Classification as a Tool for Understanding Cloud Feedback?

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With substantial assistance from

Roger Marchand and Stuart Evans

References

- R. Marchand, N. Beagley, T. Ackerman, 2009: Evaluation of Hydrometeor Occurrence Profiles in the Multiscale Modeling Framework Climate Model Using Atmospheric Classification, J. Climate, 22, 4557
- R. Marchand, N. Beagley, S. Thompson, T. Ackerman, and D. M. Schultz, 2006: A bootstrap technique for testing the relationship between local-scale radar observations of cloud occurrence and large-scale atmospheric fields. J. Atmos. Sci., 63, 2813–2830.

Can we model cloud feedbacks?

- Yes, but …
- Parameterizations continue to be the largest uncertainty in global climate model simulations of climate change
- Scale coupling is a huge problem
- Is the multi-scale modeling framework (MMF; superparameterization) a way to get process physics into a GCM?
  - Could talk about that but will not today

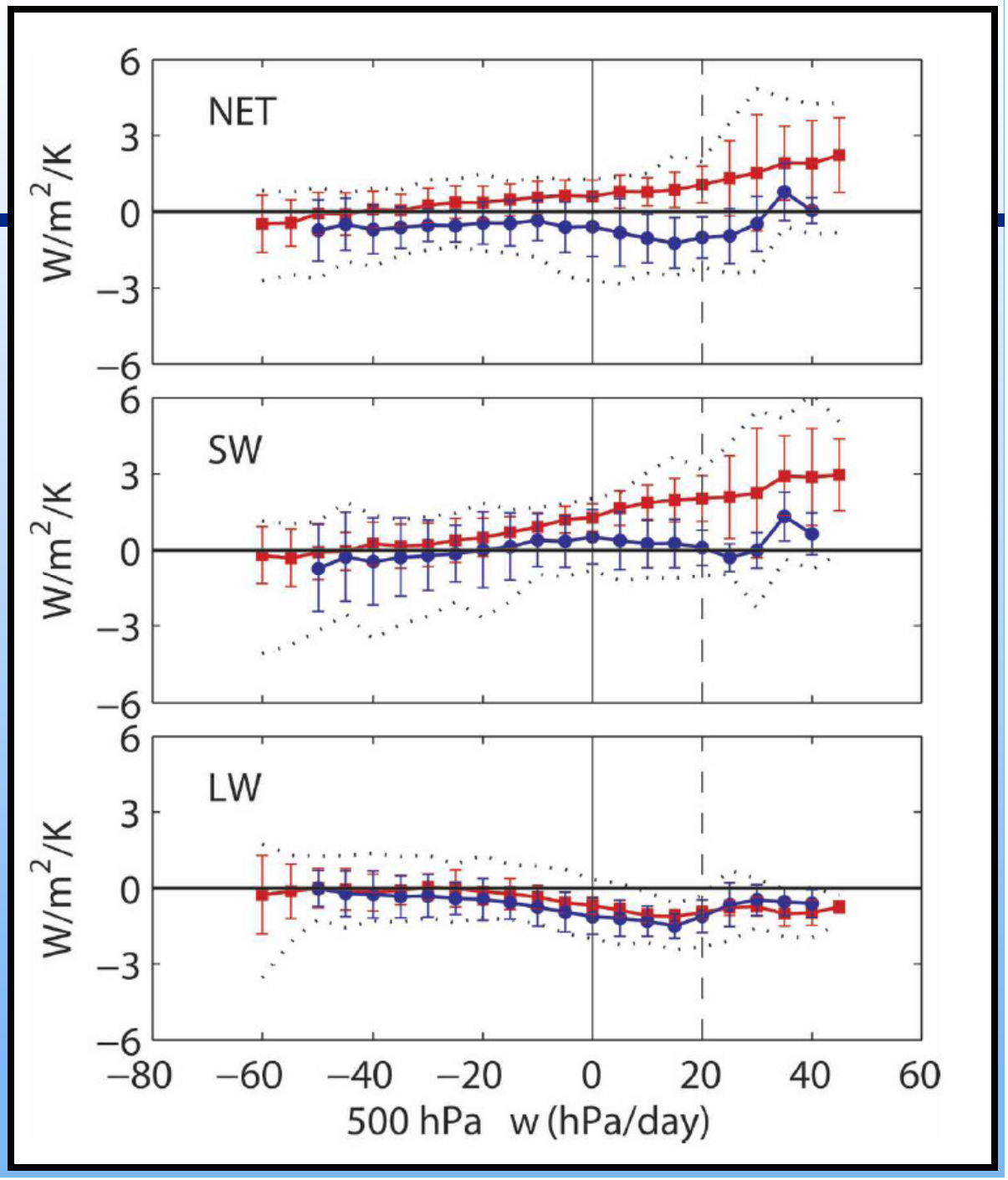
Can we measure cloud feedbacks?

- Maybe, but ….
- Current knowledge of cloud properties is uncertain because of the difficulty of measuring them, instrument differences, and lack of clarity in definition (cloud fraction?)
- EOS data really helping but data time series are likely to be discontinuous (MISR, MODIS, CloudSat, CALIPSO)
- How do we unscramble transient effects from long-term feedbacks? (regional vs. global; climate variability vs. change)

How about regime sorting?

- Popularized by Bony and DuFrense (2005)
  - Used vertical velocity (1-parameter)
  - Discussed this morning by Chris Bretherton
- Further regime sorting discussed by Joel Norris (2-parameter)

Sensitivity (in W /m2 /K) of the tropical (30°S–30°N) NET, SW, and LW CRF to SST changes associated with climate change derived from 15 coupled ocean–atmosphere GCMs . Negative values of w correspond to large-scale ascent and positive values to large-scale subsidence. [From Bony and Dufresne (2005)]



Regime sorting on the regional scale

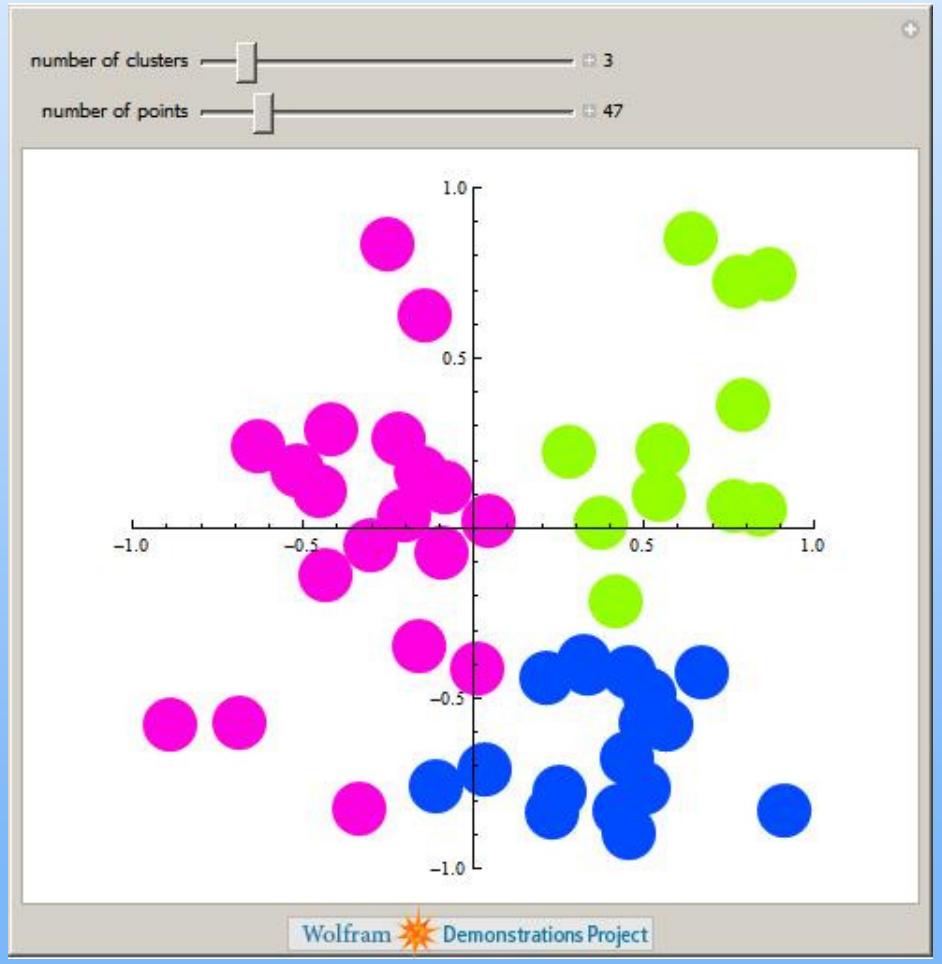
- Starting thinking about this some time ago
- Motivated by ARM data => Time series statistics of cloud properties measured by ARM at a single site (SGP) are different from statistics predicted by a model
- Why?
  - Cloud parameterization is wrong
  - Dynamical patterns are wrong (parameterization forcing is wrong)
  - How can we tell the difference?

Solution?

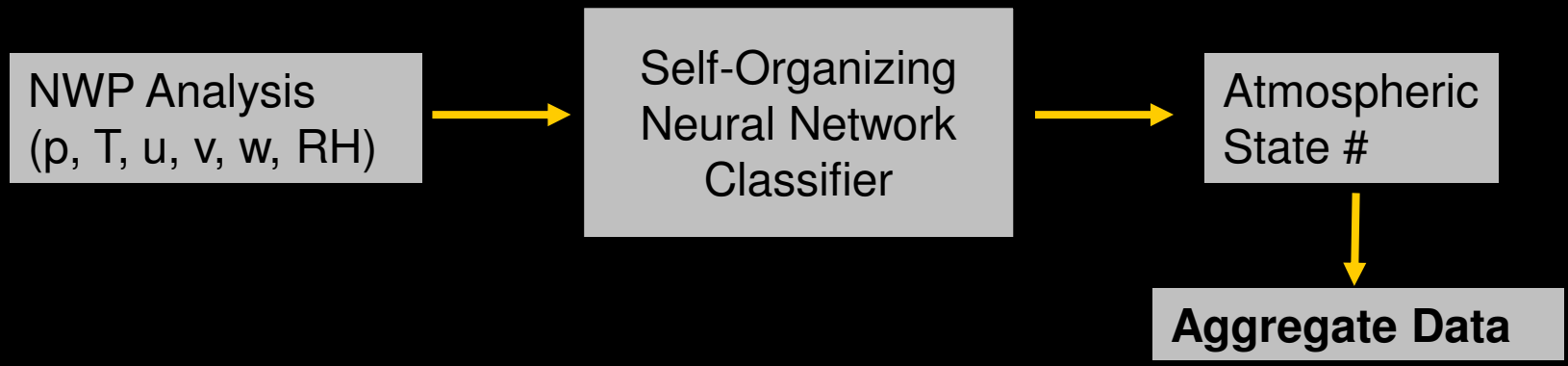
- Sort atmosphere into dynamical regimes or states using NWP re-analysis fields
- Identify clouds associated with each state using ground-based mm-wavelength radar (composite profiles)
- Sort model fields into same state and compare composite cloud profiles (use radar simulator)
- So what happens when we try this at ARM Southern Great Plains (Oklahoma) site?

Need a tool!

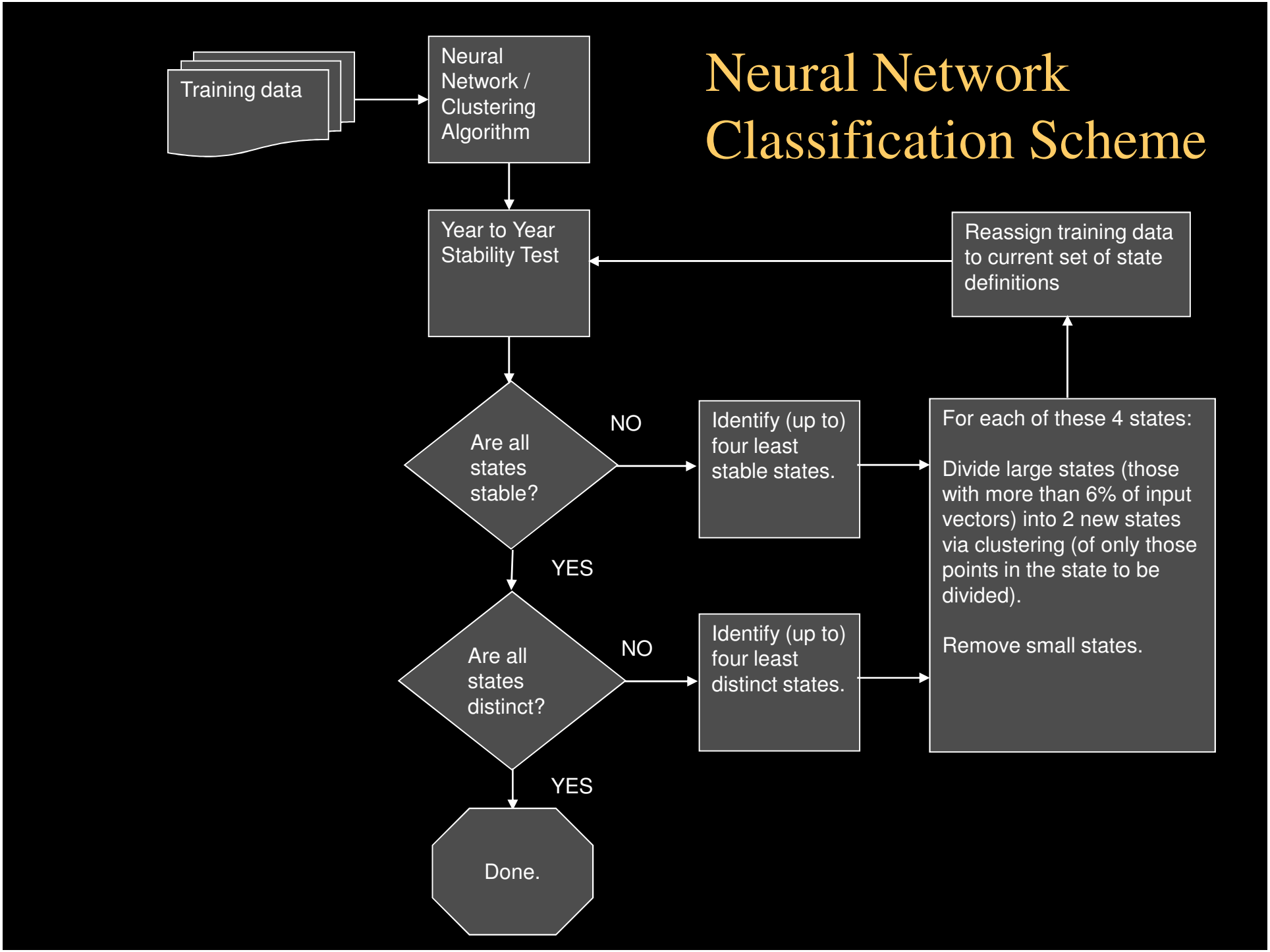
- Cluster analysis / pattern recognition



Aggregate observations based on a classification of the large-scale atmospheric state



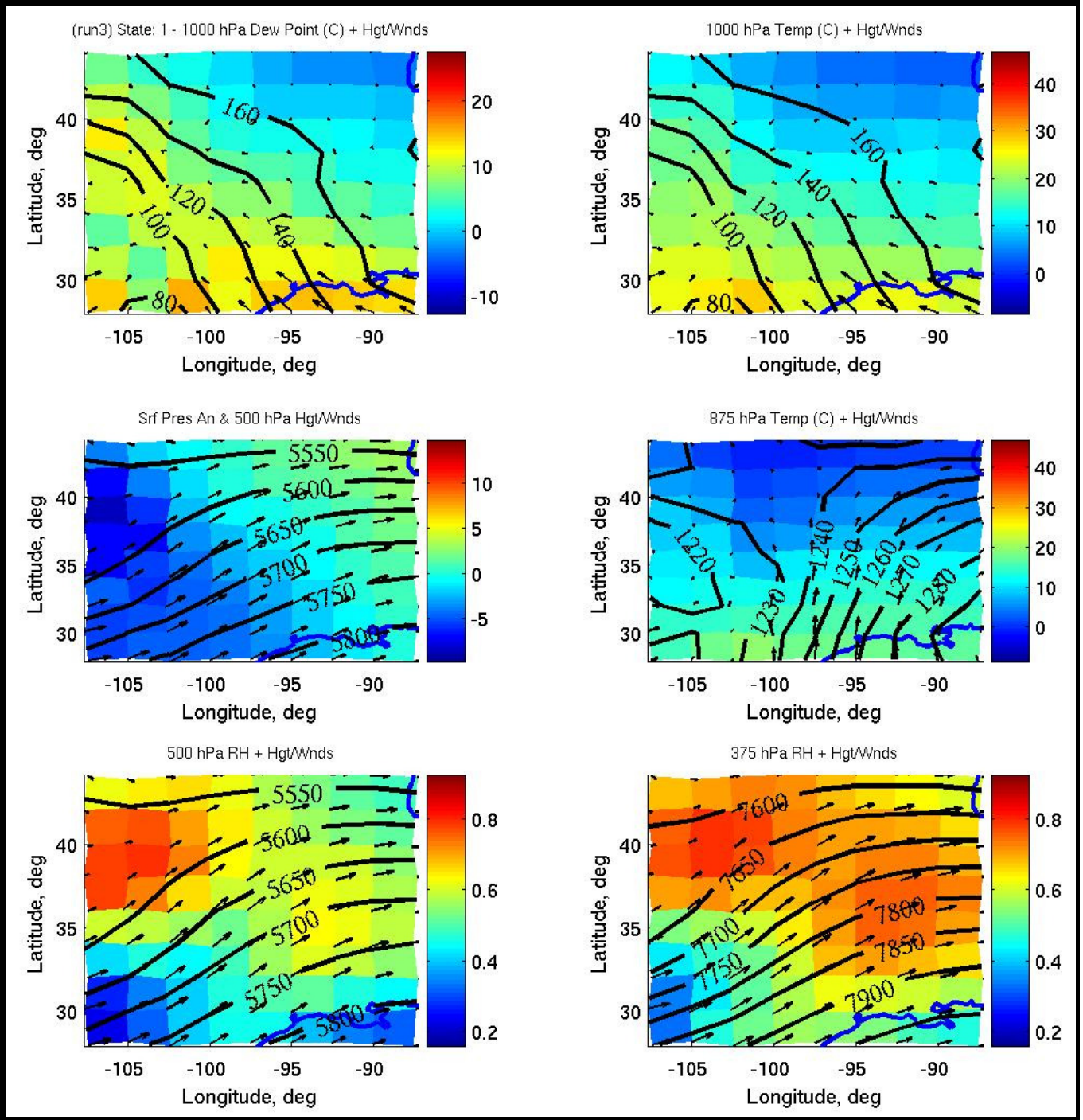
Neural Network Classification Scheme



Each atmospheric state is defined by a set of meteorological fields

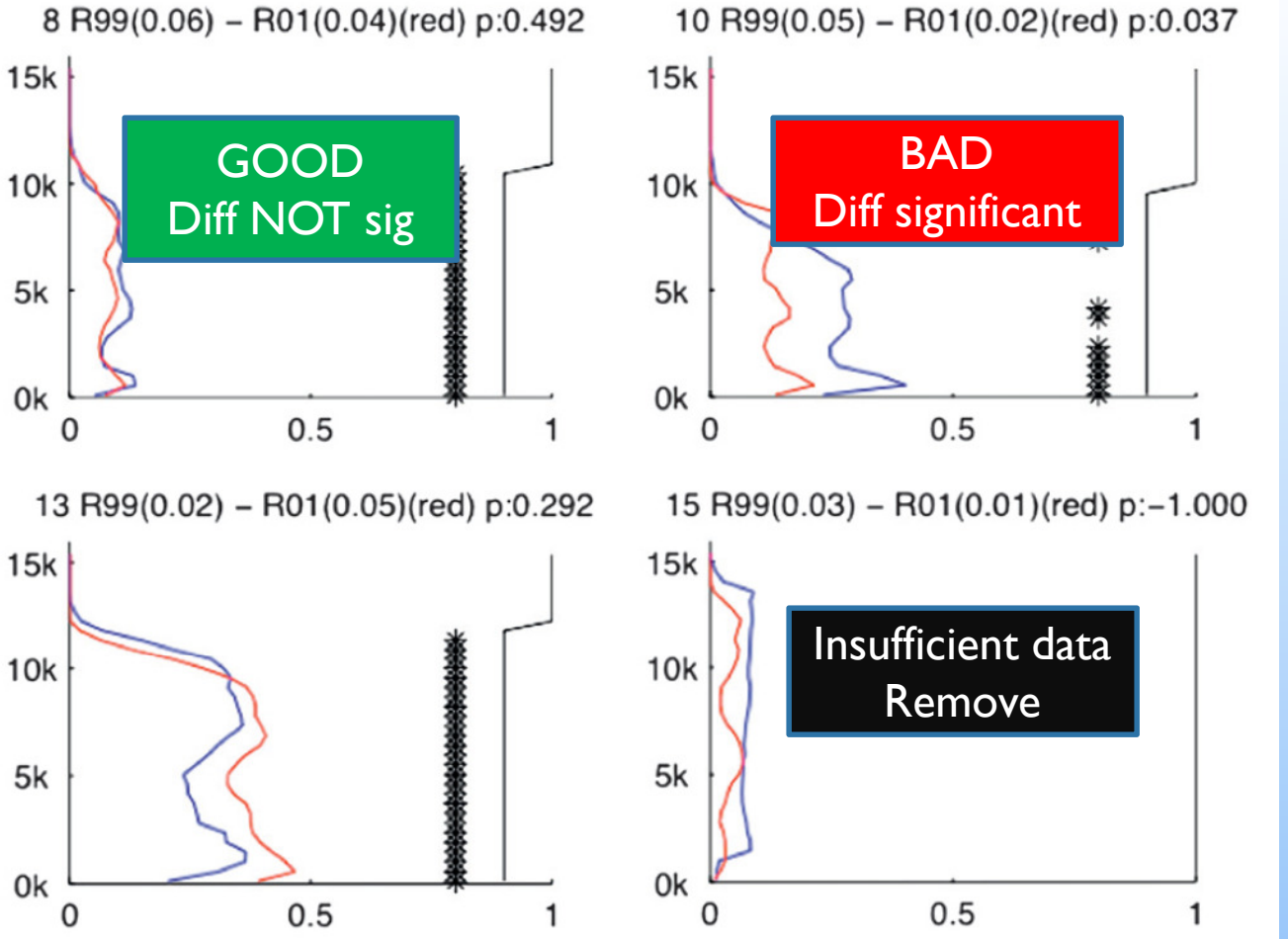
This particular state (state #1) features a front with surface easterlies over much of the domain (including at the ARM site), strong low pressure at the surface in the southwestern part of the domain, and very moist southwesterly flow at 500 and 375 hPa.

The observed cloud occurrence profiles show large fractional coverage from near the surface to about 9 km, suggesting deep ascending air.



1999 blue
2001 red

in ( ) at top gives fraction of states in that category



p = global similarity hypothesis test;

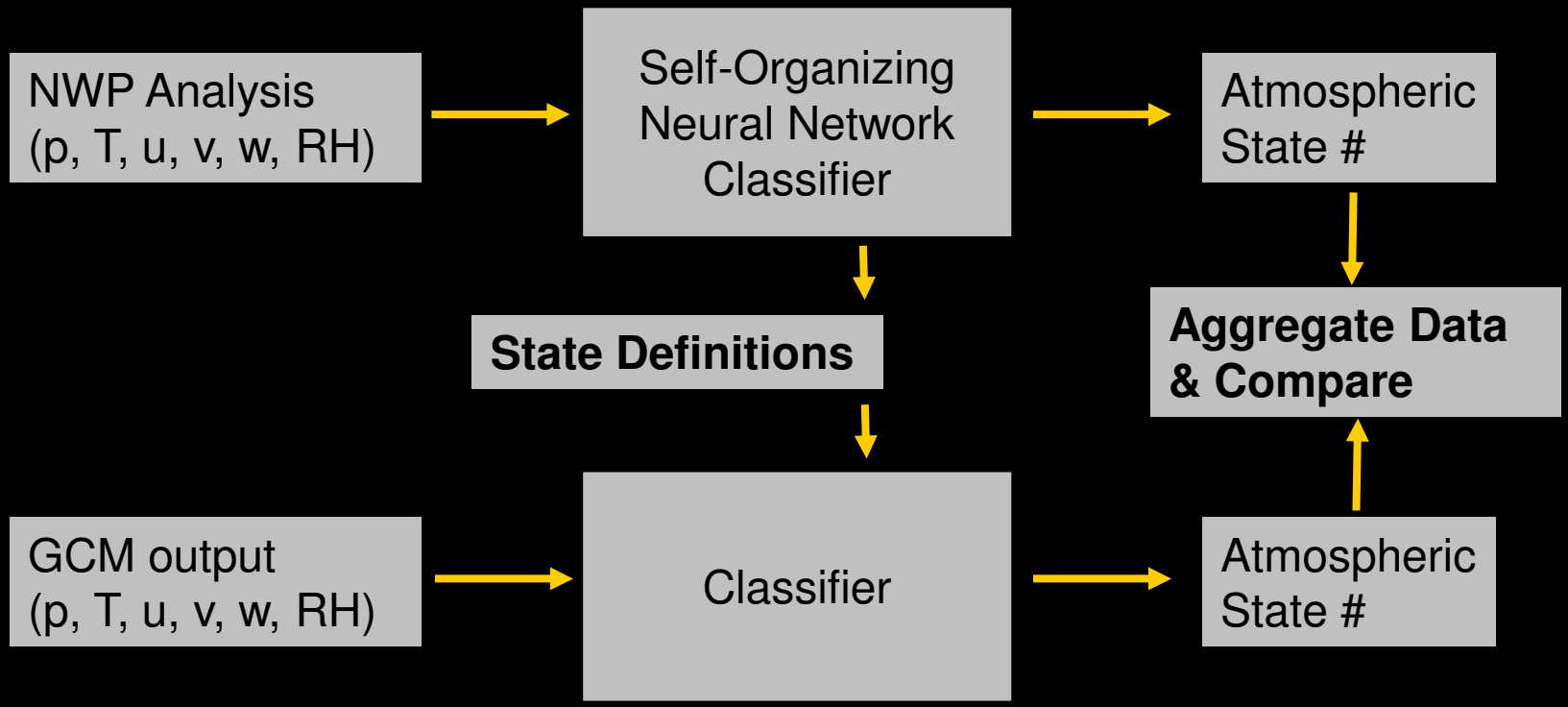
< 0.05 => Difference between profiles IS significant at 95% level

> 0.05 => Difference between profiles IS NOT significant at 95% level

Thin line => levels where we have enough data to make comparisons

* => levels where profiles do NOT appear to be different

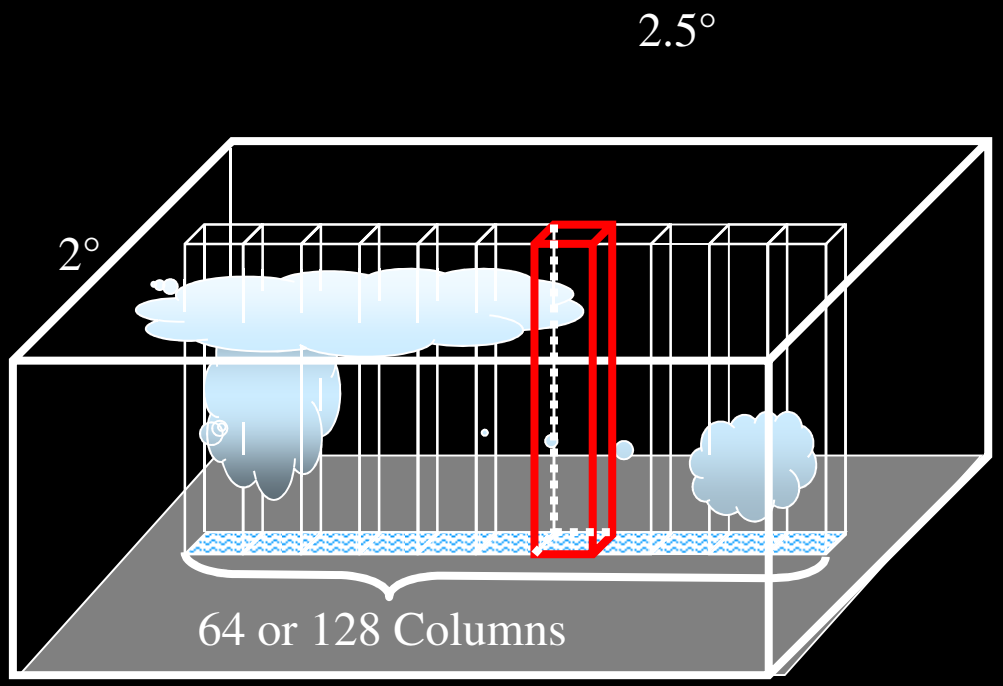
Aggregate observations and model output based on a classification of the large-scale atmospheric state



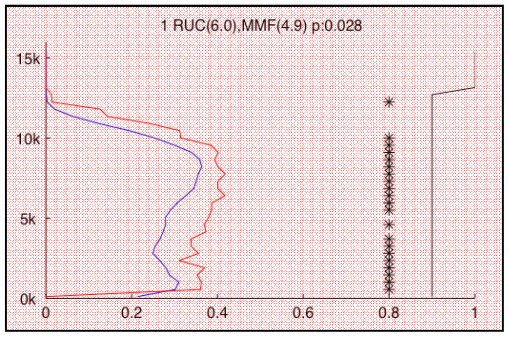
Multiscale Modeling Framework (MMF)

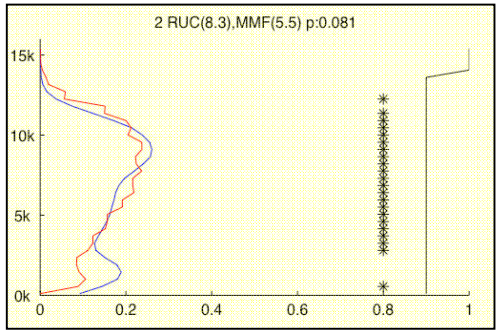
MMF Simulations :

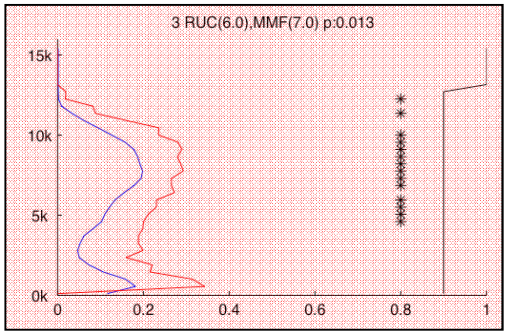
- Control
  - 4 km horizontal
  - 64 columns
  - 26 vertical layers
- Test A
  - 1 km horizontal
  - 64 & 128 columns
  - 26 vertical layers
- Test B
  - 1 km horizontal
  - 64 columns
  - 52 vertical layers

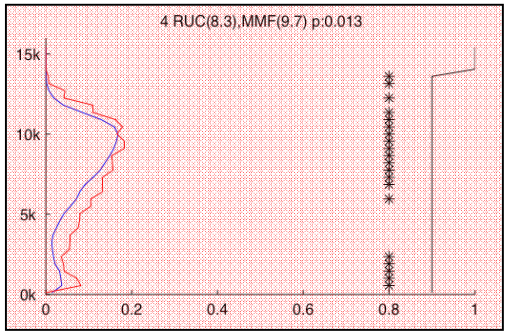


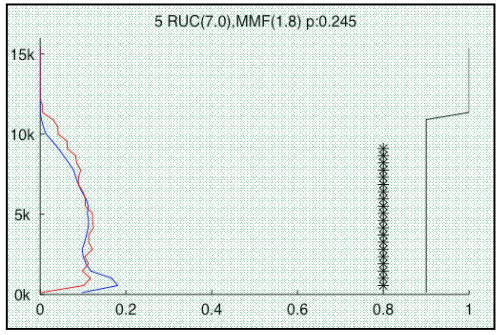
Run on PNNL MPP2 and SDSC Datastar with support from CMMAP.

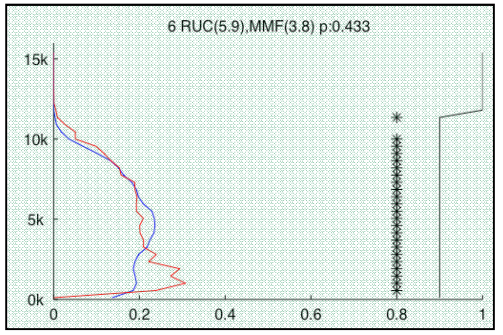


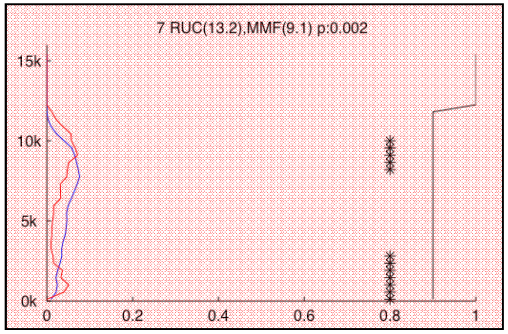


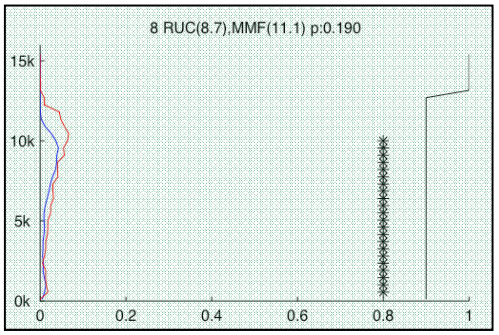


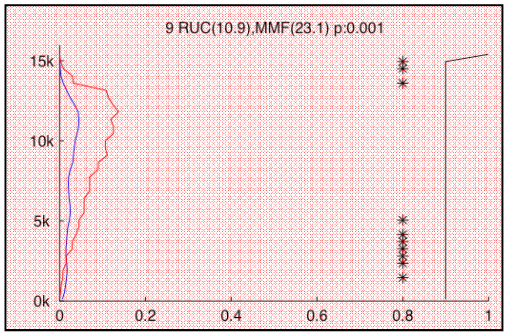


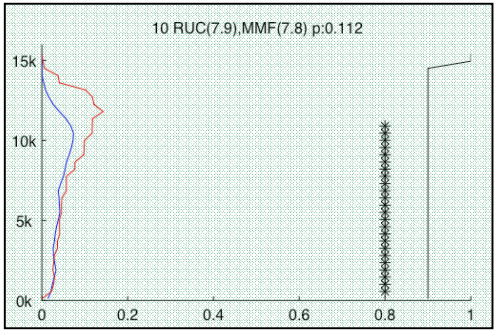


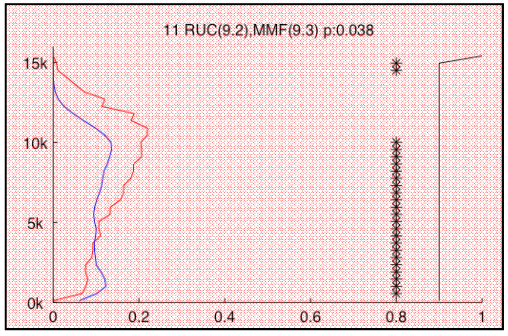


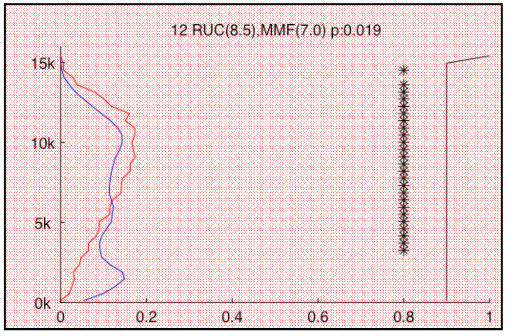








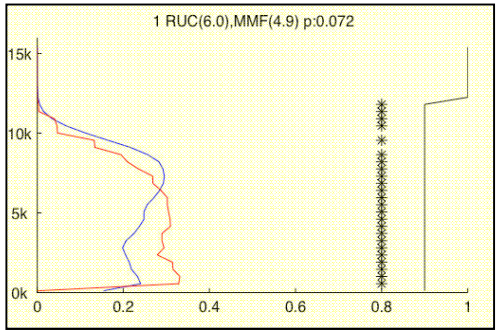


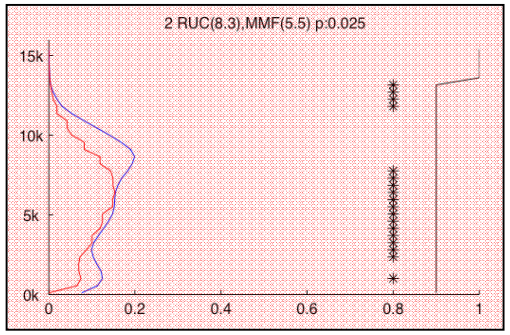


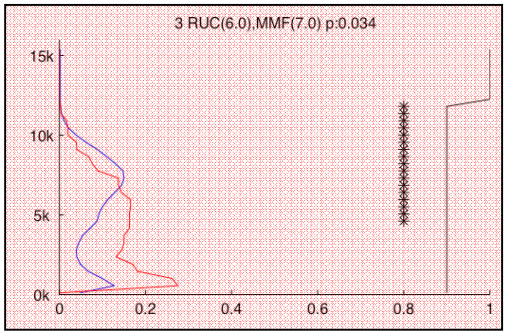
Blue = ARM (RUC)

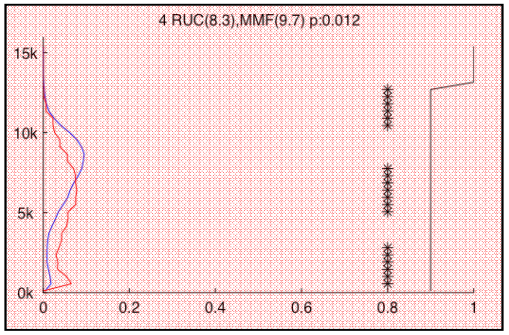
Red = MMF

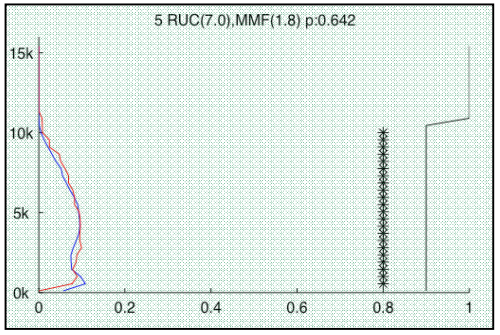
Radar cut = -40 dBz

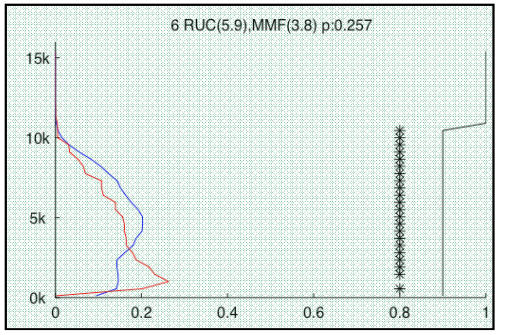


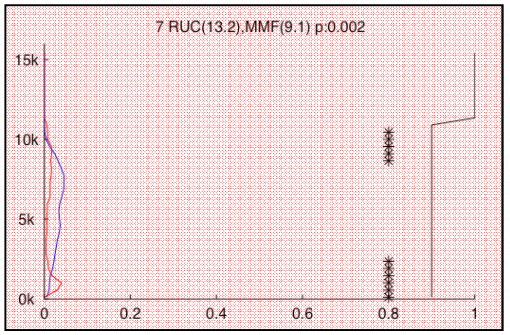


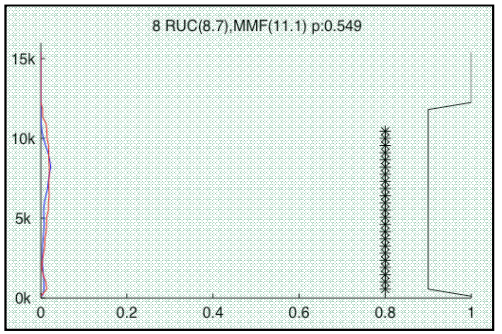


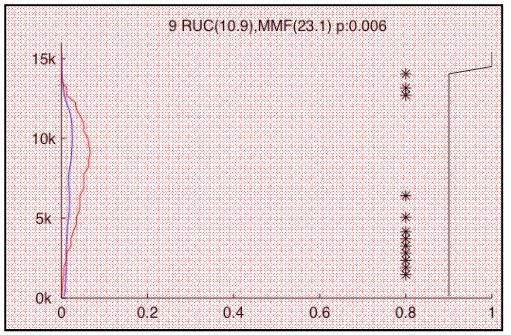


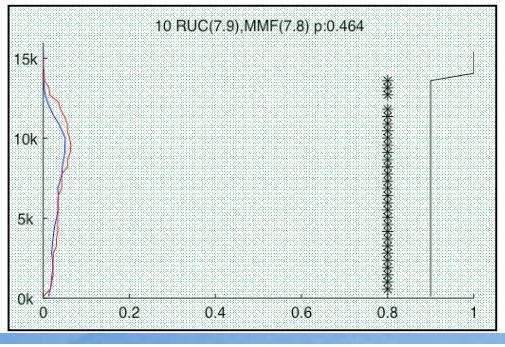


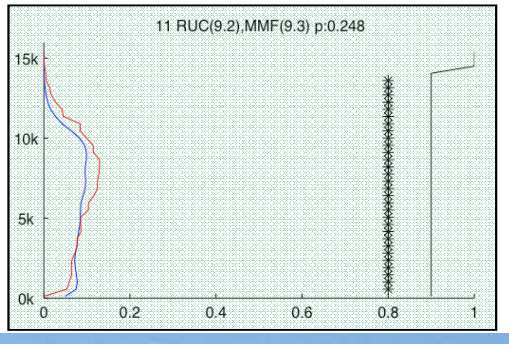


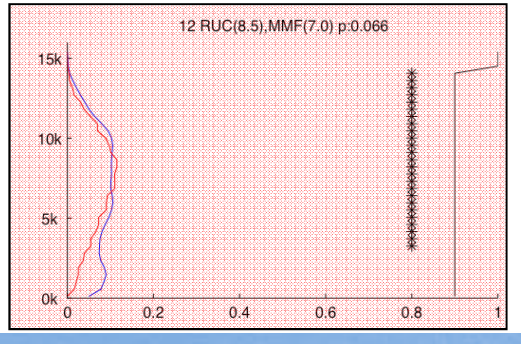












Blue = ARM (RUC)

Red = MMF

Radar cut = -25 dBz

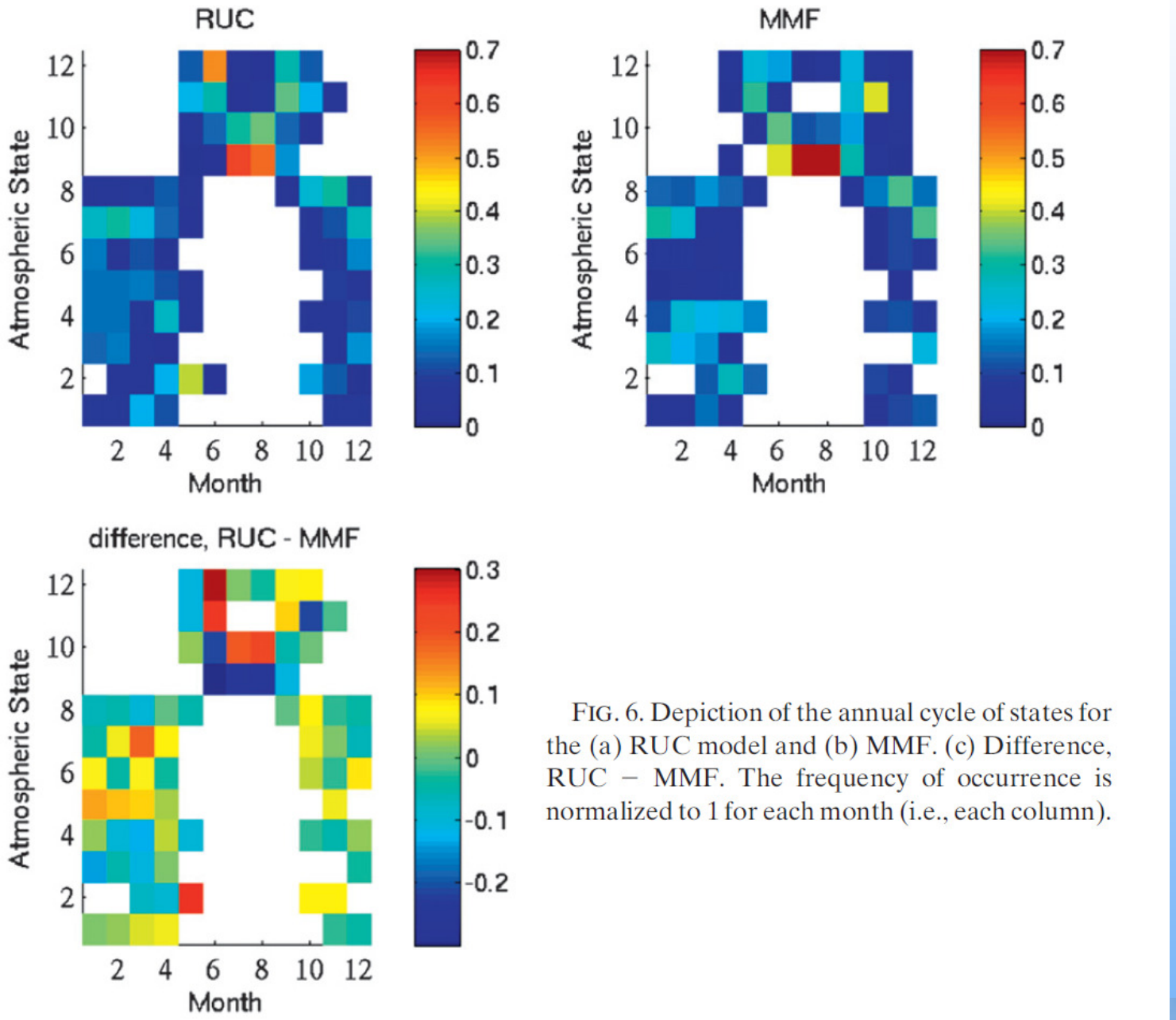


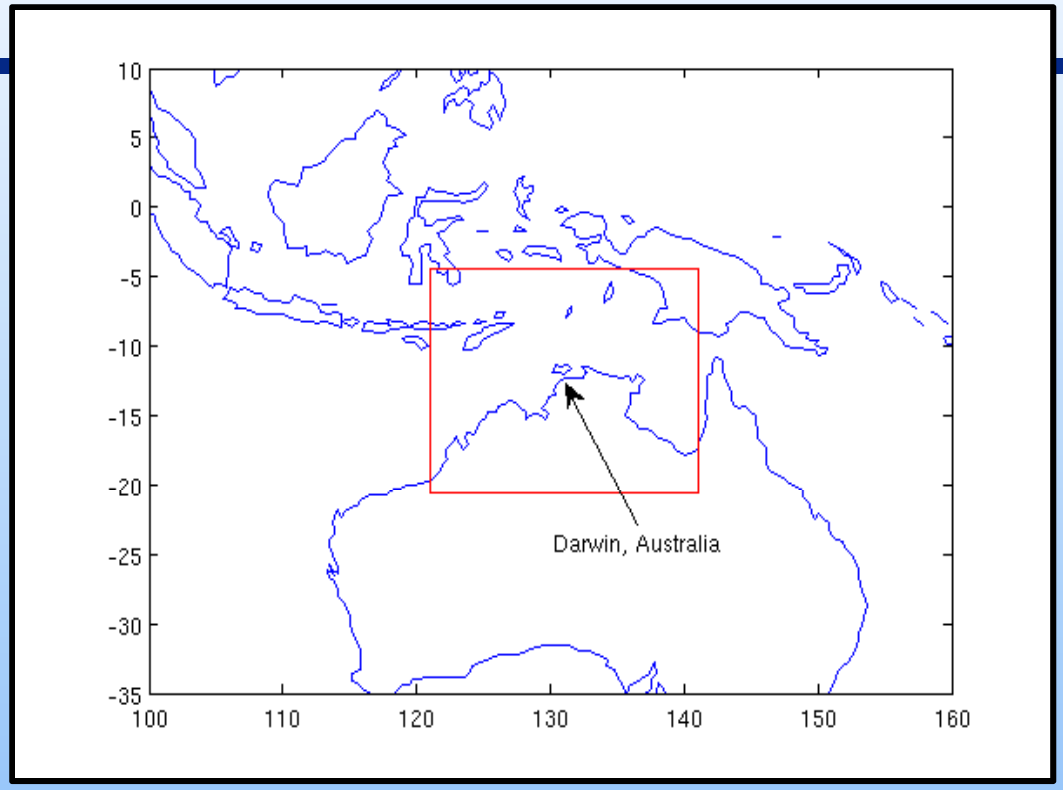
FIG. 6. Depiction of the annual cycle of states for the (a) RUC model and (b) MMF. (c) Difference, RUC − MMF. The frequency of occurrence is normalized to 1 for each month (i.e., each column).

Conclusions of SGP study

- Scheme works!
- Can now identify by regime and cloud level where model is doing well and where not
- Need more data to increase significance
- Potential next step is to figure out why model is performing poorly for certain regimes and try to improve embedded CRM physics

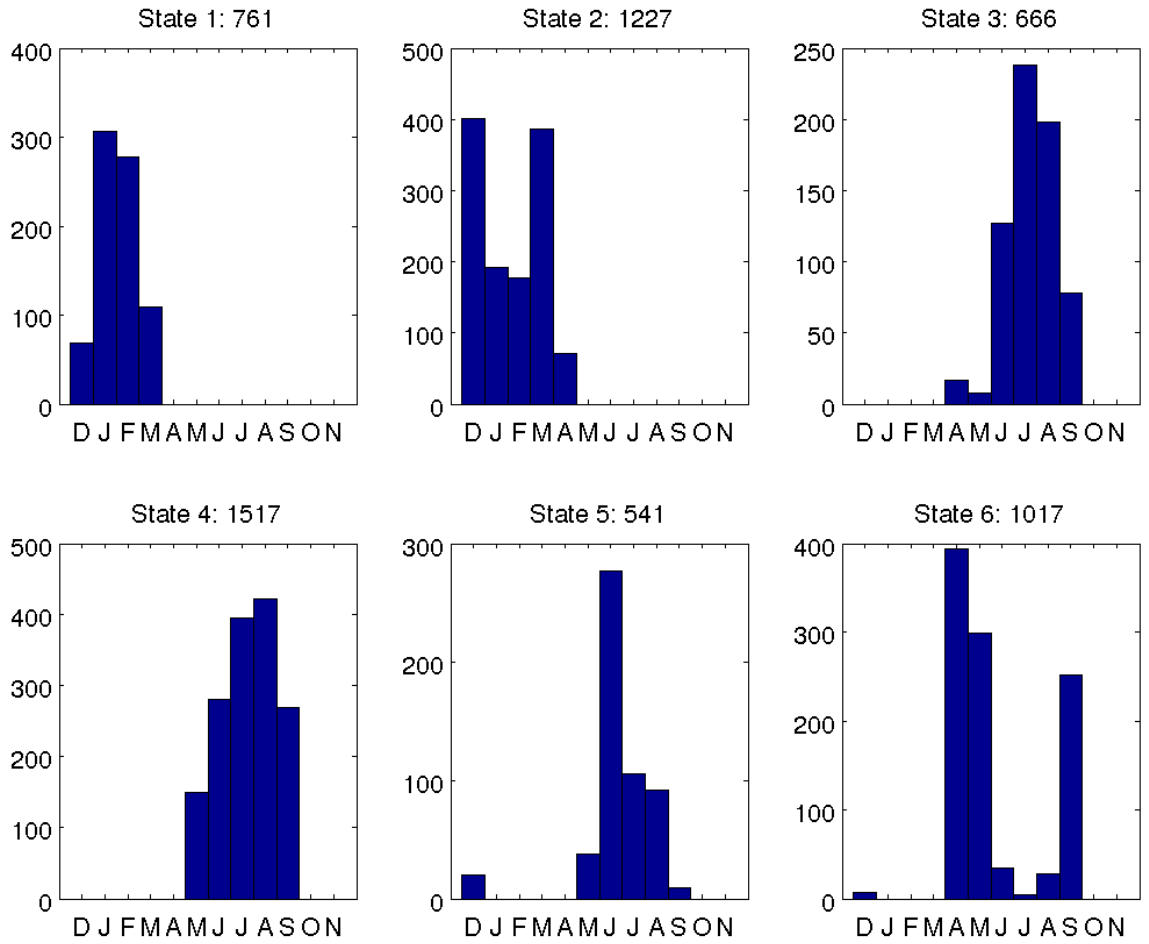
Can we export to another locale?

- Try same scheme for TWP Darwin site

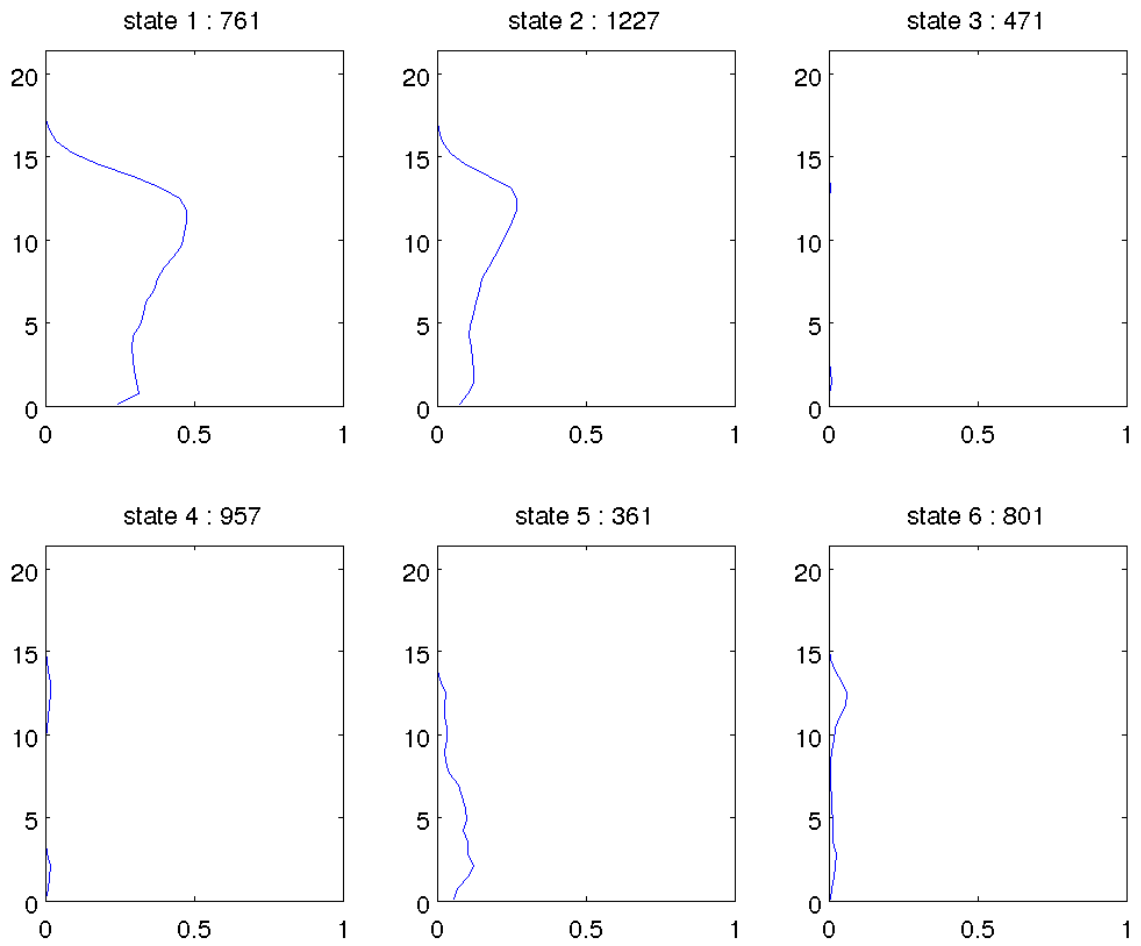


Use "data" from ECMWF re-analysis from 2006-2008.

- 8x daily
- Half degree resolution, sampled on a 9x9 grid at 2 x 2.5
- 7 vertical levels (1000,875, 750, 625, 600, 375, 250)
- Temperature, relative humidity, zonal and meridional wind, and surface pressure



Monthly histogram of occurrences of each state.
Titles indicate total number of instances of each state.



State by state cloud occurrence profiles. Altitude (km) vs. fractional occurence. Title for each subplot indicates number of instances of each state. Data from the vertically pointed millimeter radar at the ARM site in Darwin, with a -40dBz minimum reflectivity threshold applied.

State 1: Monsoon

Upper Left:
Surface dew point (C) and winds

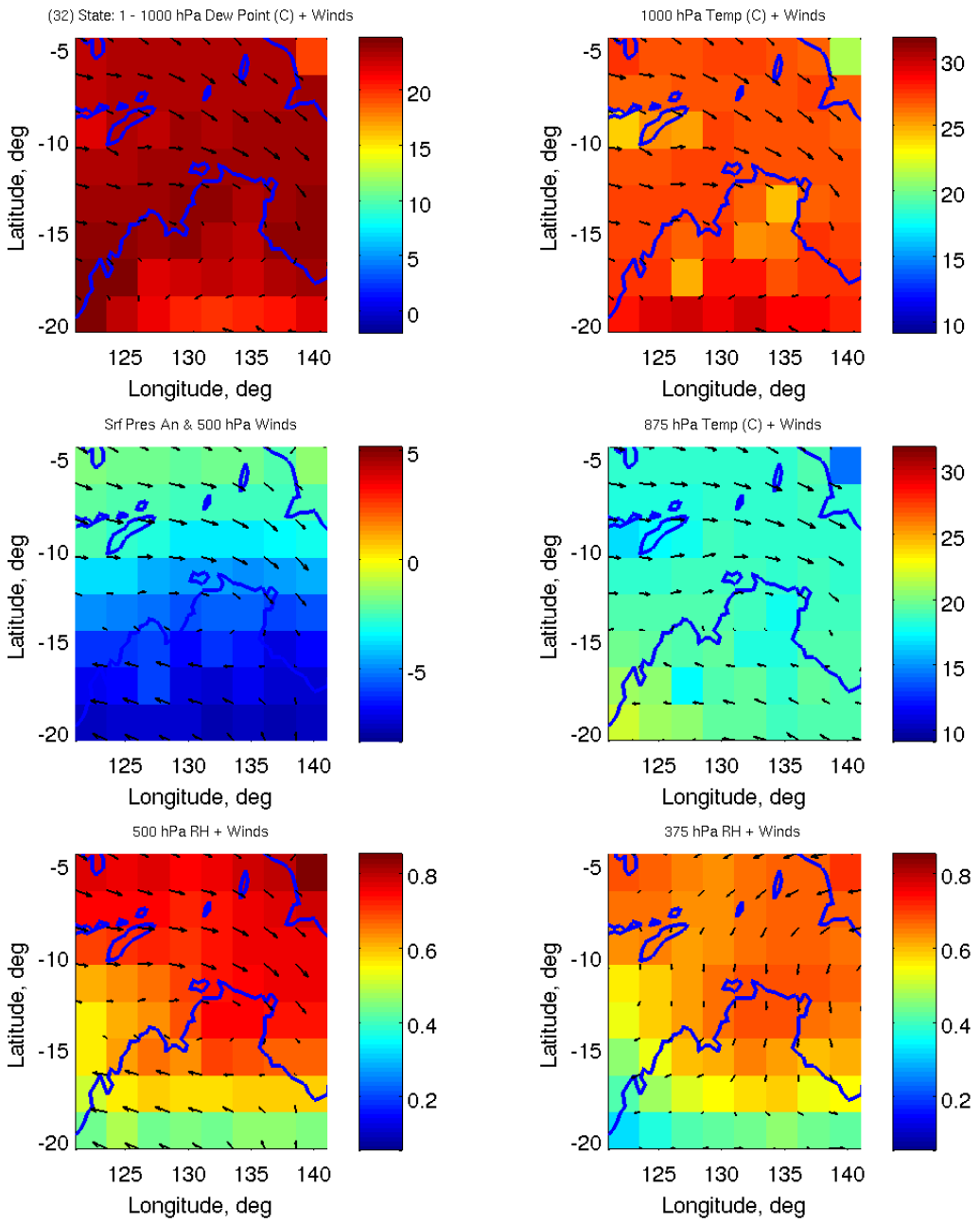
Upper Right:
Surface temp (C), and winds

Middle Left:
Surface pressure anomaly (hPa) and 500 hPa winds

Middle Right:
875 hPa Temp (C) and winds

Lower Left:
500 hPa RH and winds

Lower Right:
375 hPa RH and winds



State 3: Dry season

Upper Left:
Surface dew point (C) and winds

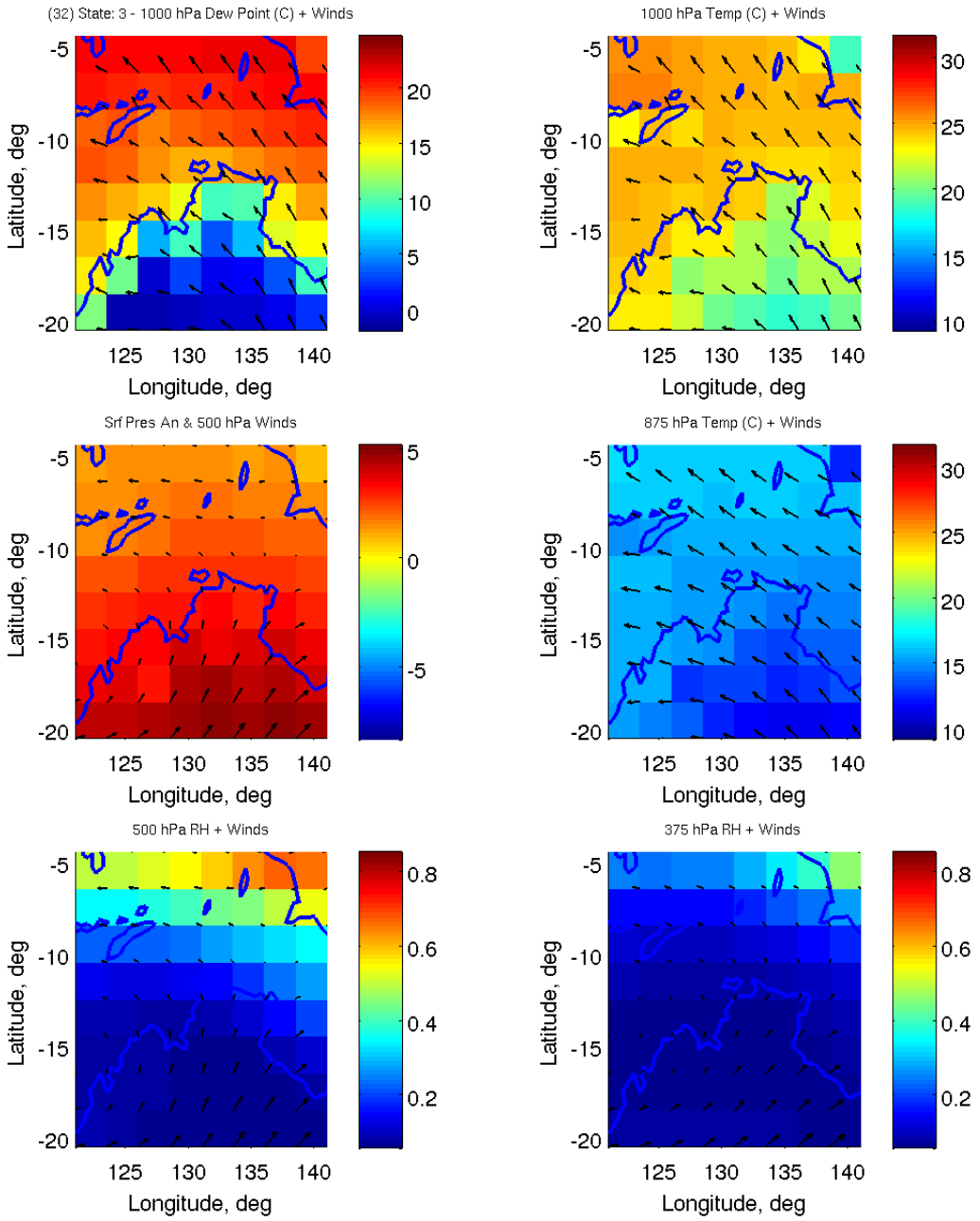
Upper Right:
Surface temp (C), and winds

Middle Left:
Surface pressure anomaly (hPa) and 500 hPa winds

Middle Right:
875 hPa Temp (C) and winds

Lower Left:
500 hPa RH and winds

Lower Right:
375 hPa RH and winds



Conclusions for TWP

- Too early to tell
- Some parts are promising but we aren't getting a lot of state discrimination
  - Take larger area?
  - Use other parameters like MJO index?
- Talk to us in 6 to 12 months …

So what about cloud feedbacks?

- Cloud properties for current climate and model climate given by
  - Sum{ f(Si) x CP(Si) }
  - f(Si) = normalized probability of state i
  - CP(Si) = cloud property of state i (remember this is a distribution itself!)
- Let's assume that CP(Si) are in good agreement for observations and model for all Si (or almost all)

So what about cloud feedbacks?

- Now perturb model (increase CO2, etc.)
- Sort model into states: $f_p(Si)$ [different from f(Si)]
- Implications:
  - Climate change can be reduced to identifying changes in state frequencies
  - Cloud changes can be computed from Sum{ $[f_p(Si) - f(Si)] \times CP(i)$ }
  - Cloud feedbacks can be related to these changes
  - Feedback of different cloud types can be related to frequency of changes of states associated with those clouds

Now the sticky parts …

- Can we do this on a global scale?
  - Break world into regions, but how big? how many?
  - Are CloudSat data spatially adequate?
- Can identify cloud property *changes* but how do we separate cloud feedback from system changes?
  - Why did the state frequency change?
- Are our state definitions robust?
  - Does climate change produce "new" atmospheric states? (may require a more rigorous definition of state)