Two sources for errors in modeled clouds

Errors in climate model predictions of cloud properties stem from some combination of (at least) two causes:

- the cloud parameterization may produce the wrong cloud properties from a correct atmospheric state (or history of states), or
- the cloud parameterization may be driven by incorrect states.

Errors seen in long-term climatologies can’t distinguish between these two error sources, but the different modes of failure have very different implications for model development.

There are two approaches to disentangling these error sources:

- ensure that the cloud scheme is driven by the correct atmospheric state by making short forecasts from analyses derived from observations (the CAPT approach).
- build up composites and compare modeled and observed cloud properties under circumstances when the atmospheric states are similar. The similarity can be gauged based on specific hypothesis (e.g. vertical velocity, CAPE, etc.) or can be identified using pattern-finding algorithms.

Here we compare the characteristic states of the atmosphere at the ARM SGP site as observed and as simulated by two climate models. We do this by using a clustering algorithm that identifies sets of thermodynamic profiles that are most like one another.

Characteristic states of the atmosphere at SGP

We summarize the state of the atmosphere at the ARM SGP site using hourly profiles of $\theta_e(z)$ and $\theta_{as}(z)$ for a three year period (1999-2001). We compare

- observations obtained from the continuous forcing dataset. These profiles are based on forecast analyses constrained with surface and top-of-atmosphere measurements.
- output from the column nearest the ARM site in two climate models (the NCAR CAM and the GFDL AM2) run with specified sea surface temperatures.

We identify the characteristic states of the atmosphere in each data set using Entropy-Constrained Vector Quantization. This iterative clustering method identifies a set of representative profiles subject to information-theoretic constraints (i.e. the algorithm chooses the number of clusters) given a parameter describing the amount of compression desired. Each “cluster” provides a single representative profile ($\theta_e(z)$ and $\theta_{as}(z)$) and the normalized mean Euclidian distance (distortion) from the representative profile to the set of profiles comprising the cluster.

Result 1: The 26,280 observations can be summarized well in a relatively small number of states (16 for this amount of compression). The seasonal cycle is a large part of the signal (this is in part an artifact of the variables we’ve chosen).

Result 2: Both models are “noisier” than the observations. More clusters are required to reproduce the range of states in the models than in the observations, and the mean distortion of the models clusters is larger than in the observational clusters, especially for the states that occur less frequently.

Result 3: The models don’t reproduce the observed states in two ways. The states produced by the model are relatively far from those observed (i.e. the percentage of model points that fall within a specified distance from any observed cluster is much less than is observed). To the extent that the models do produce states similar to those observed, the relative frequencies differ from the observations (not shown).