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Atmospheric Chemistry and Physics Discussions

Interactive comment on "Cluster analysis of midlatitude oceanic cloud regimes – Part 1: Mean cloud and meteorological properties" *by* N. D. Gordon and J. R. Norris

N. D. Gordon and J. R. Norris

n.gordon@leeds.ac.uk

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Response to Anonymous Referee No.1 SpeciïňĄc Comments

Regarding the choice of NCEP Reanalysis over ECMWF, a lot of the discrepancies mentioned in the papers cited by the reviewer are related to the polar regions and to reanalysis time periods prior to the advent of satellite observations, neither of which apply to our work. We note that Trenberth and Guillemot (1998) show good agreement between both NCEP and ECMWF reanalyses and satellite-derived precipitable water vapor for midlatitude regions. Trenberth et al (2005) show very little difference between NCEP and ERA-40 in midlatitudes, with the exception that NCEP is slightly moister in

the southern midlatitudes. Bromwich and Fogt (2004) show good correlation between reanalyses in the modern satellite era. The more important point when analyzing the effectiveness of reanalysis-derived meteorology for our research is the connection to the cloud properties. Norris and Weaver (2001) found negligible differences between statistical cloud relationships when using NCEP and ECMWF Reanalyses (see Figs. 1 and 2 from that paper). We have added a line of text mentioning this last point.

The deïňĄciencies of the Zhang et al. 2004 radiative ïňĆuxes discussed in Trenberth et al. (2009) are primarily systematic biases that affect climatological values and long-term trends. In fact, Trenberth et al. note that the ISCCP FD has the most realistic representation of cloud radiative effects among all datasets. While it is apparent that deficiencies in the ISCCP-derived cloud and radiation products exist, the largest errors shouldn't affect our results. The random uncertainties of instantaneous values are substantially reduced by averaging over many days in the composites, and we do not expect that there will be much systematic bias with respect to various cloud conditions. Zhang et al (2007) show that the largest source of uncertainty in the longwave flux calculation is in the determination of surface skin temperature, and suggest that the uncertainty in surface air temperature of 2-3K leads to an uncertainty in surface net longwave flux of about 10-15 W/mˆ2. We find in our study that the satellite-derived surface skin temperature tends to exceed NCEP Reanalysis surface temperature by about 2K (also found by Tsuang et al., 2008). We attempt to minimize the effect that large errors in surface temperature will have on our results by eliminating observations where the difference between satellite skin temperature and reanalysis surface temperature exceeded +8K or was less than -4K. We have added text discussing potential deficiencies.

Vertical motion is better constrained over midlatitudes because it is closely connected via quasi-geostrophic relationships to large-scale temperature and horizontal winds that are observed by satellite and radiosondes. As demonstrated by Norris and Weaver (2001), there is no difference among various reanalyses for statistical relationships between cloud properties and vertical motion. We have added text describing this.

With regard to the independence of the histogram bins, there is clearly potential anti-correlation between bins. If the 80% of the pixels at a given time are located in one CTP-tau bin, then the most that any other bin can be is 20%. I have attached a plot of the relative correlation between cloud types. The two-letter names refer to the ISCCP classification of each of the 9 CTP-tau bins. As you can see, there are cloud types that are negatively correlated, but there are also types that tend to occur coincidently. In particular, there tends to be a positive correlation between bins that are adjacent in optical thickness category and/or cloud top pressure category. In our previous paper (Gordon et al, 2005), we use three parameters as input to the clustering algorithm: grid-box mean cloud fraction, cloud-top pressure, and reflectivity. We get very similar results whether using a 9-dimensional histogram array or 3 variables.

Regarding the choice of number of clusters, this is an important step in the process. Other studies (Williams and Tselioudis 2007) use an automated routine to choose the number of clusters. Starting from k=2, you run the clustering algorithm and calculate the maximum correlation between two cluster centroids for increasing values of k. Eventually, two centroids are highly correlated (correlation coefficient greater than 0.9) for some value of k=n. The proper value of k is then n-1. Another metric for determining the correct number of clusters is to look at the total variance around the cluster centroids as a function of the value of K. By construction, this is a monotonically declining function of K, but by finding points where there is minimal relative decrease in total variance for an increase in number of clusters analyzed one can detect a 'correct' number of clusters. Both of these techniques do not utilize the additional information that the reanalysis provides to aid in our understanding of the cloud regimes. We did both of these calculations and the latter indicated that 6 clusters were best while the former suggested 7 were ideal. We have clarified the text to state that additional clusters beyond 7 exhibited great similarity to one of the preceding clusters.

With regards to meteorological profiles, we subtracted the climatological mean from

each point before averaging, as there would be significant differences in the profiles based on the location and time of year that the observation was made, especially in temperature. While there may not be as large of a seasonal or spatial difference in other variables, we still feel that it is most illustrative to show profiles with the local mean removed.

We have also created plots with error bars corresponding to the 95% confidence interval on either side of the profiles. In nearly every instance, the error bounds were indistinguishable from the mean profile (due to the very large number of data points contributing to each cluster). We thus chose not to show the error bars, but we now mention the above reason in the text.

The purpose of figure 7 is to check that the cloud regimes that we find in our analysis fit into a larger picture of the midlatitude synoptic wave. Similar to Lau and Crane (1995), who composited around points of high optical thickness, we find the frontal clouds preferentially oriented in a SW-NE fashion, with high thin clouds to the east, ahead of the front, and low clouds in the cold sector behind the front. We have produced these plots for all the other clusters, but they are much less interesting. For the low cloud clusters, the neighboring boxes are most likely to be the same cluster, or another type of low cloud.

The extent of the midlatitude domain is from 30 degrees to 55 degrees, so there is data poleward of 50 degrees. I have corrected the text of the manuscript to reflect that.

The white blips are a result that there are fewer data points as we move poleward in the equal-area version of the ISCCP data. I have regridded the data to eliminate these white blips.

With regards to the domain extent, we have done the clustering independently for each ocean basin and season, and we get very similar clusters, albeit with possibly different frequencies. So, I would not expect the clusters to be very different if there were small changes to the domain. The relative frequencies between the clusters may change if the domain was altered. We now mention this in the text.

Interactive comment on Atmos. Chem. Phys. Discuss., 10, 1559, 2010.

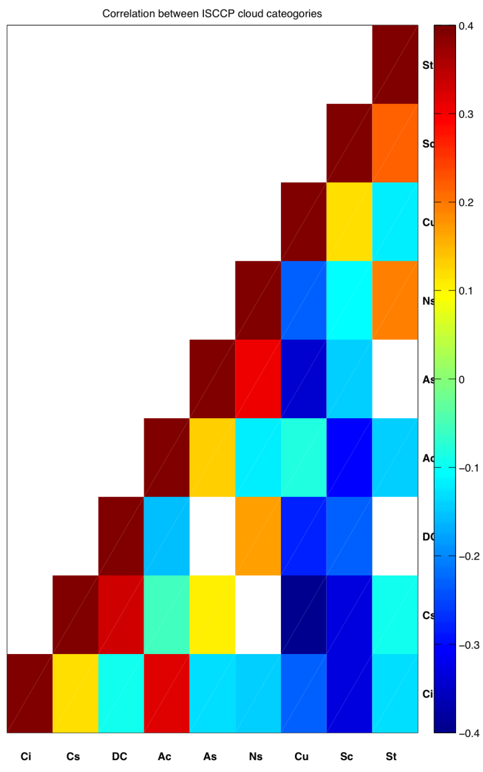

Fig. 1. Correlation between cloud types