Comment on “Variations of tropical upper tropospheric clouds with sea surface temperature and implications for radiative effects” by H. Su et al.

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[1] Using TRMM VIRS data, we attempt to replicate the analysis made by Su et al. (2008) to quantify the effect of methodological choices on the magnitude of the observed correlations between upper-level cloud cover and SST. Using brightness temperature thresholds to identify upper-level cloud, we recover a relatively small change in the normalized area of cirrus clouds with SST (~−6%/K compared to ~−2%/K found by Su et al. [2008]). We discuss the effect of several methodological choices on the magnitude of the signal, namely, the classification of cloudy regions into convective updrafts and anvils, the use of cloud weighted SST, and the truncation and sampling error of the orbital satellite data with respect to the evolution of mesoscale convective systems.

Accounting for some of these methodological differences could resolve the discrepancy between the weak signal documented by Su et al. (2008) and the stronger signal documented originally by Lindzen et al. (2001) and others, including the results reported in this comment.


1. Introduction

[2] Significant open questions remain attached to the poor understanding of cloud processes and in particular to the expected behavior of the area and properties of the tropical clouds under climate change conditions. Lindzen et al. [2001] postulated the Iris hypothesis to explain their observations of a reduction in the relative amount of upper tropospheric clouds with SST of about ~−22%/K. It was hypothesized that over warm SST regions, mesoscale convective systems rain more efficiently leaving less condensate to be detrained to form cirrus clouds. Lindzen et al. [2001] further argued that thin cirrus clouds have a positive cloud radiative forcing and changes in the cirrus area can therefore produce a significant negative climate feedback. In a recent paper, Su et al. [2008] study the variations with SST of upper tropospheric cloud fraction, ice water path, and ice water contents using data from the Atmospheric Infrared Sounder (AIRS) on the Aqua satellite and find that the normalized cloud area decreases at a rate of ~−2%/K with SST, therefore showing only a weak dependence of the normalized upper tropospheric cloud area with SST. The study by Su et al. [2008] is comprehensive and also includes a characterization of the variation of ice water path with SST and an estimation of the radiative effect of these clouds, issues that we will not address in this comment.

[1] We perform an independent analysis of variation of cloud cover with SST using TRMM infrared radiances. Using Su et al.’s [2008] methodology (which is based on work by Lindzen et al. [2001] but differs from it in some important aspects) we attempt to replicate their results. Here, we address some of the methodological issues expected to play a role in identifying a correlation between SST and cloud cover. We emphasize that the variation of upper tropospheric cloud area with SST is a key aspect of the Iris hypothesis, but perhaps more important for determining a cloud feedback is the radiative effect that these cloud changes will bring about (and which we will not discuss here).

2. Data

[4] We use infrared data from the visible and infrared scanner (VIRS) on board the Tropical Rainfall Measuring Mission Satellite (TRMM) [Kummerow et al., 1998]. The data are brightness temperatures (BT) measured from the channel 4 of the VIRS instrument at a wavelength of about 11 μm (1B01 product, version 6). The VIRS instrument has a horizontal resolution of ~2 km. We use data from January 2001 to March 2001. We also make use of TRMM Microwave Imager (TMI) SST and precipitation data, to match Su et al.’s [2008] methodology that requires precipitation instead of brightness for normalization of the cloud fractions. Both instruments, AIRS and TRMM, have similar coverage...
over the tropics, although since TRMM is in a non-Sun-synchronous orbit, it allows sampling of the diurnal cycle [Imaoka and Spencer, 2000] as opposed to the Sun-synchronous orbit of AIRS that samples only around 0130 and 1330 LST. In work by Su et al. [2008], upper-level cloud fraction is defined as the fraction of clouds below 300 hPa in pressure. Here we will use BT thresholds to define the anvil clouds as in work by Lindzen et al. [2001].

3. Results Using TRMM and TMI Data

[5] The sampling of the orbital satellites (with revisit times of about 1 to 3 days for the relevant scales) does not allow one to capture the evolution of any individual mesoscale convective system. Therefore, there is a need for integrating the results of many convective systems either in time, in space or both. The main assumption here is that by adding sufficient samples for a particular area or for a particular SST bin one is increasingly compensating for the sampling error (we will return to this point in section 4.2).

[6] Before attempting to replicate Su et al.’s [2008] methodology, we will use two different approaches to find the variation of the upper level cloud cover with SST. First, for each 1° x 1° grid in the region between 15°S–15°N, the values of A(220 < BT < 260 K) (that is, the area of pixels having brightness temperatures between 220 and 260 K) are added over a period of time that ranges from 1 to 30 days (we call this time the integration time) and then cloud cover is normalized by the sum of the area of brightness temperature below 220 K, A(BT < 220). We call this the gridded data. Figure 1 presents the results for an integration time of 30 days. The variation of the gridded data with SST shows a large scatter. In fact about 10% of the data are outside the upper bound of the plot, corresponding to grids with very few deep convective clouds over that particular sampling region/interval). Second, we construct the binned data by adding all values of A(220 < BT < 260 K) with temperatures within 0.5°C of the observed SSTs and normalizing by the sum of A(BT < 220) over each bin. The slopes of the regressions are calculated by fitting decaying exponentials using robust nonlinear least squares (since the regressions are exponential, the reported rates of change are constant over the SST range). Both the gridded and the binned regressions show a significant decrease in the area of anvil clouds as in work by Lindzen et al. [2001].

Figure 1. Scatterplot of the fraction of anvil clouds A(220 K < BT < 260 K) normalized by A(BT < 220 K). The data are for January to March 2001 for oceanic regions between 15°S and 15°N. Green dots represent the value of A(220 K < BT < 260 K)/A(BT < 220 K) for individual 1° x 1° grids over the course of a whole month. These results are referred to as gridded. The black dots are the result of adding the areas for all data within 0.5°C SST bins (the sum carried over the whole 3 month period for all 1° x 1° grids within the monthly average SST for each bin). The black curves are nonlinear least squares fits for the gridded data (dashed line) and for the binned data (solid line).
the integration time or to the size of the grid, and therefore the quantitative results using the binned data appear free from spatial truncation artifacts described by Del Genio et al. [2005].

The previous procedure has allowed us to recover a signal that is quantitatively similar to the one found by Lindzen et al. [2001]. We now apply Su et al.’s [2008] methodology to the same data set, that is, we calculate the fraction of anvil and convective cloud as defined by the brightness temperature thresholds, then we calculate a cloud weighted SST for each day over the 15°C1–15°C176°C11–15°C176°C19°C15°C27°C15°C19°C region. Next, we use TMI precipitation data that are coincident with TRMM-VIRS brightness temperature to calculate mean precipitation over the tropical oceans and we normalize the mean cloud fractions by the mean precipitation. In Figure 2a we show the result of this procedure for both the total anvil area (blue dots) and for the anvil area excluding deep convective regions (black dots). We find a negative slope of about −6%/K that should be compared with Su et al.’s [2008] result of −2%/K. The resulting values for the slopes are reasonably close so as to suggest that we have replicated the results of Su et al.’s [2008] analysis. Nevertheless, we will discuss in the next section several issues that might favor a larger effect than the one found by using Su et al.’s [2008] methodology.

4. Effect of the Methodological Choices on the Magnitude of the Signal

4.1. Normalizing the Area Changes by a Measure of Convection

In the absence of SST gradients, one expects convection to be distributed homogeneously over the tropical oceans and the amount of convection to be determined by the free troposphere energy balance. In reality SST is not homogeneous and SST gradients can pattern convection by providing low-level convergence [Lindzen and Nigam, 1987]. In studying variations in the amount of detrained clouds with respect to SST (regardless of the gradients), one must first remove the dependence of the convergence (and therefore the dependence of the amount of convective activity) on the underlying SST gradients. Lindzen et al. [2001] illustrated this point by focusing on cloud variations in only one hemisphere, where the relation between cloud area and SST is overwhelmingly controlled by the migration of the ITCZ. After applying a normalization, the tropical and hemispheric results showed a very similar variation with SST.

Su et al. [2008] use the 1 day average precipitation over the tropical region as a normalization measure; their

<table>
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<th>τ (days)</th>
<th>1</th>
<th>2</th>
<th>5</th>
<th>10</th>
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<th>30</th>
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<tr>
<td>Gridded (%/K)</td>
<td>−6.7</td>
<td>−7.4</td>
<td>−11</td>
<td>−14</td>
<td>−15</td>
<td>−19</td>
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<tr>
<td>Binned (%/K)</td>
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<td>−22</td>
<td>−26</td>
<td>−26</td>
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The regressions are robust nonlinear least squares fit of an exponential as shown in Figure 1.

Figure 2. Scatterplot of mean cloud fraction and cloud weighted SST, using TRMM VIRS brightness temperature and TMI precipitation data. The curves are nonlinear least squares fits of a decreasing exponential for each of the corresponding variables. For the blue dots, cloud fraction is defined using all pixels colder than 260 K. For the black dots the area is defined as the pixels between 220 K and 260 K. (a) Normalized and (b) nonnormalized cloud fractions. The plots are for the 15°S–15°N region in the tropics.
own criticism of their methodology is focused on the fact that the cirrus coverage is not proportional to the normalization measure. They state that “Normalization would work only if cirrus anvil coverage were proportional to cumulus coverage.” We notice first that the relation between cirrus anvil and cumulus coverage does not need to be linear or have a zero intercept. Second, and more important, is that given the small 1 day period there is no guarantee that the tropically averaged precipitation is in fact connected to the upper level cloud produced as a consequence of the convection (a point we will discuss in more detail in the next subsection). We have not quantified the effect of choosing the tropical average precipitation as a normalization variable explicitly. Nevertheless, we agree with Su et al. [2008] that there is no guarantee that the normalized results will provide a reliable quantitative climate effect (it also applies to the results we presented in section 3), but we point out that not normalizing the cloud variations by a measure of convection will surely provide a wrong answer.

4.2. Sampling in Time and Space

[10] Besides a physical reason behind the apparent disconnect between precipitation and cloud there is also a sampling issue. At the scale of each $1^\circ \times 1^\circ$ grid, the twice-daily observation provided by the Aqua satellite is inadequate to capture the evolution of a mesoscale convective system.

[11] A mesoscale convective system over the oceanic Kwajalein region will serve to illustrate this point (Figure 3). The Kwajalein radar covers a mostly oceanic region which is about the same size as a $2.5^\circ \times 2.5^\circ$ grid. The reflectivity measured by the Kwajalein radar is converted to rainfall rate and each rainy pixel is classified into convective and stratiform [Steiner et al., 1995; Yuter and Houze, 1997; Houze et al., 2004]. The sequence in Figure 3 depicts a period of 48 h, and each plot corresponds to a snapshot taken from the radar data every 3 h (the actual time resolution of the radar is about 10 min and all data were used to produce the curve in Figure 3a). Three different stages similar to the ones described by Houze [1993] can be distinguished from Figure 3a. In the formative stage from 0 to about 12 h, strong radar echoes (corresponding to individual convective updrafts) are scattered around the radar area and have little structure; most of the precipitation falls from these convective updrafts. As enough condensate is detrained from the top of the convective updrafts, a common stratiform region can be sustained and the system develops a structure with an identifiable line of storms and a trailing stratiform region (12–24 h). Finally, after 24 h, both the weakening of the convective activity and the propagation of the active line of storms outside the region covered by the radar are evident. Most of the precipitation at this stage is stratiform.

[12] Although we show the evolution of the system in terms of area of stratiform and convective precipitation rather than detrainment and convective cloud, the following arguments can be equally applied to the relation between the convective clouds and the nonprecipitating parts of the anvil cloud. For a given instant in time, the fraction of convective precipitation to the total precipitation can vary widely (as it is the case with the variation of any measure of detrainment area normalized by convective activity; see Figure 3c). Therefore the snapshot values are of little interest for quantifying an SST dependence, as it is almost guaranteed that any possible value will be observed at some instant over the life cycle of the storm.
Nevertheless, individual snapshot observations were used by Rapp et al. [2005] to study the normalized area variations with SST. Su et al. [2008] cite this study as consistent with their own results. The interpretation of the lack of signal in the study of Rapp et al. [2005] is problematic due to the large scatter that arises from correlating the snapshot values with local SST. We must note however, that the increase in scatter does not automatically prevent one from finding a signal. Our own approach to these difficulties is not free from limitations either; the binning of all samples at the same SST regardless of the spatial location and the integration over a period encompassing enough samples both require us to combine the properties of different mesoscale convective systems to compensate for the sampling error. Moreover, choosing the right integration period in the gridded analysis is a compromise between reducing the sampling error and keeping a dynamical connection between convection and average SST at the convective scale.

By adjusting the integration time of the gridded data analysis, we can indirectly quantify the impact of the sampling error in the correlations (at least in our own analysis). We find that the signal is about $-7\%$/K for integration times of 2 days (which for TRMM contains only about 2 snapshots of the size of Kwajalein) and increases in strength close to $-14\%$/K after an integration period of about 10 days (see Table 1). One could still entertain the possibility that the decrease in slope is a real dynamical effect rather than the effect of the sampling (for instance a cloud shading effect on SST, as suggested by one anonymous reviewer). Two pieces of evidence argue against a dynamical effect. First, when the data are binned, even the 1 day gridded data exhibit a relatively large slope. In other words, when the sampling error is increasingly canceled, one recovers the original magnitude of the signal. Second, when using the relatively high temporal sampling of the Kwajalein radar data set, the slope of the cloud cover variation with temperature is only weakly dependent on the integration time [Rondanelli and Lindzen, 2008].

Nevertheless, we further investigated the effect of sampling by analyzing a year of geostationary data over the tropical western Pacific. Consistent with this behavior, the decrease in slope is a real dynamical effect rather than the effect of the sampling (for instance a cloud shading effect on SST, as suggested by one anonymous reviewer). Two pieces of evidence argue against a dynamical effect. First, when the data are binned, even the 1 day gridded data exhibit a relatively large slope. In other words, when the sampling error is increasingly canceled, one recovers the original magnitude of the signal. Second, when using the relatively high temporal sampling of the Kwajalein radar data set, the slope of the cloud cover variation with temperature is only weakly dependent on the integration time [Rondanelli and Lindzen, 2008].

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However, when interpreting the anvil cloud normalized by the area of deep convection using a Lagrangian framework, benefiting from the sampling of geostationary satellites and using brightness temperature thresholds to define the cloud categories. From their plots (in particular their Figure 11a) one can estimate a decrease in the relative area of cirrus (defined using temperature thresholds) of about $-17\%$/K between what they define as the cold and medium categories, and of about $-5\%$/K between the medium and warm categories. These estimates are roughly consistent with the results shown here and also with work by Lindzen et al. [2001] and indicate a significant reduction of the anvil area normalized by convection with SST. Nevertheless, the lower bound estimate of the slope from the Horváth and Soden [2008] data is not very different from the Su et al. [2008] tropical-wide estimate. These two results might be reconciled by a simple change in the definition of the area of the cirrus anvil, as we will see in section 4.3.

Defining the Area of the Anvil Cloud

Since the area of active convective cores is small compared to the area of the anvil, correlations are expected to be largely insensitive to whether or not convective cores are separated from the anvil when considering the area variations. For instance, for the linear correlations between the stratiform area in Kwajalein reported by Rondanelli and Lindzen [2008], the magnitude of the slopes decreases from $-26\%$/K to about $-22\%$/K when convective cores are included in the anvil region (and a similar small effect is shown by Lindzen et al. [2001]). We see in Figure 2b that both the area of anvil and the area of anvil including convective cores decrease with cloud weighted SST for the whole tropics but the area of anvil decreases more rapidly with temperature. Consistent with this behavior, the normalized value of the area in Figure 2b decreases at a larger rate of $-10\%$/K.

Tropical-Wide Quantification of a Local Convective-Scale Effect

An additional difficulty arises when one uses the whole tropics (or a region much larger than the scale of a single mesoscale convective system) as a test bed for the variations in the high cloud cover that occur at the local convective scale. The cloud-weighted SST (or any other averaging procedure) acts to filter the local signal. To be sure, this effect is not substantial, but reduces the magnitude of the signal, and we have estimated it quantitatively using synthetic data. We first draw independent values of SST from a normal distribution with a mean of 27°C and standard deviation 1.6°C (similar to current climate values for the region between 15°S and 15°N. SST values are independent from each other so we assume no spatial correlation). We then assume an exponential dependence between the normalized cloud fraction and the local SST with a specified rate of change, so that each synthetic SST value corresponds to a normalized cloud fraction. (Notice that for the purpose of estimating the effect of the averaging alone, we are assuming that this exponential relation is satisfied perfectly at the local scale and therefore we are neglecting the sampling error that we discussed in section 4.2.) Then we calculate the cloud weighted SST to find the relation between the tropical cloud coverage and the tropical cloud weighted SST. For the case of an exponential dependence with a rate of change of $-28\%$/K, such as the one shown in Figure 1 for the binned data, one...
reverses a relation between cloud weighted SST and averaged normalized cloud fraction that has a rate of change of about $-22.5\%/K$. For a local $-22\%/K$ rate of change, as deduced now from the gridded data, one obtains a global rate of change of $-19.5\%/K$. (These particular numbers are not sensitive to the size of the sample.) The effect of the averaging in the strength of the tropical-wide signal is proportional to the magnitude of the local signal.

5. Concluding Remarks

[19] We have analyzed the discrepancy between the estimates of Su et al. [2008] and Lindzen et al. [2001] for the variation of the normalized upper level cloud area with SST. To some extent, we have replicated the results of Su et al. [2008], although finding a larger effect than the one reported by Su et al. [2008]. Contributions from the separation of deep convective clouds and anvil, and the effect of the cloud weighted SST seem to explain only a few percent of the discrepancy. On the other hand, we find that the slope of the regressions is sensitive to the integration time in the gridded analysis. If this sensitivity is due to the cancellation of the sampling error, it would suggest that the small negative dependence between upper level cloud area and SST found by Su et al. [2008] could be reconciled with larger values by simply increasing the sampling size at the grid scale, and therefore reducing possible biases associated to the coarse sampling. We quantify one of such biases using geostationary satellite data. The analyses in this comment provide additional confirmation for the decrease in area normalized by convection with SST as documented originally by Lindzen et al. [2001]. The relevance of these cloud variations with SST to a negative climate feedback depend critically on several issues that deserve further observational study, namely, the radiative properties of the cirrus clouds, the correct attribution of these cirrus clouds to their original convective activity and the quantification of relative magnitude of the change of precipitation (or convective activity) in a different climate. Regarding the relevance of this analysis to the climate feedback problem, we agree with Su et al. [2010] about the uncertainty of the quantitative results using the normalization in the context of the gridded analysis. However, the existence of a nonzero intercept between precipitation and cloud fraction does not invalidate the use of normalization. In fact, the nonzero intercept arises from our inability to distinguish high clouds that occur either independently from deep convection (which should not be included in the analysis) or that are incorrectly attributed to deep convection at the grid scale (this is why Su et al. [2010] observe about 40% cloud fraction associated with no precipitation in their Figure 2c).

A Lagrangian methodology [e.g., Horváth and Soden, 2008] holds promise for providing a more accurate attribution of high cloud to deep convective source and therefore providing a more accurate estimation of the cloud changes relevant to the climate feedback problem.

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References


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