To begin, the authors would like to thank the reviewer for their time, attention to detail, and thoughtful insights on the paper and research. Each comment will be addressed point by point.

General Comments

However, I am not really sure what new it brings to the table in addition to the usual procedure of generating T/RH composites about high rain events, and I think the paper oversells how useful this technique is likely to be in the future. For example, from work by Kiladis and others, we already know a lot about the temperature and wind anomalies associated with different types of convectively coupled waves in the tropics. This type of procedure, in which we project anomalies on to the types of physically known propagating 3D convectively coupled waves seems more insightful than the 1D PCA done here, in which there is no attempt to physically separate any of the myriad of influences on a particular profile.

Looking at a 1D-representation is useful because interpretation is uncluttered, which can illuminate confounding signals and relationships. Attempting to model 3D meteorological processes is extremely difficult and the results are not always straightforward due to model error and fundamental gaps in our process-level knowledge. This project is an attempt to take a step backward and ask / answer fundamental questions about the variability of thermodynamics in the MC region: Do we know which layers of the atmosphere are the most variable? How can we quantify this variability? How do perturbations to one of these layers affect adjacent and non-adjacent layers? Which thermodynamic states are most often observed? Analysis of the response of various modes of tropical convection to changes in the environment is only possible after we sufficiently understand the answers to these elementary questions (or represent them quantitatively).

This relatively simple approach uses PCA, which is not to be confused with a factor analysis. The two methods are not synonymous techniques and have unique motivations for their respective applications. PCA seeks to identify where variability occurs and remove data redundancies to reduce dimensionality. PCA has no prior assumptions about the underlying causes of the identified variability, which can be both a strength and a weakness. Conversely, factor analysis aims to attribute the known system variability to a set of predefined processes and influences. A factor analysis performed on variable layers identified from the PCA would be an interesting project, but it is outside the scope of this study.

We employed the PCA approach because it is easily implemented, the outcome is straightforward and intuitive, and it is based on observations rather than modeled output. The results can be used in several ways from both a data analysis point of view, such as expanding into a factor analysis, or from a modeling perspective. The observational RCs can be used to test whether models have accurately represented variability in the system or as initialization / boundary conditions in ensemble-based modeling techniques.

Specific Comments

(1) Section 4.1. The justification for the physical interpretations to which the various RC's are assigned is often unclear. For example, "shallow convective heating is represented in RC4".

Interpretation of the PCs / RCs is admittedly subjective. When the physical attribution was not obvious, we relied on Figure 9 as a starting point. A motivation behind this project was to rely on a statistical framework to identify variable layers, rather than preconceived ideas. Fortunately, by comparing the RCs to the time series in Figure 9 we see that oftentimes our intuition about which layers might be variable (e.g. that the melting layer, top of boundary layer, and the tropopause transition would all be good candidates for regions with significant thermodynamic variability) are also identified by the PCA. While to first order, our eyes could distinguish these layers from Figure 9, we now have a robust mathematical representation of their location and magnitude and an understanding of how variability in one layer correlates with variability in surrounding levels. The last point is the most problematic when approaching this problem from a non-statistical framework. We could infer the relationships or attempt to model them, but the signal is already present in existing observations and can be captured through the PCA algorithm.

Depending on the application of the PCs / RCs, precise physical interpretation may or may not be necessary. From a modeling perspective, whether the interpretation exists or not the information on variability is retained and can be used to initialize or compare simulations. Conversely, from a data analysis perspective, it is important that the interpretation is correct. Overall, the physical attribution has to answer two questions "where would variability in this layer originate from on a basic level, and on what time scales is it acting or being modified?"

But do we really know what kinds of temperature anomalies are likely to be associated with shallow convective heating? For example, if shallow convective clouds occur more frequently (e.g. are triggered) by the moistening and cooling associated with low level upward motion (likely, especially in the vicinity of deep convection), then perhaps shallow clouds are correlated with low level cold anomalies, and any positive correlation between shallow convection with positive RH should not be interpreted as a consequence of detrainment moistening, but some external dynamically imposed influence.

The variability associated with what we infer to be the action of shallow clouds (RH5 and T4) is captured exactly as described here. The shallow convective heating peaks at 700 hPa and has an associated cooling below 850 hPa. As stated, we can infer that the shallow clouds are correlated with low-level cold anomalies. This is also apparent in Figure 9, where *warm temperature anomalies near 700 hPa sit atop cold anomalies, and vice versa. This could be the result of cooling via ascent, evaporative cooling, and / or radiative effects.*

For example, even the net effect of precipitating shallow convection on the RH of a particular level is unclear. It is a residual of the drying associated with induced descent, moistening from detrainment and evaporative moistening, and then a slower dynamical response driven by the geopotential anomalies associated with the convective heating.

In most cases, this method does not allow ascription of the individual forcing or combination of environmental factors that go on to produce the observed variability. This sort of attribution would require an in-depth synoptic and mesoscale analysis for every observation in the dataset. While the source may be dynamic, the result is still going to manifest in the thermodynamic signature in predictable ways. Naturally, many different dynamical and / or microphysical processes could go on to produce the same thermodynamic signature, but this sort of factor analysis will have to be part of a future study.

Furthermore, in this more basic framework we can only focus on correlations between layers for one variable at a time. At this point the method is limited in that we cannot relate the thermodynamic variables to each other. Correlations between the thermodynamic variables will also have to be explored in future work.

More generally, causality between T, RH, u, v anomalies in the background atmosphere and convective clouds always goes both ways. There can't be a simple one to one relationships between certain types of T/RH anomalies and certain cloud types or heating profiles, as implied here. (Otherwise it seems to me that convectively coupled waves in the tropics could not exist.)

The tropical wave cycle is ideal for a PC analysis. The PCA results in both a positive and a negative mode for each PC (Figure 7), which would be required to describe convectively coupled waves. For simplicity, only the positive mode was displayed in Figures 8 and 10, although the opposite mode is also valid. Thus, for a convective disturbance (say a positive RH mode), there would be an associated negative RH mode preceding and following the wave.

(2) Similarly, sometimes the RC's for U and V are assigned physical interpretations and again the justification is unclear. E.g. "The overwhelmingly dominant signal in the V-component of wind is the seasonal monsoon. The MC monsoon is characterized by a complete reversal ...". I guess it is not clear to me here what exactly is meant by "monsoon" in a region of such complicated topography, or why it must have these impacts on U and V. For example, the three radiosonde locations are at quite different locations in the Marine Continent, so the dynamical signature of the monsoon must vary between locations, but the RC's of the three locations are the same almost (except for ordering).

This is noted in point 4 of the conclusion. Should the "monsoon" have the same dynamical signature in all three locations? Perhaps give some explanation of what is really meant by "monsoon". It seems that the authors have simply defined a particular RC as a monsoon signature, and then remarked that this RC is the same at all three locations, and then say the monsoonal signature is the same at all three stations. Everything proceeds from the initial categorization. But is this really more than a semantic game? Do you really know for certain what types of large scale dynamical motions are associated with a particular RC? How would you prove this? I realize there is some discussion of this in lines 13-14 of Section 4.1, but this wasn't fully convincing to me.

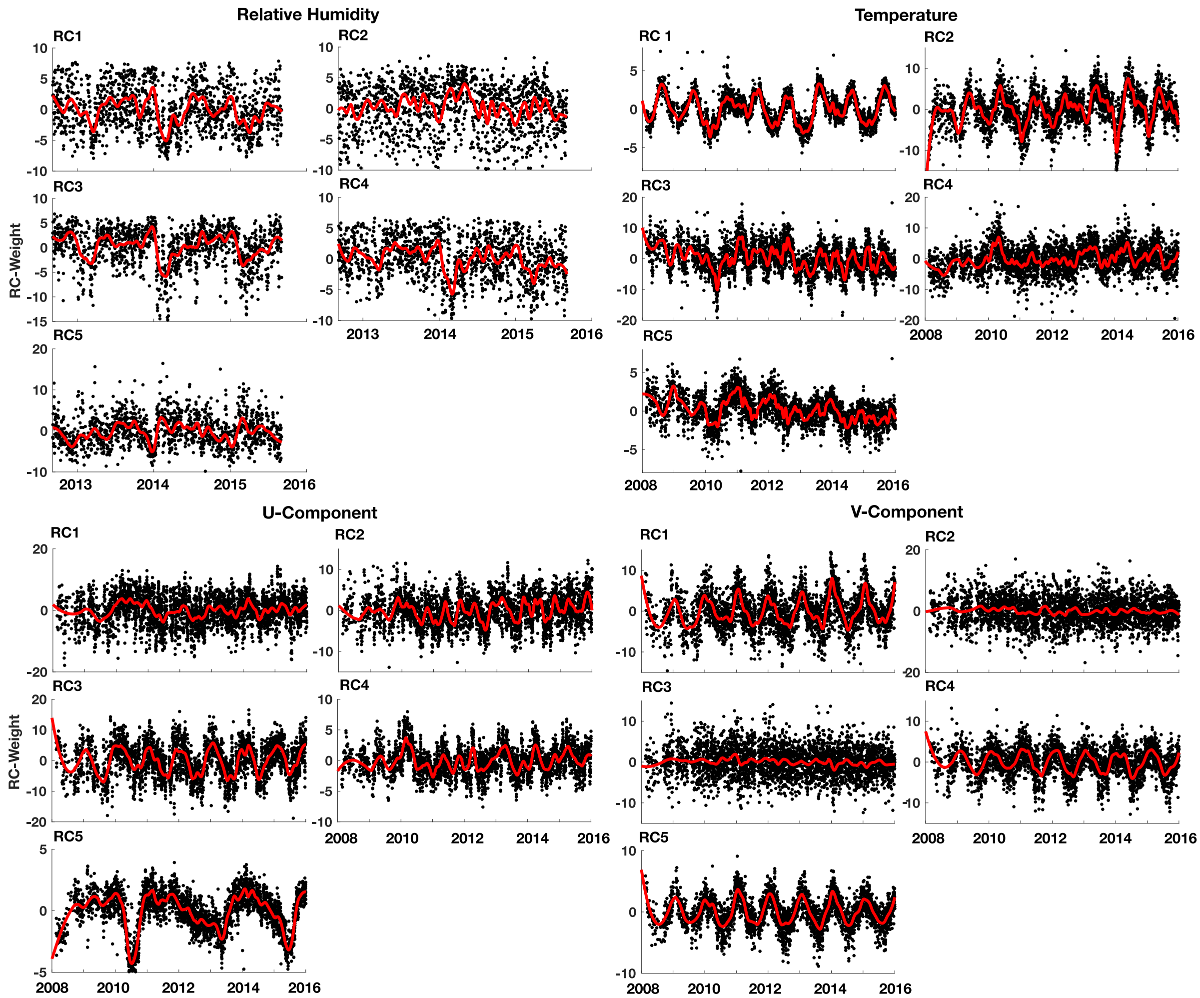
The temporal signature of variability is generally lost during PCA. However, some structure of this remains in the RC-weight time series (Supplementary Figure 1). Looking at the figure, for almost all of the RCs, the seasonal monsoon is the dominant cyclical signal. The three sites in the study are all in the South China Sea, so it is possible that at different sites the monsoon signal would be stronger, weaker, or non-existent. The sites may feel the influence of the monsoon at different times, but because the RCs in themselves are non-temporal, the physical wind reversal is all that can be captured.

Because this analysis is on a short-climatology timescale, individual dynamical motions are not the desired result. The much higher resolution time scales would be a perfect project for modelers, or would require a much more in-depth data and meteorological examination than is possible here. This is only a first step in a much larger and more complicated problem. But looking at variability in a lower dimensional subspace allows researchers to ignore system noise (the individual dynamic motions) and categorize specific modes of variability.

(3) Figure 9. I found this hard to interpret. Especially there was so much variability in the top 4 panels, that the features discussed in the text were not clear to me.

The figure has been updated to remove black spaces and has been interpolated for short time scales (< 5 days of missing data points in a row). Signals are now more apparent in the variability and matching the RCs to the panels in Figure 9 is now more intuitive.

Supplementary Figures



Supplementary Figure 1) Rotated component weight time series. RC-weights (black dots) are accompanied by a best fit line (red) to highlight their cyclic nature. The best fit line was calculated with a weighted linear least squares method combined with a 2nd degree polynomial local regression with a span no larger than 5%. In almost all of the RCs, the dominant signal is the seasonal / monsoon cycle.