The Limits of Convection Parameterization

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Abstract

Cloud-resolving models (CRMs) can be used to investigate the non-deterministic and non-equilibrium statistics of deep convection. Results suggest that even a "perfect" cumulus parameterization will have large expected errors for grid sizes used by current global models. It is also possible to use a CRM as a stochastic, non-equilibrium "super-parameterization." Tests of this approach have demonstrated major improvements in climate simulations, especially when coupled with an ocean model.

1. Introduction

The resolution of the ECMWF model has dramatically increased in recent years. The same is true of other forecast models, and also, to a lesser extent, of climate models. Increased resolution allows better simulation of the basic fluid dynamics, and it also permits a more realistic depiction of topography, coastlines, etc. It does raise some issues, however, in connection with the parameterization of convection.

For parameterization to work, the model's grid spacing must be large enough, but not too large. Arakawa and Schubert (1974) wrote: "Consider a horizontal area … large enough to contain an ensemble of cumulus clouds, but small enough to cover only a fraction of a large-scale disturbance. The existence of such an area is one of the basic assumptions of this paper." A parameterization determines the "expected" collective effects of many clouds over a large area. When the expected value of the convective heating is well controlled by the large-scale forcing, parameterization works well. This case is illustrated in the upper panel of Figure 1.

One of the issues is that, in practice, the number of large clouds within a model's grid column is not very large. In that case, the *spatial scale* of the convection is not well separated from the grid scale. This occurs when the area is not "large enough to contain an ensemble of cumulus clouds" -- at least, not a big enough ensemble. *The problem becomes worse as the grid spacing becomes finer.* On a fine grid, the statistical approach that we call parameterization is not appropriate, and random fluctuations can dominate. The middle panel of Figure 1. illustrates an intermediate case in which fluctuations are significant but not completely dominant.

A second issue is that the *time scale* of the convection may not be sufficiently separated from the time scale for variations of the weather systems that are resolved on the grid. In this case, the convection may systematically lag the changes in the resolved weather, and "quasi-equilibrium" closures (Arakawa and Schubert, 1974) are not appropriate. Note, however, that as the grid spacing is reduced, and the resolved weather systems become smaller, the time scales of these systems also decrease. For this reason, the issue of time scale separation also becomes worse as the grid spacing becomes finer.

It is also possible for the spatial scale separation to be adequate even though the temporal scale separation is not. An example is the externally forced and very important diurnal cycle of convection, especially as it relates to deep clouds. With a large grid spacing, parameterization of diurnally varying convection is deterministic (i.e., not dominated by random fluctuations), but not in equilibrium.

Parameterization is still possible, but quasi-equilibrium must be replaced by a prognostic approach (e.g., Pan and Randall, 1998), with built-in memory. This is the case illustrated in the bottom panel of Figure 1.

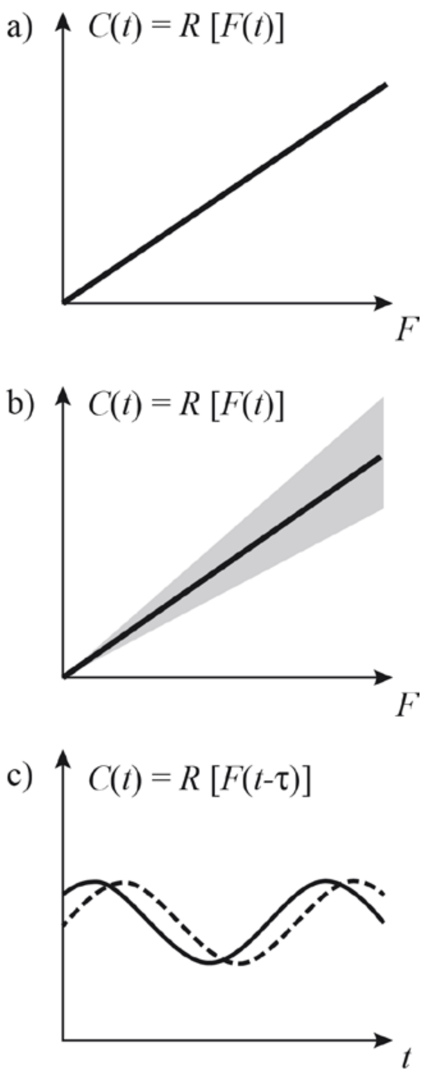

Figure 1: a) Deterministic convection, which responds in a highly predictable way to time-varying forcing. The forcing is plotted on the horizontal axis, and the convective response on the vertical axis. b) Partially stochastic convection, in which random fluctuations, represented by the grey fan, limit the accuracy of the parameterization. c) Deterministic but non-equilibrium convection, represented by the dashed curve, which lags the time-varying forcing, presented by the solid curve. The horizontal axis is time. From Jones and Randall (2011).

This discussion suggests that parameterization errors can actually become worse at higher resolution, and that beyond some limit increases in resolution will not lead to better results. Support for this idea can be found in the work of Buizza (2010). He analyzed the systematic errors of the ECMWF model as a function of resolution. He worked with ensembles of forecasts based on various resolutions, all with the same physical parameterizations. Figure 2 is taken from his paper. The open circles in the figure show the times required for the systematic errors to reach 71% of saturation (i.e., the asymptotic error for large times), in forecasts of the real world, as a function of resolution, out to T799. All of the values are between 9 and 10 days. There is no systematic improvement with increasing resolution. Buizza also used lower-resolution versions of the model to forecast the results produced by the T799 model. The results are represented by the black diamonds in Fig. 2. In contrast with the forecasts of the real world, the times to reach 71% of the saturation error increase systematically as the resolution increases. This means that increases in resolution do indeed lead to better forecasts, when the model is used to forecast a higher-resolution version of itself. The time to reach 71% of the saturation error would be infinite for the T799 model, because it is a perfect model of itself; there would be no forecast errors at all.

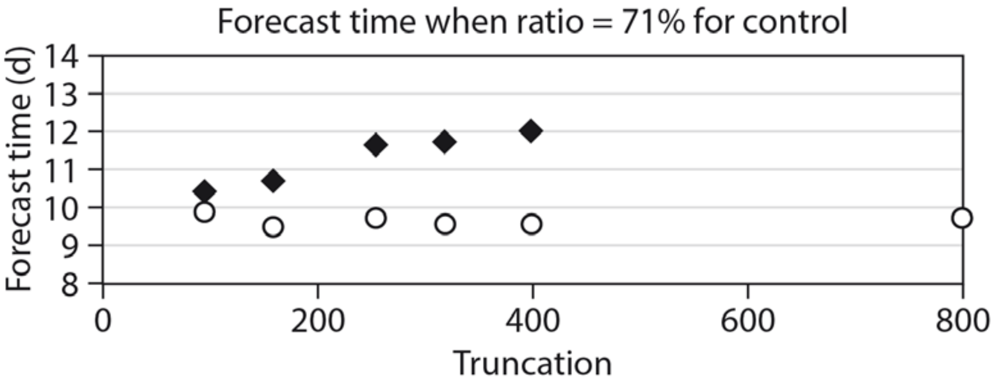

Figure 2. The dependence of systematic forecast error on resolution, from Buizza (2010). See text for details.

In the closing section of his paper, Buizza commented that “rather than resolution, it is model improvements that might lead to better predictions and longer predictability limits.” The model improvements in question are improved parameterizations of physical processes, including moist convection.

The cartoon in Figure 3 illustrates an interpretation of this conclusion. The vertical axis in the figure is the systematic error, and the horizontal axis is horizontal grid spacing, with a logarithmic scale. The

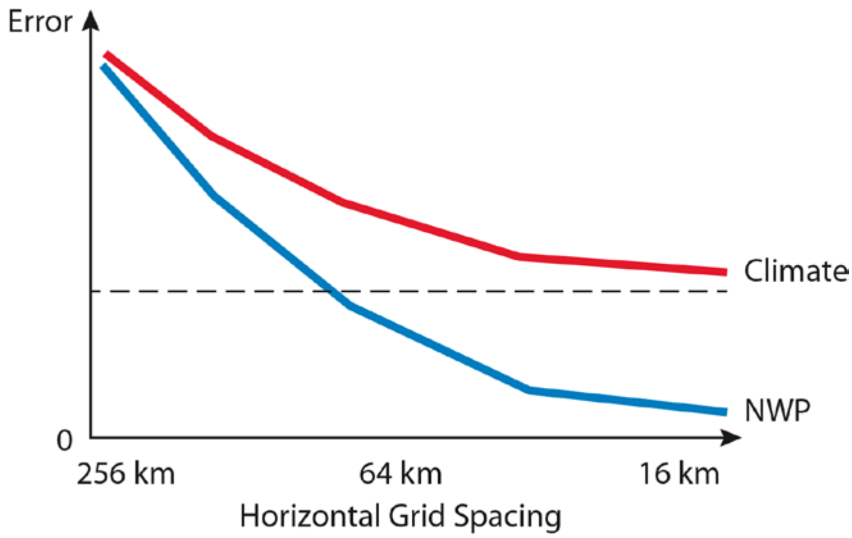

Figure 3. An interpretation of Buizza’s (2010) results. As resolution increases, parameterization errors become dominant at lower resolutions for climate than for NWP. See text for details.

blue curve (labeled NWP, for "numerical weather prediction") shows that *short-range* (a few days) forecast errors can decrease with resolution, out to a grid spacing close to what ECMWF is using operationally now. Evidence of this is presented, for example, by Buizza (2010). At long range, however, the story is different. In the limit of climate simulation (*very* long-range forecasts), the systematic errors stop decreasing at somewhat larger values. At sufficiently high resolution, the long-range errors come mostly from the physical parameterizations, and further increases in resolution don't help. The point is that although increasing resolution can be useful for both NWP and climate simulation, as resolution increases the parameterization errors become dominant at lower resolutions for climate than for NWP. The issues discussed in connection with Figure 1 can partly account for this.

2. Experiments with a cloud-resolving model

Jones and Randall (2011) used the three-dimensional cloud-resolving model (CRM) of Jung and Arakawa (2008) to explore the errors of convection parameterization as functions of both resolution and the time scale for variations of the resolved-scale weather, extending the work of Xu et al. (1992) by using a three-dimensional model (the model of Xu et al. was two-dimensional), and by analyzing the dependence of the results on subdomain size and forcing period. Jones and Randall simulated tropical deep convection using a domain 18 km tall and 256 km on a side, with 2 km horizontal grid spacing and moderate wind shear. The domain-averaged wind was relaxed to the GATE Phase 3 mean. The large-scale forcing, interpreted as advective cooling and moistening, was loosely based on GATE Phase 3, and was prescribed as a sinusoidal function of time, with various periods. Radiative cooling was also prescribed rather than computed. The results were sampled on subdomains of various sizes.

Figure 4. summarizes a few of the results. The red curve in each panel shows the phase of the prescribed advective forcing, for reference. The black curve shows the ensemble mean of the surface precipitation rate, and the shaded region shows the range encompassed by plus or minus one standard deviation. The top-right panel of the figure shows a "long" (120-hour) forcing period, sampled over the full domain (256 km square). The precipitation lags the forcing by a small fraction of the 120 hour period, and the standard deviation is fairly small compared to the mean. This case therefore corresponds to deterministic convection in quasi-equilibrium, as in the top panel of Figure 1.

A perfect deterministic parameterization of the CRM, with a perfect prognostic (non-equilibrium) closure, should reproduce, perfectly, the ensemble means, shown by the black curves. The figure shows that individual realizations depart significantly from the ensemble means, especially for the smaller subdomain sizes. In other words, the ensemble mean is not necessarily a good estimate of what will happen in a particular realization (a particular forecast).

The central panel of the figure shows the results for forcing with a 30 hour period (comparable to the length of the diurnal cycle), sampled over a subdomains 128 km square. The lag of the convective response, relative to the forcing, is now very obvious, and the standard deviation is comparable to the mean. The figure also shows seven additional combinations of forcing period and subdomain size.

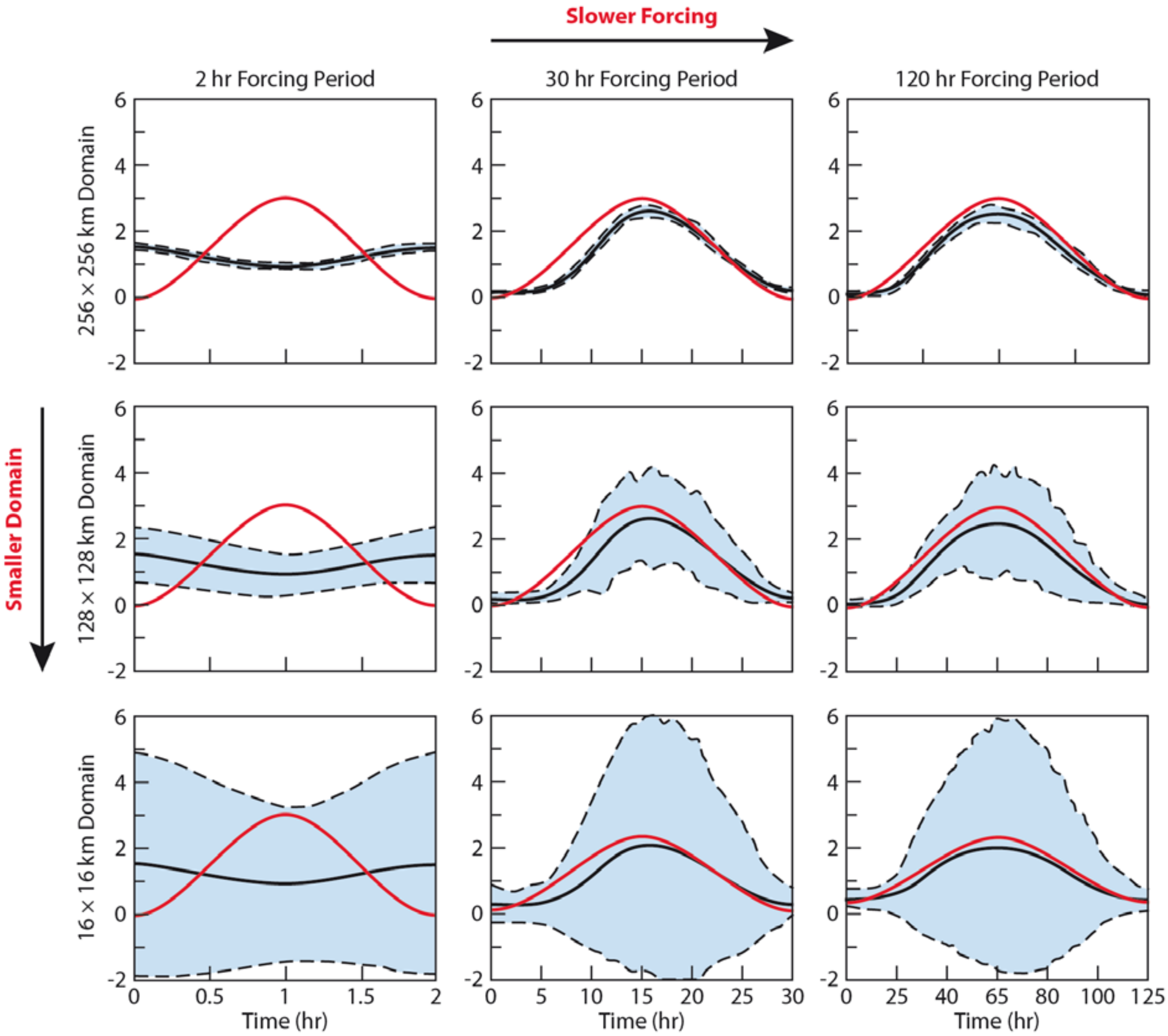

Figure 4: Surface precipitation rate as a function of time, for three different forcing periods and three different subdomain sizes. From Jones and Randall (2011). See text for details.

Further results are summarized in Table 1. The numbers shown are "coefficients of variation," which are defined as the ratios of the standard deviation to the mean, for the surface precipitation rate, for various forcing periods and averaged over various subdomain sizes. For the full domain, 256 km square, the standard deviation is on the order of 10% of the mean. For the 128 km subdomains, the standard deviation increases dramatically, to about two thirds of the mean. For smaller subdomains, the standard deviation is even larger relative to the mean.

These results suggest that, for the GATE-based case considered here, a model with a grid spacing of 256 km can be expected to produce *at least* a 10% error in the surface precipitation rate, for individual realizations. The 10% error would apply for a perfect deterministic non-equilibrium parameterization, in the sense discussed above. With a 128 km grid spacing, the expected errors for individual realizations increase to about 65%. These numbers represent rather discouraging upper bounds on the accuracies of deterministic convection parameterizations. Non-deterministic or "stochastic" parameterizations are, therefore, required (e.g., Palmer and Williams, 2008).

3. Super-parameterization as a stochastic parameterization

One approach to stochastic parameterization is "super-parameterization," in which moist convection, stratiform clouds, and radiative transfer are represented by embedding a simplified two-dimensional CRM in each grid column of a large-scale model. The large-scale model supplies advective tendencies to the CRM, and the CRM feeds back by providing heating and drying rates to the large-scale model. Early examples of the super-parameterization approach were described by Grabowski and Smolarkiewicz (1999), Grabowski (2001), and Khairoutdinov and Randall (2001). For a more complete and up-to-date list of publications relating to super-parameterization, see http://www.cmmap.org/research/pubs-mmf.html. Results to date show that, relative to conventional parameterizations, super-parameterization leads to major improvements in the simulation of the Madden-Julian Oscillation, the diurnal cycle of precipitation, and the Asian summer monsoon. A super-parameterized atmosphere model gives better results when coupled to an ocean model than when driven by prescribed sea surface temperatures (Stan et al., 2010; DeMott et al., 2011).

	Subdomain Side Length (km)				
Period (hr)	256	128	64	32	16
15	0.125	0.698	1.205	1.745	2.215
30	0.113	0.656	1.177	1.693	2.185
60	0.116	0.664	1.222	1.760	2.227
120	0.147	0.707	1.282	1.815	2.257

Table 1. For the surface precipitation rate, the ratio of the standard deviation to the mean, for various forcing periods (shown in the left-most column) and subdomain size lengths From Jones and Randall (2011).

A super-parameterization is based on a nonlinear CRM, so it exhibits sensitive dependence on its past history, just like the CRM used by Jones and Randall (2011). It therefore behaves stochastically, and it can be viewed as a stochastic parameterization. Because of the CRM's assumed two-dimensionality, the number of grid columns in the CRM domain is too small (usually 64 or 32) to give a good sample of the convective activity, so the CRM probably exaggerates the stochastic component of the convection. We do not know to what extent this stochastic behavior is important for the successes of the method.

Because each embedded CRM has a "memory," which comes from its prognostic equations and the various forms of inertia in the system, a super-parameterization can simulate the lag between the large-scale forcing (as provided by the large-scale model) and the convective response. This non-equilibrium behavior may be important for the super-parameterization's ability to simulate the diurnal cycle of precipitation.

4. Conclusions

CRMs can be used to analyze the non-deterministic and non-equilibrium aspects of convection, as functions of subdomain size and forcing period. Our results suggest that parameterizations of deep convection have large expected errors with grid spacings of 128 km and finer. We are currently performing additional studies similar to that of Jones and Randall (2011), using interactive radiation and alternative forcing scenarios.

CRMs can also be used directly as non-deterministic and non-equilibrium “super-parameterizations.” The computational cost is high, but the results obtained are interesting and may lead to future improvements in conventional parameterizations.

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