Statistical Characterization of Simulated Cumulus Convection: Toward Improving Stochastic Convective Parameterizations

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Background

The goal of cumulus cloud parameterization is to realize changes in the simulated large-scale environment as a function of the collective influence of multiple cumulus clouds, thereby gaining computational efficiency by being able to operate atmospheric models at larger than cloud-resolving scale resolution. This is often accomplished by assumption of radiative-convective quasi-equilibrium (QE) whereby, for example, increases in convective available potential energy (CAPE) brought about by upper level radiative cooling and surface evaporation are assumed to be in an approximate balance with CAPE-reducing warming and drying caused by large-scale subsidence induced by cumulus convection.

The desire to create stochastic convective parameterizations (SCPs) has developed from the realization that QE-based (or otherwise diagnostic and deterministic) convective parameterizations fail to reproduce the full spectrum of convective variability, when employed in global circulation models (GCMs) with low spatial resolution, that is found, mainly at the small-scale, in CRM ensembles and observational data. For example, sufficiently large amplitude convective heating variations exhibit a departure from QE that may temporarily stop convection, thus removing constraints of QE. Such intermittent departures from QE are inherent to convection, and the use of SCPs has the effect of interrupting QE and thereby corrects the variability of the convection.

Implementation of SCPs can be as simple as introducing a random multiplier to variables in a given parameterization to increase overall ensemble spread and improve probabilistic precipitation forecasts, but such an approach is not a true physical parameterization, directly linked to resolved processes. A more complex, yet physically based, method requires an understanding of the nature of the deviation from QE to be able to direct convective variability in a more informed manner. Stochastically adding in this previously lacking variability is a task which will need to take into account a number of parameters, including the chosen grid spacing and the time scale of the large-scale forcing.

Objectives

This study sought to explore the following:

- Under QE, the convective response of the system is tightly coupled to the large-scale forcing applied. In a more realistic simulation, how does the convective response deviate from a variety of applied forcings?
- Does a CRM under constant large-scale forcing match well with the expected QE convective response?
- Xu et al. (1992) showed QE departures derived from a series of periodic (in time) large-scale forcings in a 2-D cloud-resolving ensemble. Would the same results be observed in a 3-D cloud-resolving model (CRM)?
- A QE-type convective response is not expected *a priori* when a sample size (model grid box) is "small." How small is "small"? At what grid size is QE no longer a good parameterization? How does the response vary across different domain sizes?

Methods

To obtain a characterization of 'true' convective variability, the three-dimensional Jung-Arakawa anelastic cloud-resolving model (CRM), which uses the vector vorticity equation in its dynamical core, is used in this study. Convective statistics were compiled using the model with a 2-km horizontal resolution and a 35-level stretched vertical grid (to ~20 km) in place of an observational dataset. A doubly periodic grid covering the domain of (256 km)^2 on an *f*-plane at 15 degrees North latitude was used. The simulations were initialized with a GATE-III sounding containing moderate vertical wind shear.

A number of simulations were performed to study the non-equilibrium, stochastic component of moist convective heating and drying. Following Xu et al. (1992), the response of the non-deterministic component of the numerical simulations is tested by means of 13 simulations using cyclic prescribed large-scale forcings with periods ranging from 2 to 120 hours. As a function of time, the periodic forcing follows the form

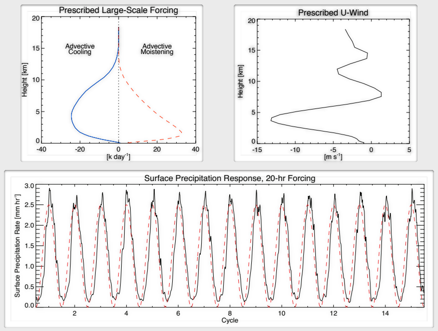
$$f(t) = \frac{1-\cos\left(\frac{2\pi t}{T}\right)}{2}$$

where T is the period of the time variation. Each of the periodic forcing simulations were run to a length of 15 cycles, representing 15 realizations of the same event. Statistics of the composite of the cycles are heavily relied upon. The dependence of the simulation characteristics on the size of the computational domain was investigated by sub-sampling the full domain.

Additionally, 10 3.5-day simulations were run at increments of 10% of the maximum large-scale forcing from the periodic simulations.

Characteristics of six variables were used to describe the convective activity: surface precipitation, cloud fraction, cloud mass flux through a layer, non-precipitating condensate, and horizontal and vertical eddy kinetic energy in both raw and mesoscale-filtered form.

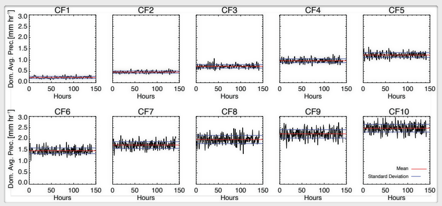
Model Initialization and Time-Varying Forcing



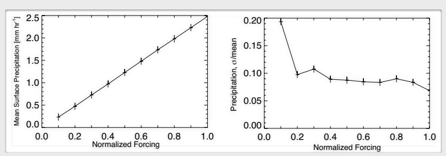
The model is forced with prescribed large-scale advective cooling and moistening rates (top, left), and the sheared u-wind profile (top, right) is set as a constant component of the geostrophic wind to maintain wind shear.

The average surface precipitation response to the periodic forcing (20-hour shown) is denoted by the black curve in the bottom panel. Note that due to the relatively short period of the forcing that the convective response tends to lag the forcing. Also, the response has some scatter deviating from a smooth response. These features agree, principally, with the results of Xu et al. (1992).

Convective Response to Constant Forcing

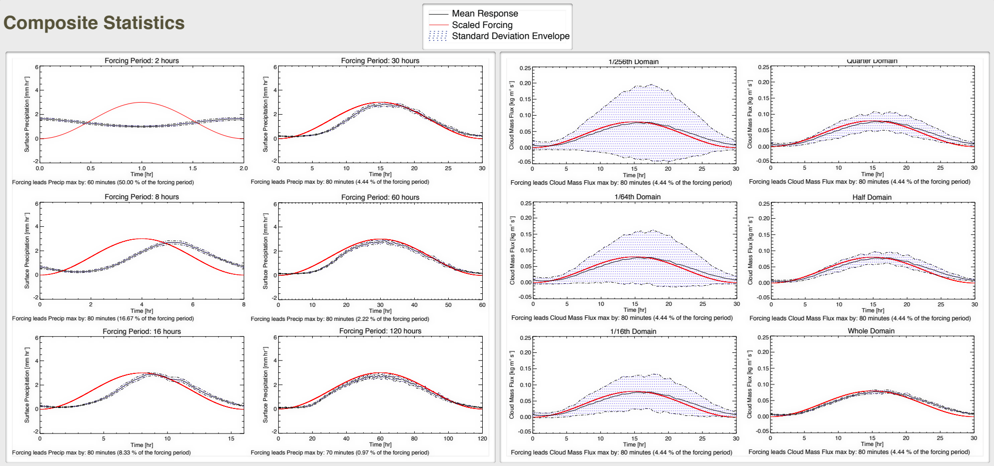


In each of the panels above, the domain-averaged surface precipitation is shown. The number in the title of each panel denotes tens of a percent of the prescribed large-scale forcing shown in the previous box. When the model is run at constant forcing, the response is closer to QE than for the case of variable forcing.



In fact, the mean domain-averaged surface precipitation equilibrium response increases linearly with increasing constant forcing. Standard deviations of the same parameter also increase with increasing forcing, and as the figure on the right shows, the variability of the forcing scales with the mean convective response. This observation is important to note in development of a stochastic convective parameterization.

Composite Statistics

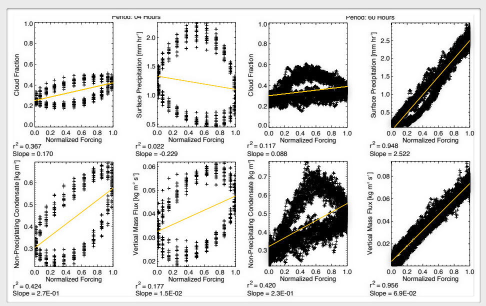


By compositing the 15 cycles shown in the box to the left, most of the non-QE scatter-like response can be averaged out, as shown by the solid black curves in the above figures. Each of the plots on the left is a composite for a different length periodic forcing. As the forcing period decreases, the response is more out of phase with the forcing in a relative sense, but in an absolute sense, the forcing tends to lead the response by ~80 minutes. For a short period forcing, it is difficult for the convection to keep pace. Though it is difficult to see here, the variability of the response about the mean tends to decrease slightly with increasing length of the forcing period.

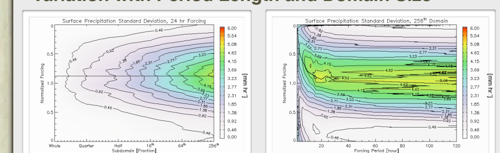
On the right are composites of the cloud mass flux response through the 3-km level for various subsections of the domain for a forcing with 30-hour periodicity. As in the previous case, the response lags the forcing by ~80 minutes. Here is seen a tendency for variability of the convective response to increase with decreasing domain size. For this variable, the change in variability with domain size appears gradual, with a possible step between 1/16th of the 256 by 256 km domain and a quarter of the domain. In the case of the precipitation response, there is a very sharp shift in the variability of the convective response between one-half of the total domain and the total domain.

Correlation Analysis

Below are a sample of results from the calculation of the correlation between four different convective response variables and the normalized forcing. Shown are data calculated on the full domain for forcing period lengths of 4 and 60 hours. An important trend to note that holds across all period lengths tested is that the correlation coefficient squared improves dramatically for surface precipitation and vertical mass flux responses. Correlations for cloud fraction and non-precipitating condensate do not strengthen or even weaken. Part of the reason for this involves the fact that for longer period forcings, these variables begin to lead the forcing as can be ascertained from the hysteresis loop form that the scatter plots create.



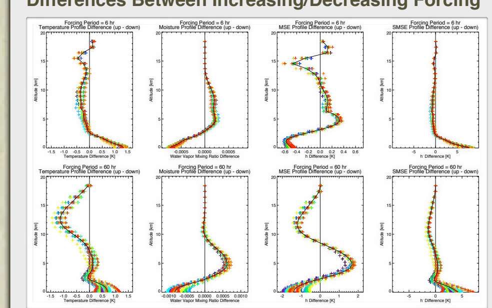
Variation with Period Length and Domain Size



The thick solid black line in the plots above represents the maximum of the precipitation response to the prescribed forcing.

The variability around QE is itself variable with dependencies on multiple parameters. It varies most strongly with changes in the size of the CRM computational domain (i.e. grid size in a GCM). It also varies strongly with forcing, as expected, and to a lesser extent with changes in the forcing period length.

Differences Between Increasing/Decreasing Forcing



MSE=Moist Static Energy, SMSE=Saturated Moist Static Energy

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