Cloud Spatial Variability: It's Not Just About Radiation Anymore

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Introduction

Clouds just aren't like American cheese

Although they are often represented quite simply, clouds are neither perfectly flat on the top and bottom nor is liquid water content constant everywhere. The amount of variability observed in cloud water content within a domain increases with the size of the domain. Large-scale models of the atmosphere, though, (NWP and climate models) assume that clouds are both plane-parallel and homogeneous within the cloudy portion of each model grid cell.

Why might this be important? Cloud albedo is a convex function of cloud optical thickness τ, which is determined from liquid water content q. Large-scale models predict the mean values of q and optical thickness τ in each grid cell and perform a single cloudy-sky radiative transfer calculation. But model grid cells are so large that values of τ and q within the domain are certain to be variable, so the true average albedo is lower than the albedo computed from the average optical thickness. This is known as the Plane Parallel Homogeneous (PPH) albedo bias.

But radiation is only one of many non-linear processes acting in a large-scale model. In the presence of sub-grid scale variability the average rate of any process, which depends non-linearly on condensate concentration differs from the rate computed using the average concentration. In particular, the rates of microphysical processes in prognostic cloud schemes $R_i(q)$ are strongly non-linear in q.

When q varies at spatial scales smaller than a model grid cell, the average process rate within each cell is defined by integrating the process rate across the domain. Cloud physical processes are most often local, so integration over the spatial domain is equivalent to integration over the probability distribution function (PDF) of condensate concentration. We define the Sub-grid Scale Homogeneity (SSH) bias as the relative bias between the average process rate and the process rate computed from the average value of q.

$$B_{SSH} = \frac{\overline{R(q)} - R(\bar{q})}{R(\bar{q})} = \frac{\int_0^\infty P(q)R(q)dq}{R(\bar{q})} - 1$$

If a process rate $R(q)$ is non-linear in q, the process rate computed with the average value of q will be biased relative to the average process rate $\overline{R(q)}$ computed from the probability distribution function P(q). The size of the bias depends on how non-linear the process is and how much sub-grid scale variability exists in liquid water content. The sign of this effect depends on the second derivative of R with respect to q.

Some processes in prognostic cloud schemes (e. g., autoconversion) occur only when q exceeds a threshold value q_0. Rates computed from $\bar{q}$ jump from 0 to a finite value, but if q is variable the concentration in denser parts of the cloud may exceed the threshold even when the mean is below q_0, implying small but finite process rates. If q is allowed to vary within a grid cell, rates for processes with a threshold will vary more smoothly with $\bar{q}$.

Back of the Envelope Calculations: How big might the SSH bias be?

To evaluate the size of the bias in a global climate model (GCM) grid cell we need estimates of P(q) and models of the process rate. P(q) depends on spatial scale, so climate models, with larger grid sizes and longer time steps, will have larger SSH biases than NWP models. We partition variability in q into vertical and horizontal components. Vertical variation is linear in q, as is observed in cirrus and stratiform boundary layer clouds. We chose the horizontal variation of q to yield a log-normal distribution of optical thickness. Process rate $R(q)$ depends are parameterized as $R(q) \propto q^n$. The bias resulting from this simple model is shown in Figure 1.

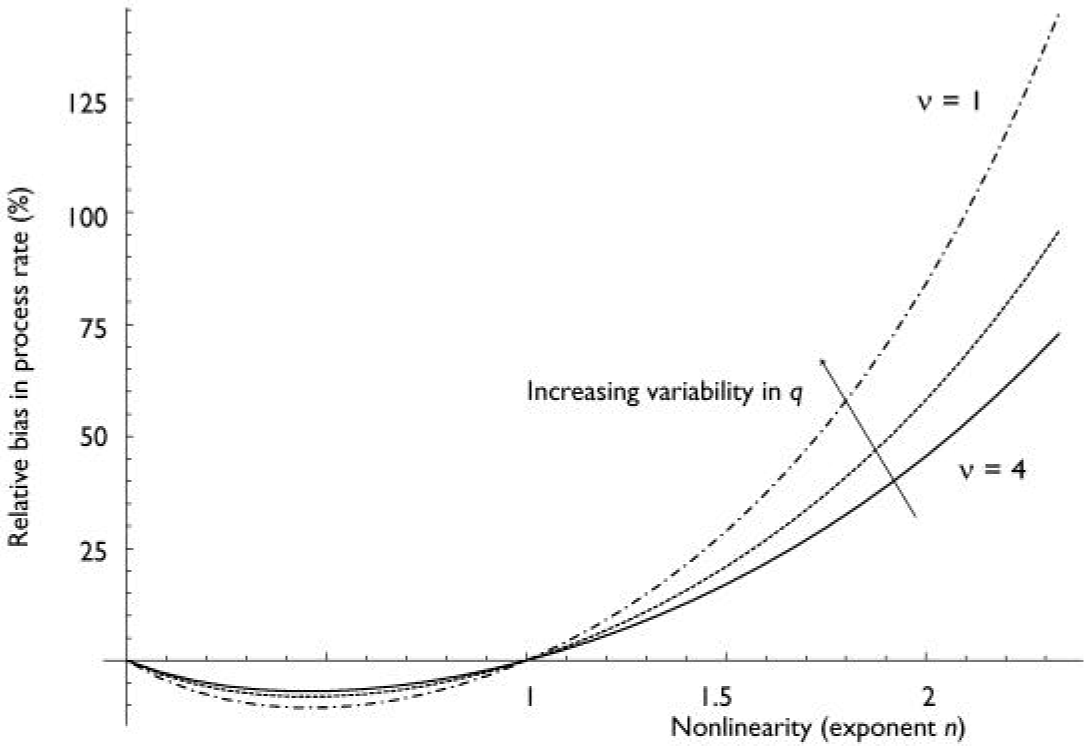

Figure 1. The SSH bias as a function of the amounts of variability and non-linearity in a simple model. Cloud liquid water content increases linearly with height and horizontal variation in cloud optical thickness is constrained to follow a gamma distribution. Process rates are proportional to liquid water content raised to some power *n*. For strongly non-linear processes the bias is as large as the process rate itself.

Real world computations: Computing process rates from Atmospheric Radiation Measurement (ARM) data

We use the millimeter wavelength cloud radar at the Southern Great Plains (SGP) Cloud and Radiation Testbed (CART) site during winter 1997 to estimate q as a function of time (every 10-s) and height (at 45-m resolution). We assume a drop concentration of 300/cm^3, and omit observations from strongly precipitating or mixed-phase clouds. We accumulate P(q) in each 3-h segment, which we use as a proxy for a model grid cell. The transformation of cloud to rain water (the autoconversion rate) in the Geophysical Fluid Dynamics Laboratory (GFDL) climate model proceeds as $q^{7/3}$ once a threshold drop radius r_0 has been exceeded. Detailed calculations suggest that the proper value for r_0 about 10 μm; in the climate model this radius is tuned to 7 μm so that the model-produced clouds agree with observations. We compute the average autoconversion rate predicted using P(q) and the larger value of r_0, and compare this to the autoconversion rate computed using $\overline{q}$ and two values of r_0.

Accounting for P(q) allows thresholds to be more realistic. The 3-h average autoconversion rate computed with r_0= 10 μm can exceed 100 g kg^{-1} day^{-1} when q varies with time, as Figure 2 shows. The drop radius inferred from $\overline{q}$ is always less than 10 μm, so autoconversion rates computed using $\overline{q}$ and a realistic value of r_0 are always 0. Autoconversion rates computed from $\bar{q}$ are much closer to $\overline{R(q)}$ when r_0 is set to the unrealistically low value of 7 μm. This suggests that large-scale models must account for sub-grid scale variability with ad-hoc adjustments of physical parameters.

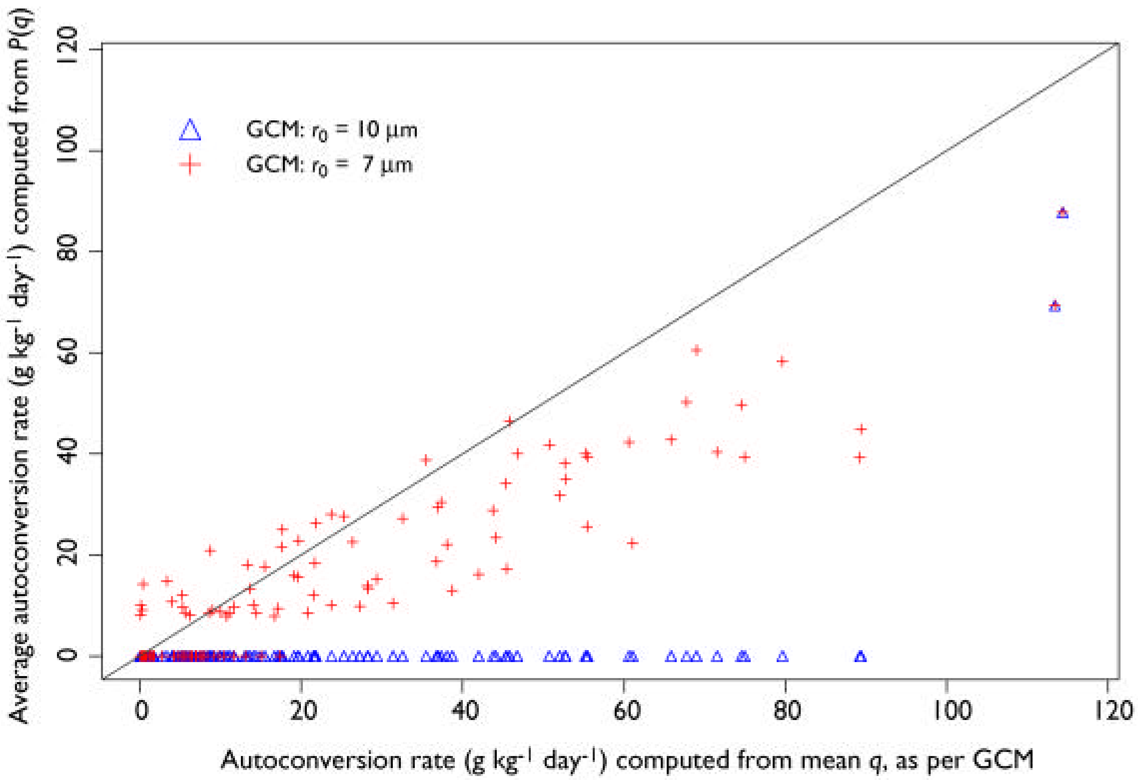

Figure 2. Autoconversion rates computed from probability distributions of liquid water content observed by the millimeter cloud radar (MMCR) at the ARM SGP CART site. Rates are computed using parameterization used in the GFDL large-scale model, which includes a threshold value. Rates computed accounting for sub-grid scale variability allow for a more realistic threshold in drop size to be used.

Implications

The SSH bias exists in all large-scale models of the atmosphere, including those in current use that successfully predict the current climate. These models have been tuned (through the arbitrary adjustment of a few key physical parameters) so that the SSH bias is not a problem. Unfortunately, these adjustments have no physical basis, and are uncoupled from one another, so that changes to parameters in the radiative transfer scheme are made without references to changes in the microphysical scheme, for example. Because the amount of sub-grid scale variability changes with model resolution, models must be re-tuned each time the grid size is changed. We propose that an explicit treatment of sub-grid scale variability will make large-scale models more robust.