STATISTICAL ANALYSES OF SATELLITE CLOUD OBJECT DATA TO STUDY CLIMATE SENSITIVITIES

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1. INTRODUCTION

One of the largest uncertainties in the climate system is cloud feedback. Current climate models continue to struggle to accurately model cloud feedbacks. One of the persistent problems is the difficulty of comparing cloud observations with climate models to the accuracy requirement of climate sensitivity studies. Achieving a statistically significant sampling of observing cloud feedbacks without the influence of weather “noises” requires a minimum of a month of data over a region, and often up to a year. This is because significant cloud feedbacks can result from changes in global mean cloud properties as small as 1% per decade, or regional change of 1% per year. Use of classic gridded monthly or annual mean cloud data invariably includes a wide range of atmospheric states and cloud types/conditions. It then becomes very difficult in this time-averaged Eulerian view to diagnose which type of cloud is being poorly represented in climate models. This diagnosis is, however, crucial to improve these models’ representation of cloud processes.

On the other hand, a Langragian approach, called the “cloud object” approach, groups instantaneous satellite cloud footprints by cloud-system type, independent of where and when the cloud-system type occurs. Simulation of these cloud objects is also performed, driven by the nearly simultaneous atmospheric state data. This approach offers two advantages: it reduces cloud variability by grouping data from the same cloud-system type and it reduces sampling noises by combining results from a wide range of geographic regions. Because of its large sample size (hundred to thousand cloud objects), the integrated observational and modeling results can be stratified according to some measures of atmospheric states such as sea surface temperature (SST) so that the partial derivatives between radiative fluxes and atmospheric variables can be obtained to study cloud feedbacks from observations and model simulations. This comparison will also offer helpful hints for further improvement of climate models.

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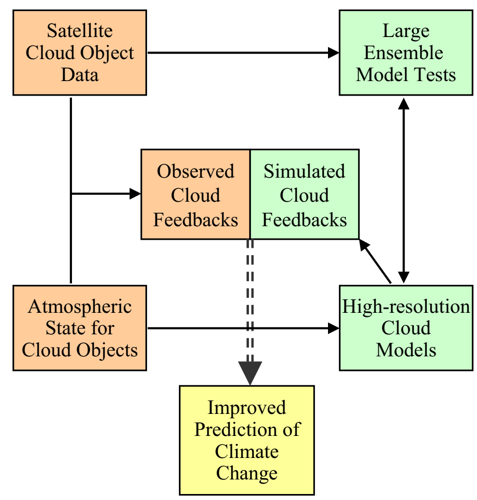

Fig. 1: *A schematic of the approach for cloud object observation and modeling to understand cloud feedbacks.*

This study presents a statistical validation of the fixed anvil temperature hypothesis of Hartmann and Larson (2002) using the cloud object data. They proposed that the emission temperature of anvil clouds remains unchanged during climate change because longwave cooling is rapidly declined around the anvil top due to inefficient radiative emission from water vapor (i.e., Clausius-Clapeyron relation).

2. A NEW METHODOLOGY

Observational data analysis and high-resolution modeling are integrated in the new cloud object approach to improve the understanding of cloud feedbacks (Fig. 1). In order to reach climate accuracy, satellite data from the Earth Observing System (EOS) are analyzed to generate large ensembles of cloud objects for different cloud-system types. The atmospheric state is matched to each cloud object in space and in time. Then, the grand mean statistics of observed cloud objects, i.e., the combined probability density functions (PDFs) over an ensemble of cloud objects, are stratified according to some independent measures of atmospheric states in order to derive the partial derivatives of cloud properties vs. atmospheric states, thus cloud feedbacks

The atmospheric state is also used to drive the simulations of high-resolution cloud models. The statistics of the simulated cloud objects are vigorously compared with those of satellite observations for large ensembles of cloud objects so that systematic errors can be identified and further improvements to the high-resolution cloud models can be made without the need of arbitrary model tuning [see Eitzen and Xu (2004) for a preliminary study]. The simulated cloud feedbacks can be analyzed and compared with those from satellite cloud object analysis to further improve the high-resolution cloud model. Further testing of the improved cloud models can be performed by embedding them into a global climate model for selected seasonal and interannual simulations. This revolutionary method of climate modeling is called an "multiscale modeling framework" (MMF; Randall et al. 2003). Once these tests are passed, decadal climate prediction can be performed to provide a more accurate prediction of climate change than that obtained using a conventional climate model.

3. ANALYSIS OF CLOUD OBJECTS

A cloud object is defined as a continuous region composed by individual cloud footprints that satisfy a set of physically-based cloud-system selection criteria. Due to the limited width of satellite swath and the selection criteria, a cloud object can just include part of a cloud system. The limited width of satellite swath can truncate a cloud system. The selection criteria can break a large cloud system into several smaller cloud objects. A "region-growing" strategy based on imager-derived cloud properties is used to identify the cloud objects within a single satellite swath (Wielicki and Welch 1986). A key part of this task is to label the boundaries of an individual cloud object along the scan lines of satellite. Two scan lines are examined simultaneously to identify the boundary footprints of a large continuous cloud region. Assuming that footprints are square, a cloud footprint is flagged as a cloud edge footprint if one or more of its sides is adjacent to a clear footprint. A cloud object is uniquely determined if no cloud edge footprints are adjacent to another cloud object. Please refer to Xu et al. (2004) for further details.

This study will examine only the cumulonimbus and its associated thick upper tropospheric anvils over the Pacific Ocean using TRMM (Tropical Rainfall Measuring Mission) data. Four criteria are used to define the tropical deep convection type: 1) the footprints must have 100% cloud fraction; 2) a minimum value of 10 for the cloud optical depth is used to eliminate thin anvil clouds; 3) the cloud top height must be greater than 10 km and 4) the cloud footprints must be located within 25° S and 25 ° N of the Pacific Ocean. After individual cloud objects have been identified, grand mean statistics in terms of probability density functions (PDFs) are produced for a group of cloud objects as a function of SST, geographic location and size. A number of measured and retrieved variables is available from the TRMM, EOS-Terra and EOS-Aqua satellites. A few PDFs will be shown below to illustrate the sensitivity of cloud properties in tropical convection to SST changes.

4. RESULTS

Table 1 shows the number of tropical deep-convective cloud objects in the Pacific during January-August 1998. The numbers of cloud objects are obtained for five processing cycles and two cloud-object size classes. Each processing cycle of the TRMM satellite is 46 days long. A processing cycle gives a complete sampling of the diurnal cycle at a given location. The cloud-object size class is defined in terms of the equivalent diameters of cloud objects. It appears that the size class with equivalent diameters greater than 100 km has roughly the same number of cloud objects for the five processing cycles except for the April-May cycle. The large size class with equivalent diameter greater than 300 km has a higher number of cloud objects at the beginning of the January-August period, corresponding to the peak phase of the 1997/1998 El Niño. This suggests that higher SSTs are preferred by larger cloud objects in the Tropics. As expected, relatively fewer numbers of large cloud objects were observed during the April-May cycle.

Table 1: Number of observed cloud objects during the five processing cycles for two cloud object size classes. The cloud object size is in terms of its equivalent diameter.

Equivalent Diameter	Jan. - Feb.	Mar. - Apr.	Apr. - May	June - Jul.	Jul. - Aug.
> 100 km	429	448	295	407	484
> 300 km	122	90	64	87	96

Figure 2 shows the PDFs of SST associated with the large cloud objects with equivalent diameters greater than 300 km. From January to August 1998, the numbers of cloud footprints occurring over warmer SSTs decreases as the El Niño dissipates. The SST PDF is close to be normally distributed in the July-August cycle. In the other four cycles and the entire eight-month period, the SST PDFs are skewed toward the higher values of SSTs. This is an interesting result. One may wonder whether or not the differences in SSTs are statistically significant among the processing cycles?

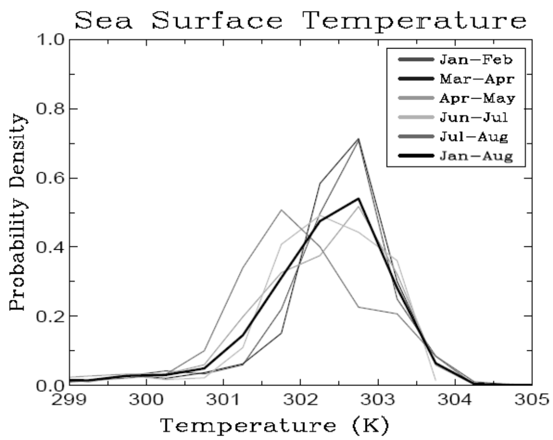

Fig. 2: Probability density functions of sea surface temperature for the five processing cycles and January - August period. Cloud objects with equivalent diameters greater than 300 km are included in PDFs.

To address this question, statistical tests are used to detect statistically significant differences between two grand mean PDFs. These are done in the following ways. First, the differences in PDFs are measured by a root-mean-square method for two PDFs of the same parameter, which is called the Euclidean distance or L2. This PDF distance measure is defined as

$$L2 = \left\{ \sum_{i=1}^{N} [f(x_i)\Delta x_i - g(x_i)\Delta x_i]^2 \right\}^{1/2},$$

where f and g are two PDFs, with a total of N bins where the ith bin is located at x_i. The bin width is denoted by Δx_i. The frequency of occurrence is normalized by the bin width. That is, f and g satisfy $\sum_{i=1}^{N} f(x_i)\Delta x_i = \sum_{i=1}^{N} g(x_i)\Delta x_i = 1$. The bin width Δx_i is uniform for the PDFs examined here. The maximum possible value of L2 is $\sqrt{2}$, which occurs if two single-point PDFs are not collocated. The minimum value of this measure is zero, which indicates no difference between the PDFs.

Second, the bootstrap method (Efron and Tibshirani 1993) is used to determine whether the difference between two grand-mean PDFs is statistically significant. A statistically significant difference between two grand-mean PDFs means that the individual cloud objects forming the two grand-mean PDFs came from two different populations. Cloud objects, but not their individual footprints, are assumed to be independent from each other. The null hypothesis is that all cloud objects came from one population. The probability, calculated taking the null hypothesis to be true, that we would observe a statistic value greater than or equal to the one we did observe is the significance level. The test statistic chosen in this study is L2.

Specifically, the two populations of m and n cloud objects are first combined into one population. Then, two sets of cloud objects of sizes of m and n are resampled randomly from the population, and the values of the distance measures between the two bootstrapped sets are calculated. Any cloud object in the population can be sampled once, more than once, or not all at any given time. This procedure is repeated B (B is chosen to be 5000) times to generate a statistical distribution of the test statistic (L2). The bootstrapped distance value is compared to the value from the true arrangement of cloud objects, i.e., two separate populations. If the bootstrapped value is greater than the true value between two populations in less than 5% of a total calculation of B times, the two populations are deemed to be statistically different. That is, the null hypothesis is rejected at the 5% significance level. Therefore, the two grand-mean PDFs are deemed to be statistically different.

For the PDFs shown in Fig. 2, the L2 distances between the last cycle with the earlier cycles are 0.320, 0.350, 0.197 and 0.197, respectively. That is, the differences from the first two cycles are greater. This is consistent with the visual inspection. The bootstrap method also determines that the grand-mean SST PDFs are different at the 5% significant level, except for the difference between the first two cycles, which are statistically similar.

The most important parameter for validating the fixed anvil temperature hypothesis is the cloud top temperature. Figure 3 shows that the PDFs of cloud top temperature for all five cycles and the January-August period. All PDFs are nearly normally distributed except for being slightly skewing towards the high values of cloud top temperature. The most striking feature shown in Fig. 3 is that all PDFs are not statistically different

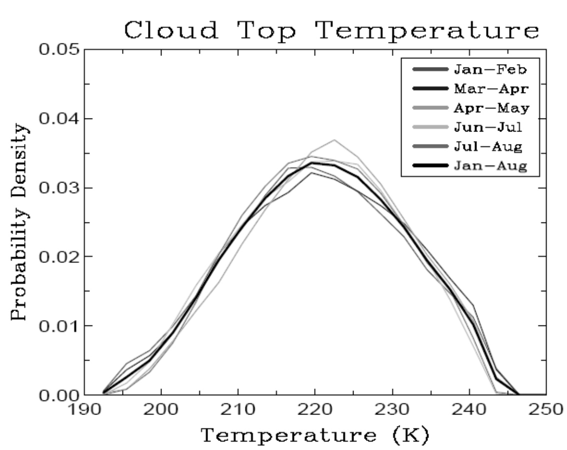

Fig. 3: Same as Fig. 2 except for cloud temperature.

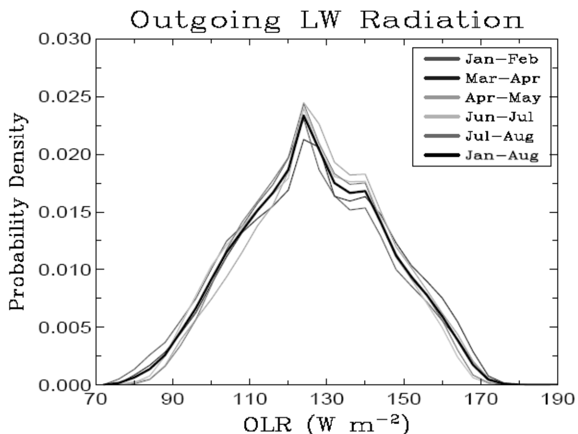

Fig. 4: Same as Fig. 2 except for outgoing longwave radiation fluxes.

from each other, except for between the January-February and April-May cycles, despite the large changes of SSTs (Fig. 2). This result suggests that the fixed anvil temperature hypothesis of Hartmann and Larson (2002) is basically valid. The difference between the January-February and April-May cycles may be related to the small number of cloud object observed during the Apr.-May cycle (Table 1). That is, this cycle does not have statistically large samples of cloud objects.

The outgoing longwave radiation (OLR) fluxes also show small differences among the five cycles (Fig. 4). However, the difference between the first and the last two cycles are moderately significant, according to the bootstrap procedure. This is because the OLR flux is proportional to the fourth power of cloud top temperature for thick anvil clouds. A small difference in cloud top temperature very likely becomes a significant difference in OLR.

Ice water path (IWP) is a measure of cloud microphysical properties, which distributed lognormally (Fig. 5). Apparently, there is no significant differences in

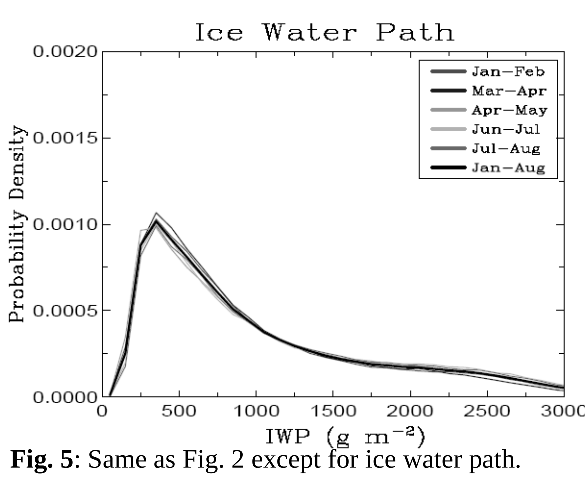

Fig. 5: Same as Fig. 2 except for ice water path.

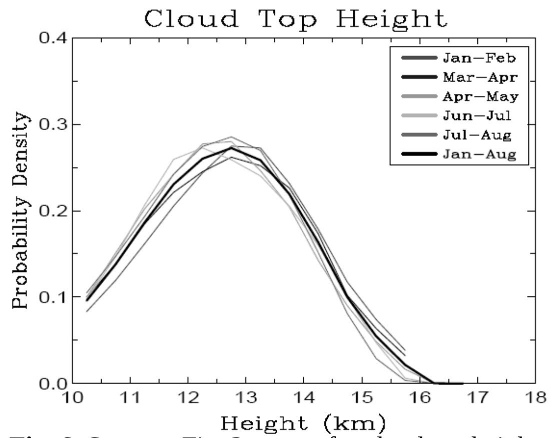

Fig. 6: Same as Fig. 2 except for cloud top height.

IWPs among the cycles despite of the large changes in SSTs shown in Fig. 2.

The cloud top height is a measure of cloud macrophysical properties. Figure 5 shows that there is a strong dependency of cloud top height on the SSTs. The cloud tops are slightly higher for higher SST cycles. Because cloud top temperature is nearly independent of the SST in a statistical sense, this result suggests that the lapse rates are slightly smaller for the high SST cycles. This is plausible because the more intense convection is, the more strongly it tends to stabilize its environment.

5. CONCLUSIONS

This study has presented a new methodology for studying cloud feedbacks in the climate system through an integrated observational and modeling approach. Satellite data have been analyzed to produce large ensembles of cloud objects for different size classes, SSTs or climate regimes. In this study, the statistics of the observed cloud objects are analyzed to understand the cloud feedbacks, in particular, to validate the fixed anvil temperature hypothesis.

It has been found that the differences in the statistics of cloud objects are very small in cloud top temperature, cloud microphysical and optical properties (not shown). But cloud top height shows slightly stronger dependency on SST. Further studies will be performed to compare statistics between observations and high-resolution cloud model simulations to firmly validate the fixed anvil temperature hypothesis.

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