A Comparison of ARM Cloud Radar Profiles with MMF Simulated Radar Profiles as a Function of the Large-Scale Atmospheric State

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Methodology: Analysis using Atmospheric Classification

- Use an atmospheric classification scheme based on large-scale fields that are predicted by global climate models and numerical weather prediction models to define a finite set of “weather types” or “regimes”.

- Aggregate ARM local-scale observations or retrievals as a function of the atmospheric state, where the atmospheric state is determined using numerical weather prediction “analyses” .

- Aggregate climate model output as a function of the same atmospheric states.

- Compare statistics of the observations with model output as a function of these atmospheric states.

- Of course, for this approach to work we need to find a set of atmospheric states which have statistically-temporally stable properties.

- The idea of weather regimes is not a new one but has been used extensively in meteorology (Zivkovic and Louis 1992; Michelangeli et al. 1995). It has been used as a tool in evaluating global climate and weather models (Hewitson and Crane 1994, 1996; Tennant 2003) including cloud properties (Jakob et al. 2003, 2004).

Why use an Atmospheric Classification ?

- **Global Climate Models (GCMs) predict climate not weather.**
  - Whereas a Numerical Weather Prediction (NWP) model predicts specific weather events, GCMs predict climate. Thus, one cannot simply ask if the GCM predicts the same cloud field on August 10th as is observed at that time. Rather, one must aggregate the observations over some period of time and analyze to what degree the predicted distribution matches the observed distribution. <u>When a difference is observed between observations and model output, it is difficult to determine the source of the problem (what physical processes or situations are not sufficiently represented by the model) or to determine a corrective action.</u>
  - The atmospheric classification provides a physical context from which to understand any differences between the model output and observations.
  - The atmospheric classification also separates differences (in total distribution) that are caused by having different weather regimes (or synoptic scale activity) rather than problems in the representation of clouds for a particular regime.

Why use a Multi-scale Modeling Framework?

- The MMF has several attractive features including:

  (1) The CRM permits explicit calculation of cloud-scale dynamics and its links to radiation and precipitation.

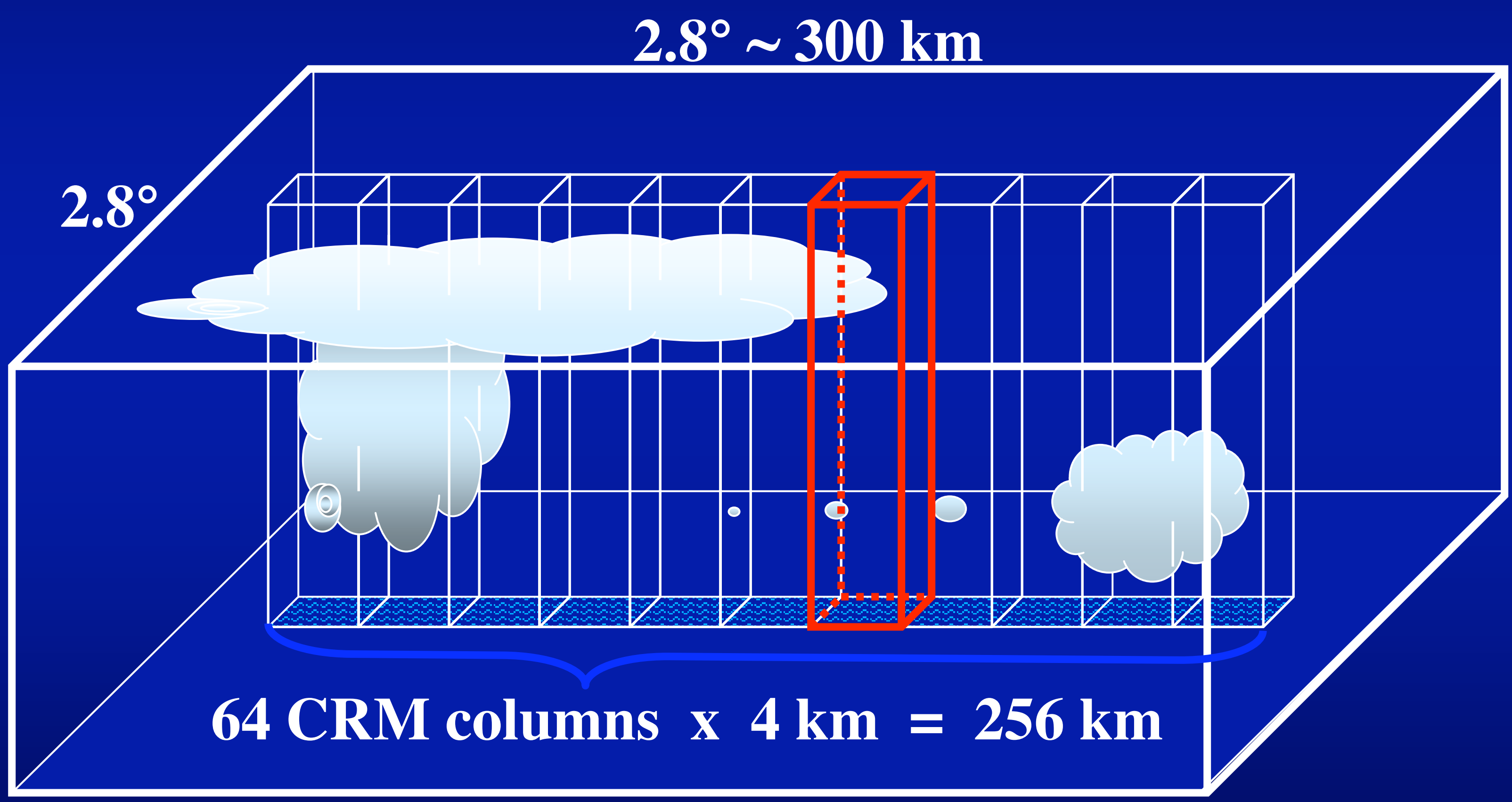
  (2) Comparison studies show that CRMs generally outperform GCM parameterizations when tested in single column models [Ghan et al., 2000; Xie et al., 2002; Bechtold et al., 2000; Gregory and Guichard, 2002].

  (3) The MMF provides an explicit framework for including aerosols and atmospheric chemistry in climate simulations, and could also be expanded to include other sub-GCM-grid-scale influences (e.g. topography or air-sea interactions).

  (4) It allows for comparison of model output with point observations without the need for assumptions about subgrid-scale cloud structure.

- There is a big downside to the MMF approach. Even using a relatively simple cloud resolving model, the baseline MMF we have used is about 200 times more computationally expensive than its parent parameterized model.

Depiction of MMF Approach:



In this study …

- We created an objective atmospheric classification for the SGP site.
  - Based on a competitive neural network.
  - Classifies the atmosphere into 1 of 25 possible states.
  - We trained the neural network using Rapid Update Cycle (RUC) analyses over a large domain surrounding the SGP site.
  - The result is a time series with one value (from 1 to 25) for each 3 hour period from April 1998 to June 2002.
  - Details on the approach are given in a recent JAS paper (Marchand et al. 2006).

- We applied the neural network classifier to output from the Multiscale Modeling Framework climate model.

- We aggregated ARM cloud radar data to obtain profiles of cloud occurrence for each atmospheric state, and did the same for the model output.
  - By profiles of cloud occurrence, we mean (at given altitude above ground level) the relative frequency that a cloud was detected by the radar.

- Finally, we compared the similarity of the profiles using a robust statistical difference test.

Results …

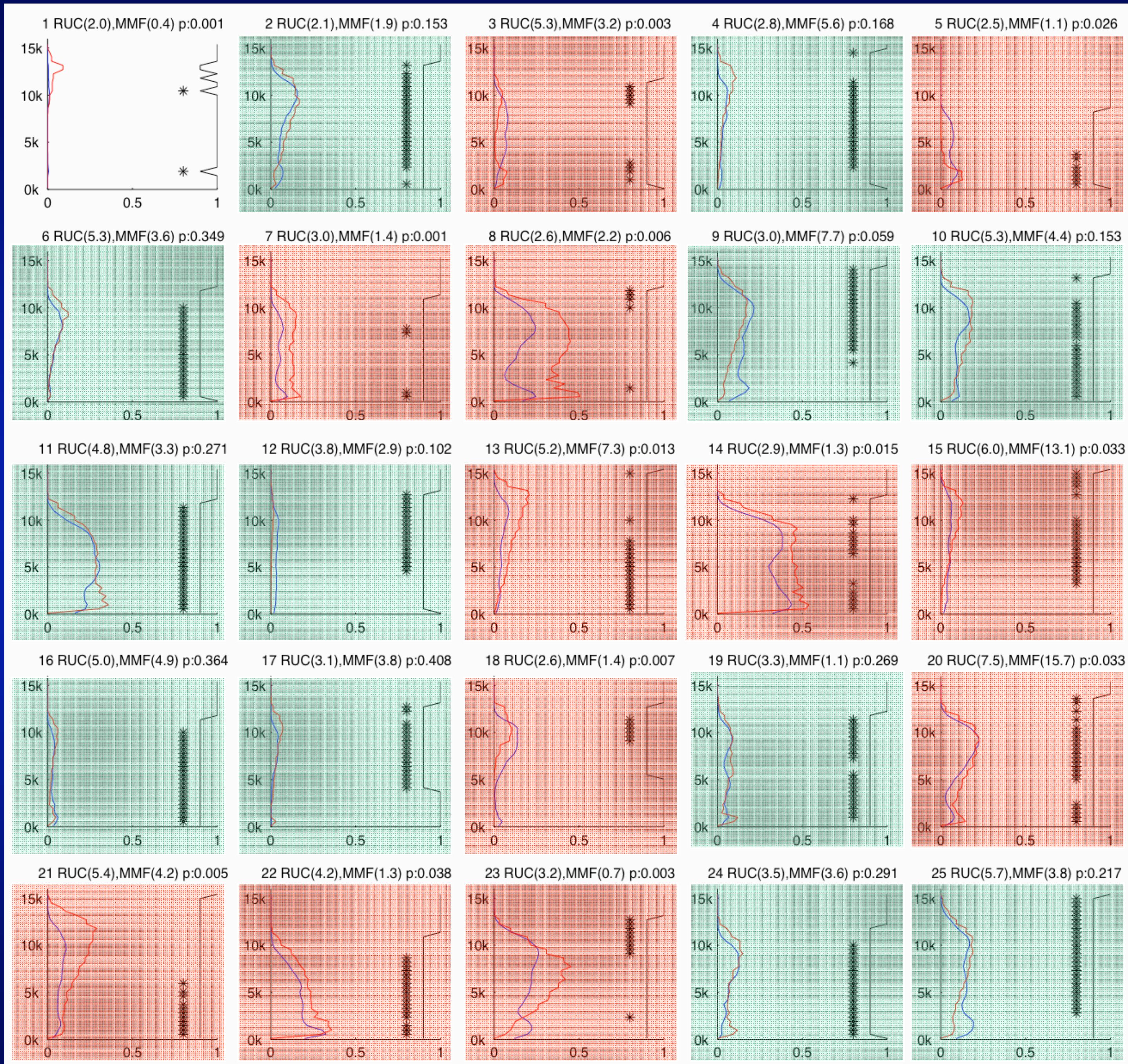
- The figure to the right shows 25 sub-plots, 1 panel for each of the 25 Atmospheric States.
- Each subplot compares the ARM/RUC cloud profile (blue line) and MMF cloud profile (red line).
- In some of atmospheric states the cloud profiles look quite different, while in others there are strong similarities. It is not always clear whether the differences are significant or whether they could be due to the finite length of the datasets examined. We therefore compared the similarity of the profiles using a robust statistical technique.
  - In the statistical analysis of atmospheric properties it is often desirable to compare sets of data taken from different sources, either from different times or locations, or to compare observational data with model output.
  - Many of the standard statistical tests of differences, for example the traditional t-test, assume that data points are independent of each other and that the underlying distribution of the sample is known.
  - These assumptions limit the applicability of such tests to remote-sensing observations from the atmosphere (such as the data examined here) where there are both strong spatial and temporal correlations in addition to unknown (and likely non-Gaussian) underlying distributions.
  - One can account for the spatial and temporal correlation in this analysis using a moving-blocks bootstrap resampling method.
  - A detailed description on how to apply the bootstrap approach to this dataset can be found in the recent JAS paper by Marchand et al. (2006).

Results (cont'd) …

- The result of the statistical comparison is a p-value or significance level.
  - The p-value is an estimate of the likelihood that the two-curves could be two realization drawn from the same underlying distribution.
  - A p-value less than 0.05 means there is less than 5% chance that the difference between the curves could be due to the finite size of the sample.
  - Therefore when the p-value is less than 0.05, we can say that the two radar profiles are different with a confidence of 95%.
  - The p-value obtained by comparing the RUC/ARM and MMF profiles is listed above each subplot.

- Those states where the statistical test indicates the two profiles are different at the 95% confidence level are shaded red.

- Those states where the statistical test indicates the two profiles are NOT different at the 95% confidence level are shaded green.

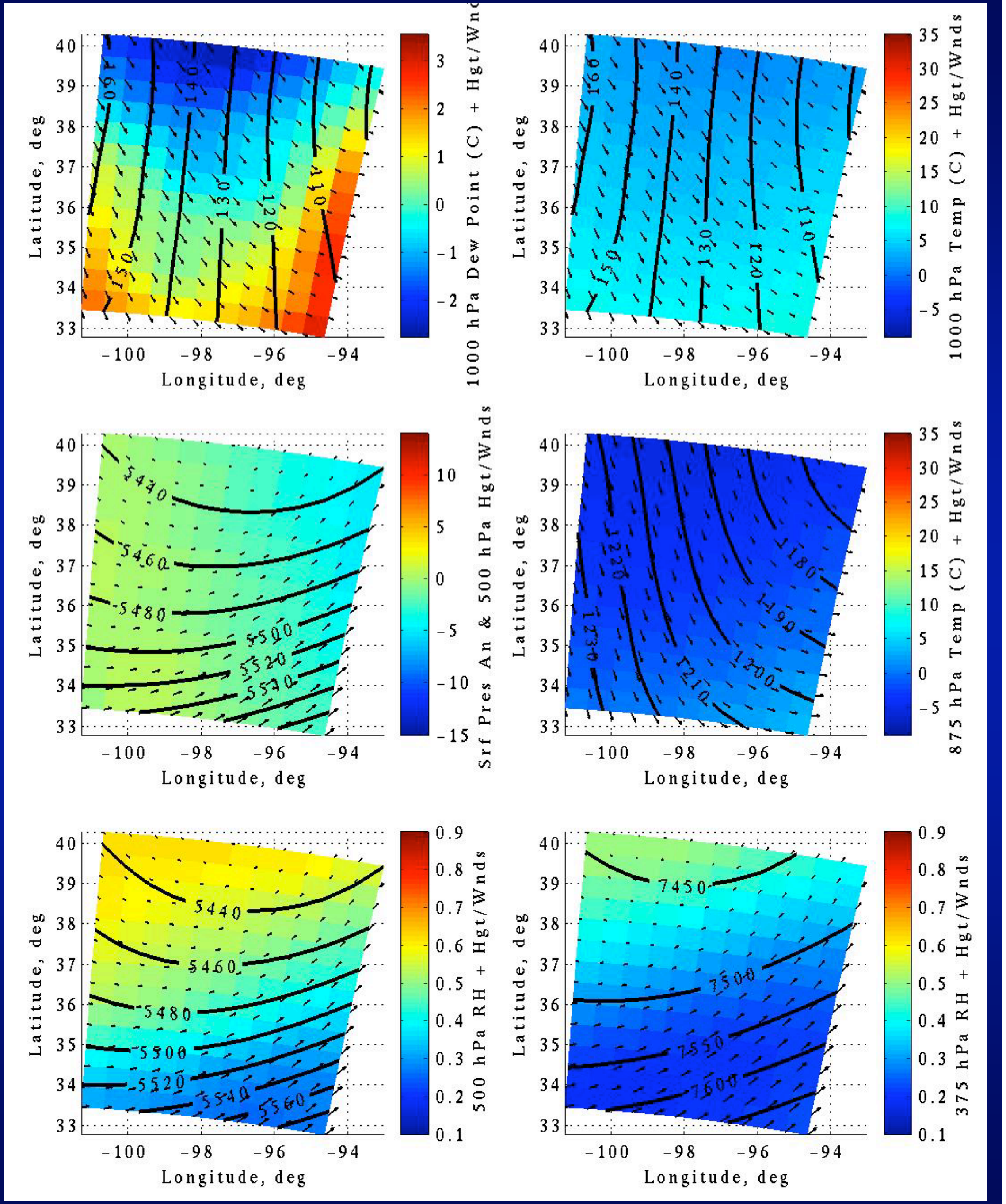


1 RUC(2.0),MMF(0.4) p:0.001
2 RUC(2.1),MMF(1.9) p:0.153
3 RUC(5.3),MMF(3.2) p:0.003
4 RUC(2.8),MMF(5.6) p:0.168
5 RUC(2.5),MMF(1.1) p:0.026
6 RUC(5.3),MMF(3.6) p:0.349
7 RUC(3.0),MMF(1.4) p:0.001
8 RUC(2.6),MMF(2.2) p:0.006
9 RUC(3.0),MMF(7.7) p:0.059
10 RUC(5.3),MMF(4.4) p:0.153
11 RUC(4.8),MMF(3.3) p:0.271
12 RUC(3.8),MMF(2.9) p:0.102
13 RUC(5.2),MMF(7.3) p:0.013
14 RUC(2.9),MMF(1.3) p:0.015
15 RUC(6.0),MMF(13.1) p:0.033
16 RUC(5.0),MMF(4.9) p:0.364
17 RUC(3.1),MMF(3.8) p:0.408
18 RUC(2.6),MMF(1.4) p:0.007
19 RUC(3.3),MMF(1.1) p:0.269
20 RUC(7.5),MMF(15.7) p:0.033
21 RUC(5.4),MMF(4.2) p:0.005
22 RUC(4.2),MMF(1.3) p:0.038
23 RUC(3.2),MMF(0.7) p:0.003
24 RUC(3.5),MMF(3.6) p:0.291
25 RUC(5.7),MMF(3.8) p:0.217
15k
10k
5k
0k
0
0.5
1

Each atmospheric state is defined by a set of meteorological fields as shown here.

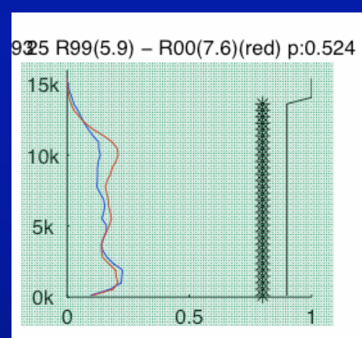
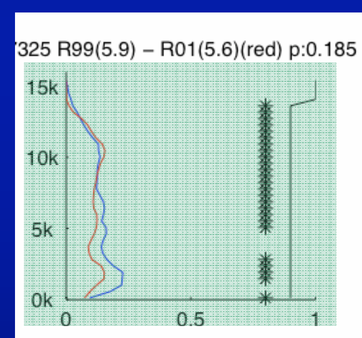
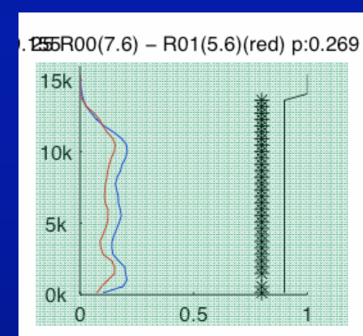
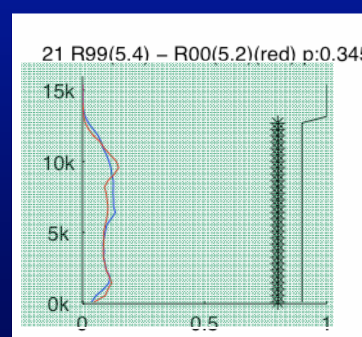
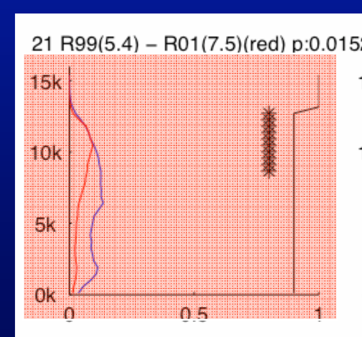
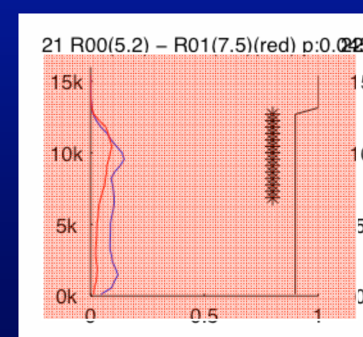
This particular state (state 22) features north-westerly surface winds and southwesterly flow at 500 and 375 hPa. Such flow patterns are typically after the passage of an equatorward-moving cold front.

This atmospheric state is associated with shallow post-frontal cloudiness (see cloud occurrence profile for atmospheric state 22).



Discussion – Temporal Stability

- For this analysis approach to work we need to find a set of atmospheric states which have statistically stable properties.
- We can measure the stability of the states by comparing the observational data from one year to the next, using the same statistical test that we used to compare the observations with model output.
- Most of the currently identified states show good stability, but some do not.
- We are working on an automated process to identify the unstable states and either divide the states into stable sets or to remove these states from consideration.

	1999/2000	1999/2001	2000/2001
State 25 ARM/RUC data shows good year to year stability			
State 21 ARM/RUC data shows marginal year to year stability			

Discussion / Future Directions

- Our result suggests that large-scale atmospheric fields of the type produced by NWP models and GCMs can be mapped in a stable and statistically meaningful way to (distributions of) local-scale observations of cloud properties - at least much of the time.

- We are working on an automated process to identify the unstable states and either divide the states into stable sets or to remove these states from further consideration.

- The results shown here demonstrate that the MMF model produces cloud occurrence profiles that sometime match and sometimes differ from ARM cloud radar observations depending on the atmospheric state.

- The goal of the next phase of this research project is to understand the cause of differences, where differences exists.

- As a first step, we plan to run the Cloud Resolving Model (CRM) which is embedded in the MMF using the atmospheric states to define the large scale fields to see if such “off-line” calculations will produce cloud profiles which match those generated in the global runs.