization appears to be able to simulate at least a part of the total convective variance that is often underestimated by GCMs. Secondly, the sensitivities of the model to autocorrelation time suggest that inclusion of second-moment effects are more complex than might be expected. It is not clear in advance what τ_ξ should be, as the unresolved convection represented by the stochastic parameterization ranges in timescale from days for mesoscale motions, to hours for clouds. Here, longer τ_ξ tends to yield results more similar to observations. This suggests that not only variance amplitude is important in parameterizing unresolved second-moment effects, but that autocorrelation time is also important, and that longer timescale unresolved mesoscale motions may be important to explicitly include in convective parameterizations. Finally, these results imply that relatively short timescale noise (1 day and less) can affect tropical variability at longer, intraseasonal timescales. It may thus be useful for GCMs to explicitly include higher-order moments into the parameterization of sub-grid processes.

Acknowledgments. This research was partially supported by National Science Foundation grant ATM-0082529 and National Oceanic and Atmospheric Administration grant NA86GP0314. This study benefited from discussions with A. Arakawa, C. Chou, J. Gao, A. Majda, B. Mapes, J. Meagher, H. Su, and N. Zeng. Thanks to J. Meyerson for help with figures. The MSU precipitation data was obtained from the NOAA-CIRES Climate Diagnostics Center, Boulder, Colorado (from their Web site at http://www.cdc.noaa.gov/) and the National Center for Atmospheric Research data archives.

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(Received June 28, 2000; revised August 10, 2000; accepted August 18, 2000.)