Comparing the Lagrangian evolution of sub tropical stratocumulus between GCMs and observations

Ryan Eastman1 (contact: rmeast@atmos.washington.edu), Christopher Teraï2, Daniel Grosvenor3, Robert Wood1
1) University of Washington, Department of Atmospheric Sciences, 2) Lawrence Livermore National Laboratory, 3) National Centre for Atmospheric Science (NCAS), University of Leeds

1) Trajectory Regions & Mean Lagrangian Evolution

This Lagrangian work allows us to compare the mean behavior of clouds in models (CAM5, UKMET) to observations (A-Train) and compare the time evolution of clouds and responses to predictors.

Above: Mean trajectories are similar for all three platforms (Observations/ERA-Interim, CAM5 GCM, and UKMET GCM) for year 2009. ~30,000 trajectories are calculated using winds in both models and the ERA-Interim. All trajectories share the same starting points within these four subtropical ocean basins. Regions are chosen to capture the maximum marine in models and the ERA Interim reanalysis wind fields above 2200m, the CAM5 is free running.

Left: Mean evolution of cloud variables from all trajectories from each platform, sampled at 12-hour intervals coinciding with the A-train flyover at local times 1:30 and 13:30. Means differ, but trends are more consistent. The PBL height is estimated from histograms of cloud top heights ascertained from each platform. Models show a significantly greater number of shallow convective cloud tops overshooting the trade inversion, so the “PBL” is shown in quotes due to the differing morphologies, reflecting the likelihood that the model “PBL” is too deep.

Right: Composites showing the mean evolution of predictor variables. Again, means differ, but Lagrangian tendencies are comparable. For the observations, predictor variables are sourced from the ERA-Interim. Results 1: Different platforms show differing means, particularly for cloud variables and the “PBL”, but Lagrangian tendencies tend to agree.

2) Characteristic Time Scales of Cloud Variables

Below: Mean cloud cover anomalies, calculated in 1° lat/lon boxes with the diurnal and seasonal cycles removed, are compared at trajectory hours $T = 0$ and $T = 12-48$ for bins of trajectories. A somewhat linear relationship is seen between 0-hour anomalies and subsequent anomalies in the observations and models. Slopes are fit using a robust linear least squares regression. Overall, cloud anomalies appear to evolve in a similar way, regressing to the mean with similar time scales in models and observations.

Above and below: $e$-folding times $\tau$ are estimated using the slopes of the fits at each time interval. The variable $\tau$ is defined as the time it takes for an anomaly to decline by a factor of $1/e$:

$$\tau = \frac{-1}{\log(r(r')]}$$

In the equation above, $Ti$ is the trajectory time in hours, and $r(r')$ is the slope fit to the points above. This work shows that the degradation of cloud variable anomalies over time is well-characterized as red noise: Showing a zero-mean, constant variance, and showing partial persistence over time.

3) Cloud Variable Responses to Environmental Predictors

In order to compare the power of predictor variables in this Lagrangian framework, we must modify the data in a few ways: The red noise behavior shown in section (2) must be removed, creating a “residual” change that is independent of initial values. Also, predictor variables must be standardized (divided by their standard deviation $\sigma$) in order to compare their relative strengths.

Above: Trajectories are divided into four bins based on initial values of standardized predictors: $2 < n_1 < 1$, $0<n_1 < 1$, and $n_1 < 0$. The mean residual change observed after 24 hours in each cloud variable is calculated for each bin, then a slope is calculated using the four points. This process is repeated within bins of constant predictors in order to reduce the effects of confounding predictor variables. Mean slopes are represented above and below. The figure above shows that when subsidence increases over 24 hours, both models and the observations produce a decline in cloud cover.

Below: Slopes calculated as in the top figure are summarized in the histogram (blue box) for all predictors on all cloud variables. Cloud variable anomalies are also used as predictors. Negative histogram values indicate negative slopes as shown above, and vice-versa.

Results 3: All three platforms show consistent cloud and cloud LWP responses to wind, and $n_1$, though strengths differ significantly. The $n_1$ and PBL responses are inconsistent.

Conclusions: Mean values of cloud variables differ between models and obs, with fewer and deeper clouds in models, but Lagrangian tendencies are similar. Time scales of anomalies are comparable and models reproduce observed red noise behavior well. The effects of predictors vary from qualitatively identical (cloud response in UKMET and observations), to very noisy and inconsistent in the cases of the PBL depth and $n_1$ responses. Future work seeks to add many additional models, so please contact the authors if you are interested in contributing.