GPS RO Water Vapor & GRUAN

E. R. Kursinski[1]

A. Kursinski[1], T. Gebhardt[2], C. Ao[3]

Special thanks to Feiqin Xie (Texas A&M) & Mark Ringer (Met Office)

[1] Space Science & Engineering, Golden, CO

[2] University of Colorado, Boulder, CO

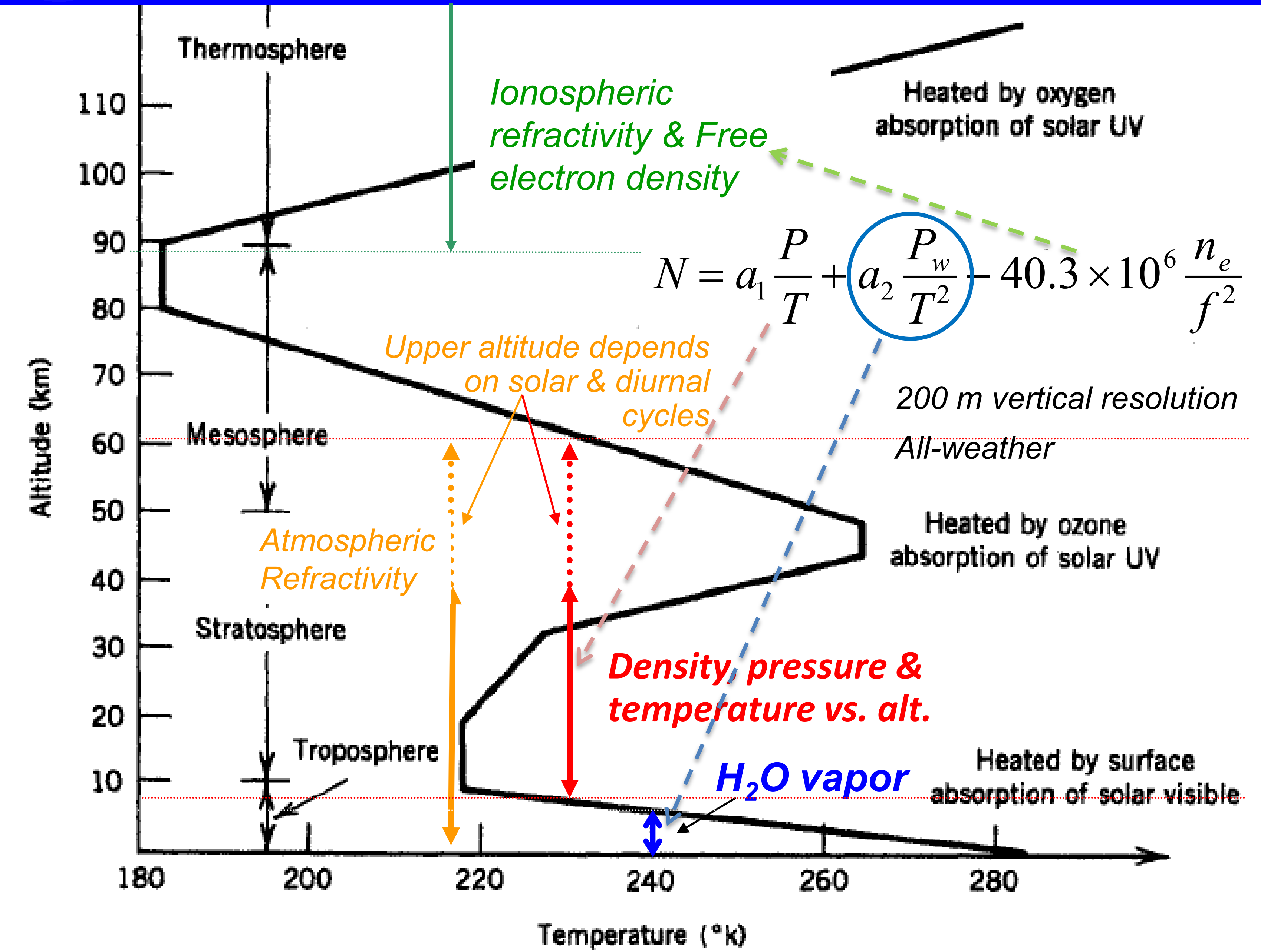
[3] Jet Propulsion Laboratory (JPL), Pasadena, CA

IROWG4 April 20, 2015 Melbourne, Australia

Outline

- Background on GPS RO water vapor
- Moisture histograms & Error estimates
- Moisture histogram comparisons
  – 346, 547 & 725 hPa

GNSS RO Information vs. Altitude



What does GNSS RO offer for H_2O?

$$N = a_1 \frac{P}{T} + a_2 \frac{P_w}{T^2} - 40.3 \times 10^6 \frac{n_e}{f^2}$$

$$\alpha = \int d\alpha = 2a \int_{r_0}^{\infty} dr \frac{dn}{n\, dr} \frac{1}{\sqrt{n^2 r^2 - a^2}}$$

- Refractivity is sensitive to tropospheric water vapor
  - Bending angle particularly sensitive to water vapor
- Very high vertical resolution (~200 m) well matched to observing vertical scale variations of water vapor
  - Corresponding **horizontal resolution** is ~70 km
- Profile thru clouds to observe very wet air in & below clouds
- Focus on free troposphere
  - Avoid super-refraction problem for now

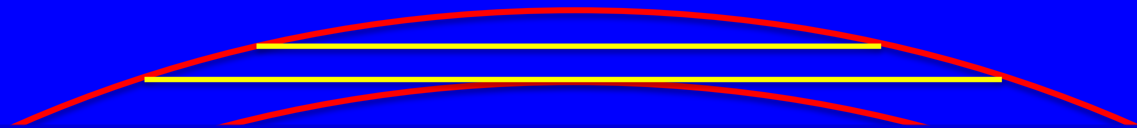
- Anticipated impact of GPS RO humidity information on NWP has not yet materialized
  - Reason: GPS RO sampling very sparse globally thus far

GPS RO Features Summary

- Least biased data set available?
  - Global coverage
  - Diurnal coverage with ≥ 6 satellite constellation like COSMIC
  - Works in clear & cloudy conditions (λ ~ 20 cm)
  - Works over land & water (insensitive to surface emissivity)
  - Unique relation between bending angle & refractivity (except super-N) insensitive to initial guess

- Vertical range
  - Useful to **~240 K level** in troposphere (~9 km alt. at low latitudes) (can go colder & higher if doing zonal averages)
  - Extends down very close to surface in extra-tropics
  - If we can deal with ***super-refraction***, profiles can extend down to the surface at low latitudes

Horizontal Resolution of RO

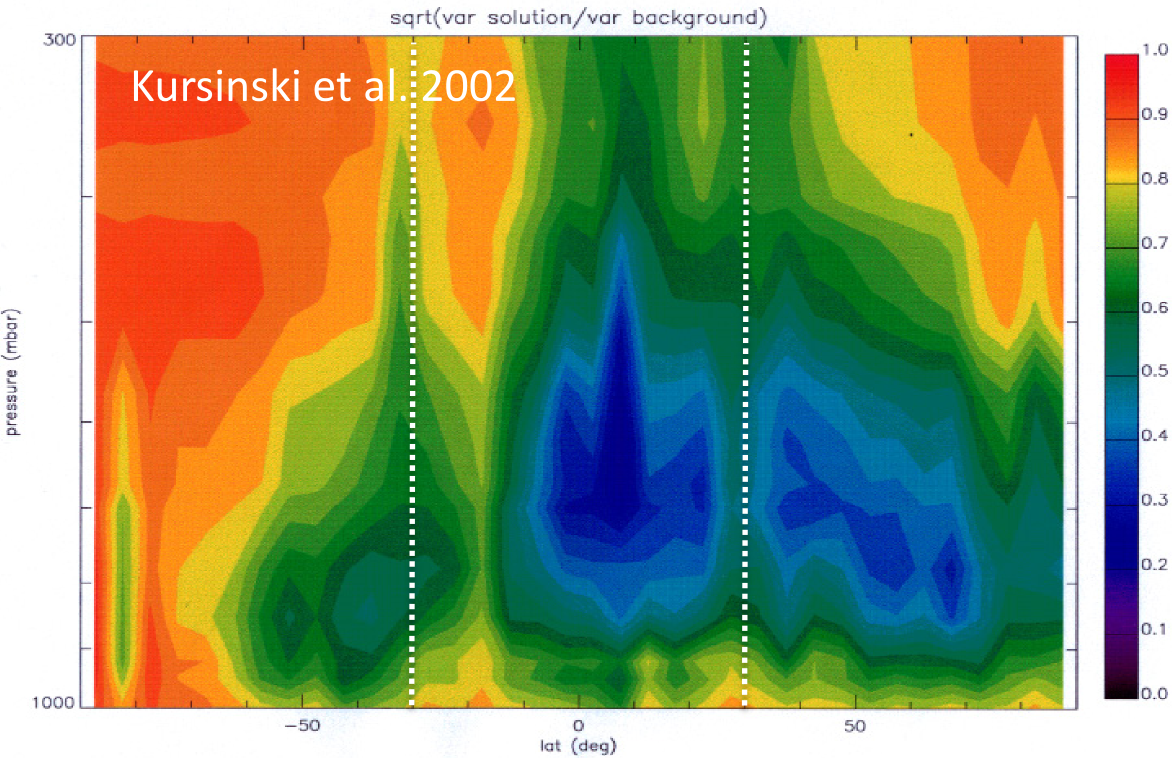


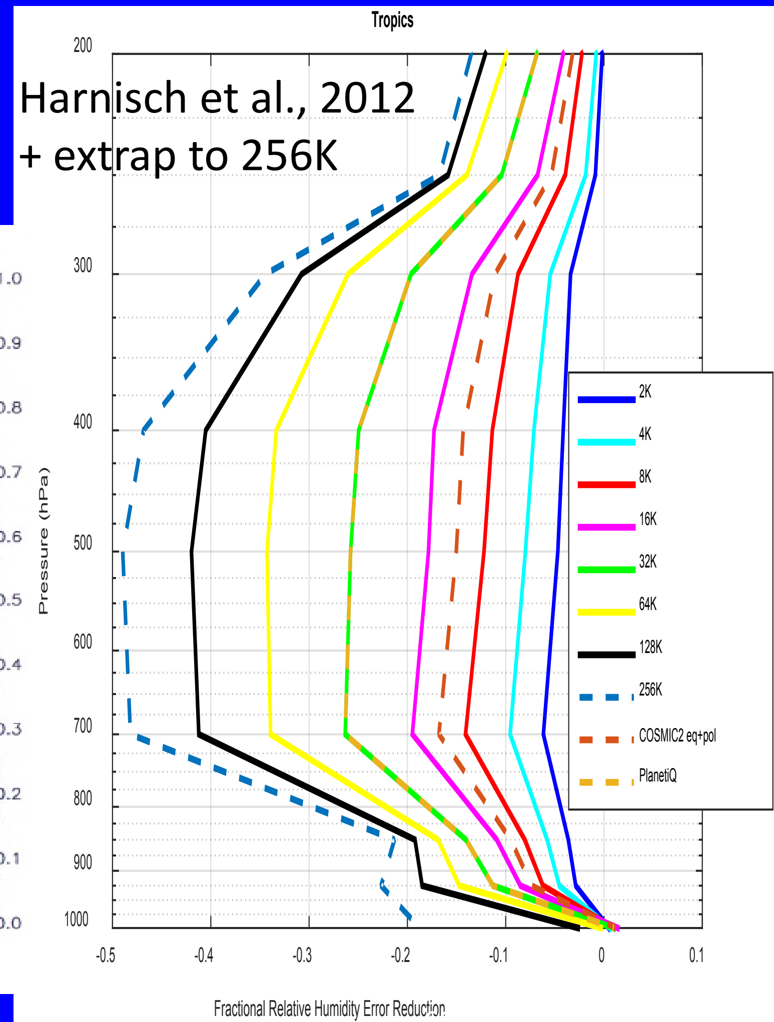
- Evidence suggests that 300 km horizontal res is too conservative/coarse:
  - GPS RO sees more extremely wet air than other obs, GCMs and analyses (except for MERRA in mid troposphere)
  - Harnish et al. estimated water vapor impact at 128,000 (- 256,000) occ/day looks much closer to 1DVar estimates than previous estimates. (~63 km res)
- Kursinski et al. 1997 defined horizontal resolution as the path length thru the **bottom** of the lowest layer: $\Delta L = 2\sqrt{2\,R\,\Delta Z}$
  - For ΔZ=200 m, $\Delta L \cong$ 100 km
- Perhaps a better definition is through the **center** of the lowest layer: $\Delta L = 2\sqrt{R\,\Delta Z}$
  - For ΔZ=200 m, $\Delta L \cong$ 70 km
  - Geometric average path length across the interval is 66 km.
- Horizontal resolution improves as vertical resolution improves
- Depends on how close the atmosphere is to spherically symmetric
- Should be a study to better define the GNSS RO horizontal resolution

Predicted Impact on Moisture Analyses

- Local 1DVar estimate based on GPS-MET
- Harnich et al. EDA estimate up to 128Kocc/day
- Background covariances differ

Left Panel Right Panel
(0.3 - 1 = -0.7)

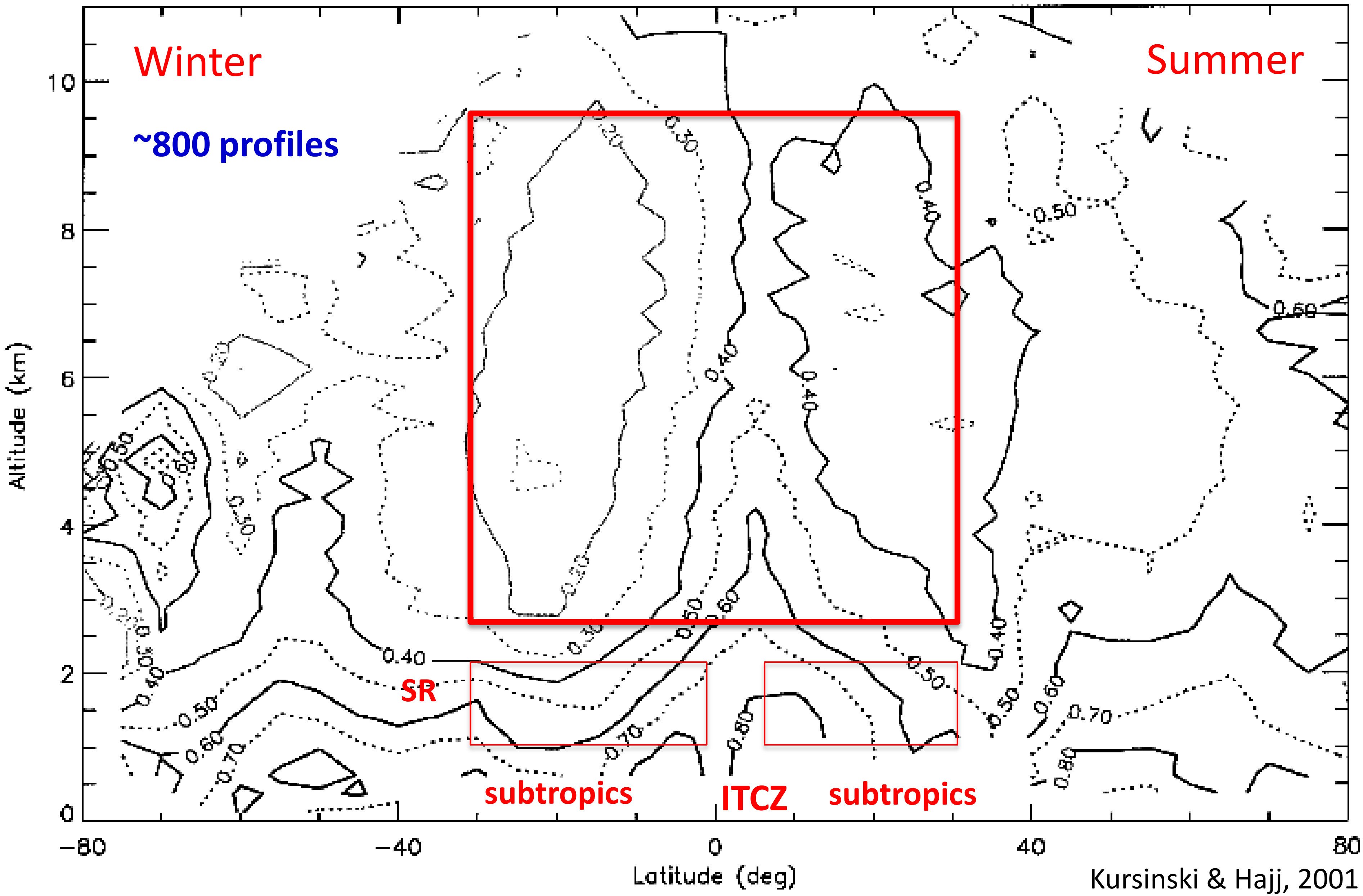




GVAP

- These features have gotten the attention of the GEWEX Water Vapor Project (GVAP)
- Moisture histograms are now endorsed as a product for GVAP
- Heading a histogram group writeup

Zonal Mean Relative Humidity GPS-MET Jun 21-Jul 4 1995



Kursinski & Hajj, 2001

Two Methods for Extracting Water Vapor from GPS RO Refractivity Profiles

1. Direct Method: $N_{wet} = N_{tot} - N_{dry}$
   - Determine dry refractivity (N_{dry}) from analysis temperature profile and hydrostatic equation
   - Scale N_{wet} to get water vapor

2. (1D) Variational Method
   - Combine GPS refractivity with
   - Analysis temperature & water vapor profiles and surface pressure
   - and error covariance estimates

   $\Rightarrow$ Over-determined, least squares solution

Advantages of Direct Method:

- Not affected by biases in background water vapor forecast/analysis
- Can derive water vapor information to higher altitudes

Moisture Histograms

- Low order moments like mean & variance provide limited insight into water vapor distribution and the hydrological cycle
- Histograms of moisture on individual pressure levels provide much better indication of full range of behavior
- As well as insight into processes at work and adequacy of their representation in models

Negative *q* and Error Deconvolution

Direct Method can and does produce negative *q* estimates

=> Produces an unphysical, negative tail in the *q* histograms

- This can be fixed by deconvolving the error distribution from histograms
  - Linearize error model: $q_{measured} = q_{\mathrm{true}} + \varepsilon_q$
  - Measured histogram (PDF) is then the convolution of the true PDF and the error PDF

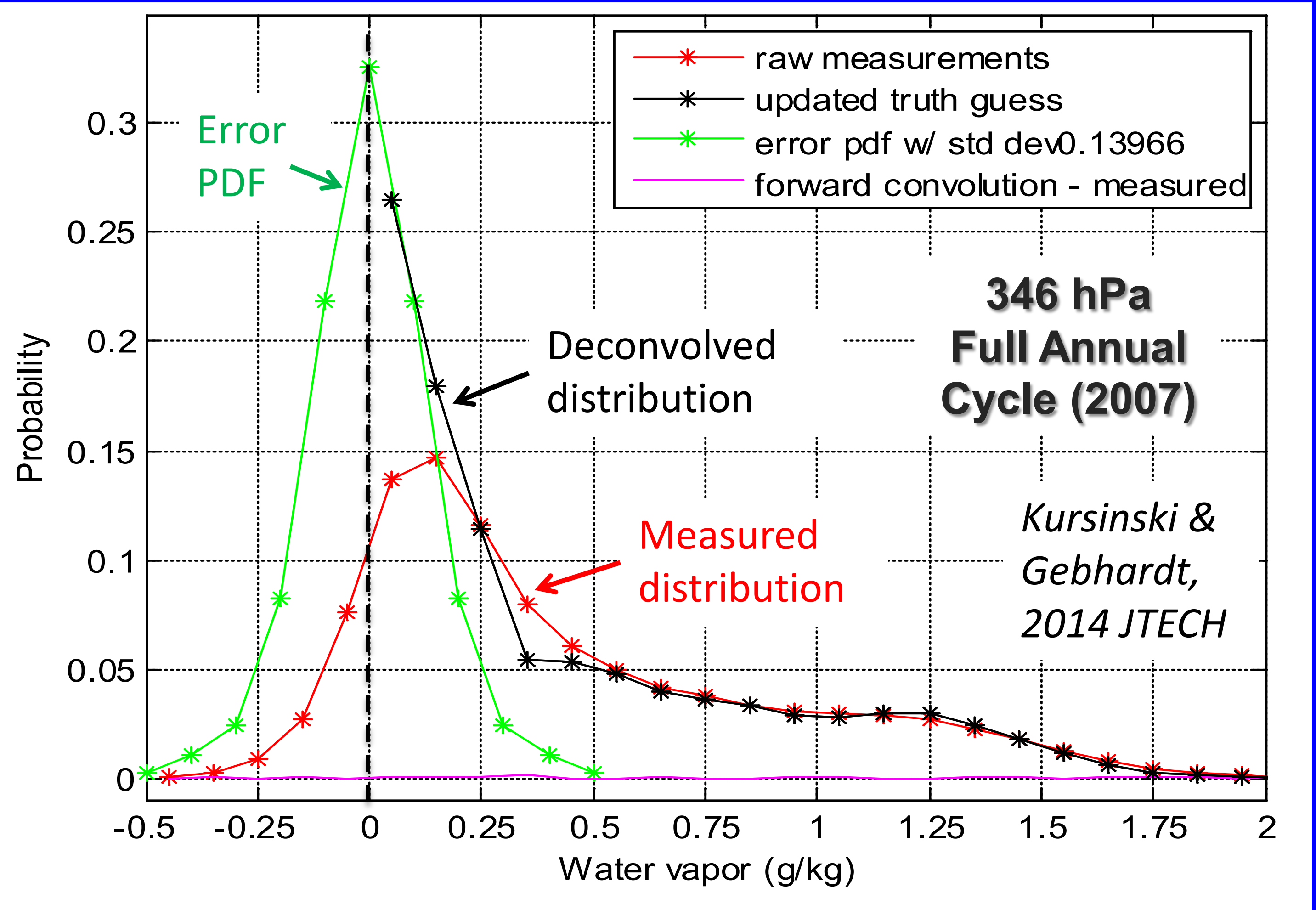
$$\mathrm{PDF}_{q\mathrm{meas}} = \mathrm{PDF}_{q\mathrm{true}} \otimes \mathrm{PDF}_{\varepsilon}$$

- *IF* we understand the error PDF, we can then deconvolve it from the measured PDF to recover the true PDF
  - Negative tail tells us shape of the error distribution

- Described in Kursinski & Gebhardt (2014) in JTECH

Error Deconvolution Low Latitude

- Adjust (1) (symmetric) Error PDF & (2) “true” *q* distribution PDF,
- Convolve them to generate estimate of “measured” PDF,
- Iterate adjustments until best fit to measured PDF is achieved



Estimating the Accuracy of GPS-derived Water Vapor

- Kursinski et al. 1995: Initial estimate of GPS water profile accuracy
- Kursinski & Hajj, 2001: Error in specific humidity, *q*, due to errors in *refractivity, N*, *temperature, T*, and *pressure, P*, from GPS

$$\sigma_q = \left((C+q)^2 \left(\frac{\sigma_N}{N}\right)^2 + (C+2q)^2 \left(\frac{\sigma_T}{T}\right)^2 + (C+q)^2 \left(\frac{\sigma_{P_S}}{P_S}\right)^2 \right)^{1/2}$$

where $C = a_1 T m_w / a_2 m_d \sim 35$ g/kg

$\sigma_q \sim 0.2$ g/kg in mid & upper troposphere.

$\sigma_q \sim 0.4$ g/kg in lower troposphere

Analogously, the error in relative humidity, *U*, is

$$\sigma_U = \left[(B_s + U)^2 \frac{\sigma_N^2}{N^2} + \left(B_s + U(2 - \frac{L}{R_v T}) \right)^2 \frac{\sigma_T^2}{T^2} + B_s^2 \frac{\sigma_P^2}{P^2} \right]^{1/2}$$

where *L* is the latent heat and $B_s = a_1 TP / a_2 e_s$.

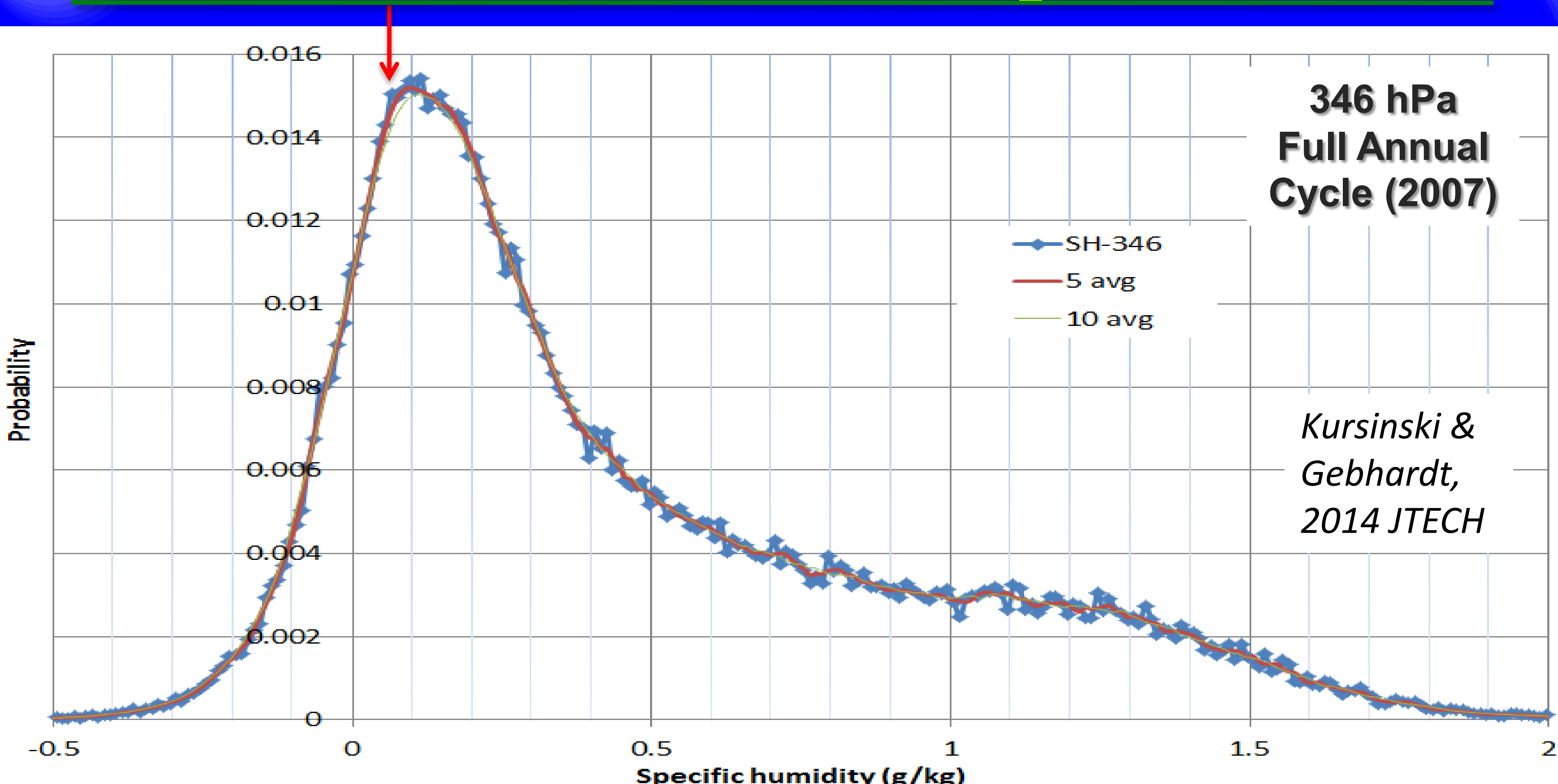
Kursinski & Kursinski 14

Separating the Errors

- Estimate water vapor error from negative tail of distribution (Kursinski & Gebhardt, 2014)
- Resulting errors somewhat smaller than predictions of Kursinski & Hajj, 2001
  - In part because low lat. analysis temperature errors are smaller

	Specific Humidity Error (g/kg)		Fractional Refractivity Error (%)		Temperature Error (K)		Reference Pressure Error (%)	
Pressure level (hPa)	KH01	Error deconv	KH01	Error deconv	KH01	Error deconv	KH01	Error deconv
346	0.24	**0.14**	0.2	0.2	1.5K	0.85K	0.3%	0.19%
547	0.31	**0.25**	0.5	0.6	1.5K	0.85K	0.3%	0.19%
725	0.47	**0.39**	0.9	1	1.5K	0.85K	0.3%	0.19%

Constraining the GPS RO H_2O Vapor Bias



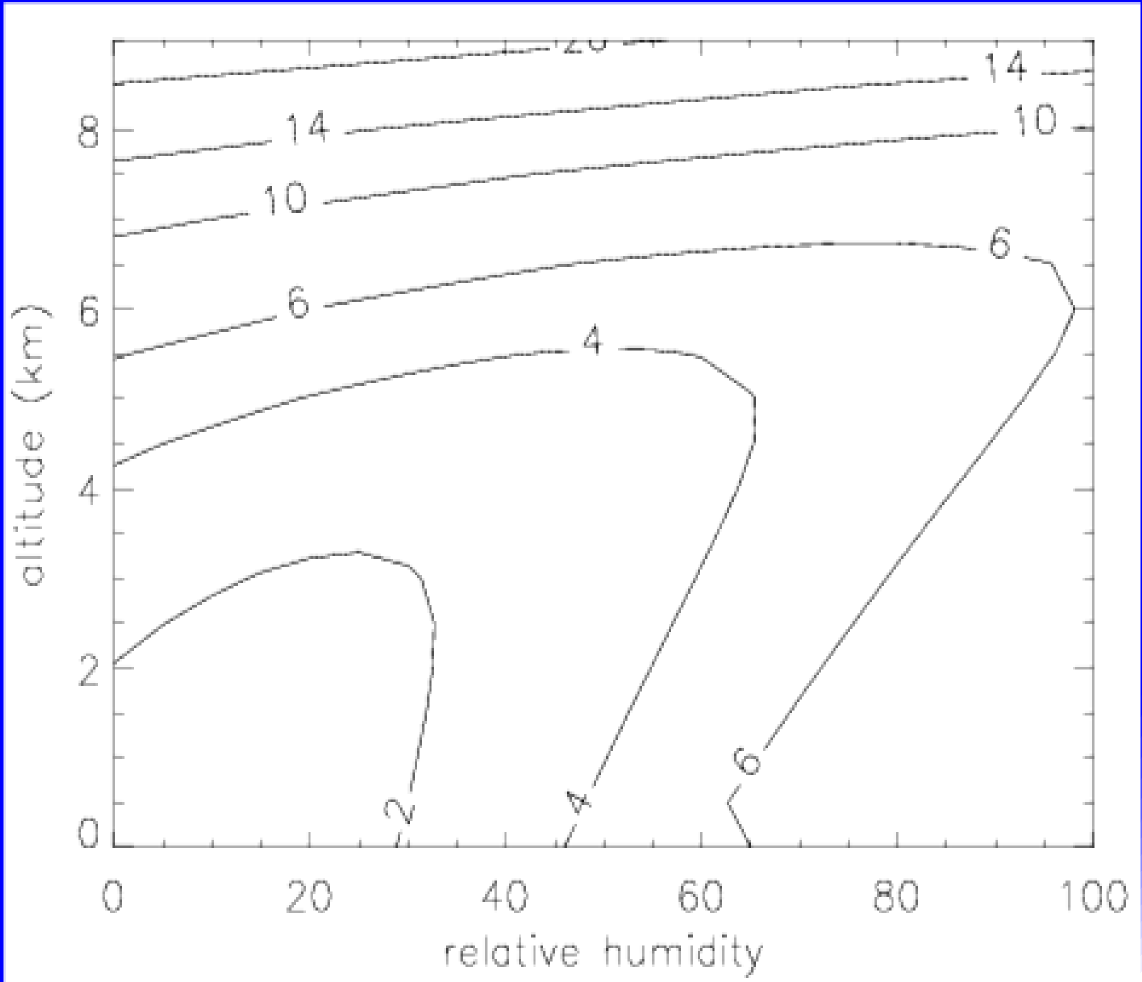
- 0.01 g/kg wide bins at 347 hPa => Sharp roll-off below 6th positive bin
- Expected due to coldest detrainment near 200 mb that returns to troposphere (Hartmann et al., 2001)
- Suggests bias is no more than 0.03 g/kg (Kursinski & Gebhardt 2014)

Expected Relative Humidity Errors

$$\sigma_U = \left[(B_s + U)^2 \frac{\sigma_N^2}{N^2} + \left(B_s + U(2 - \frac{L}{R_v T}) \right)^2 \frac{\sigma_T^2}{T^2} + B_s^2 \frac{\sigma_P^2}{P^2} \right]^{1/2}$$

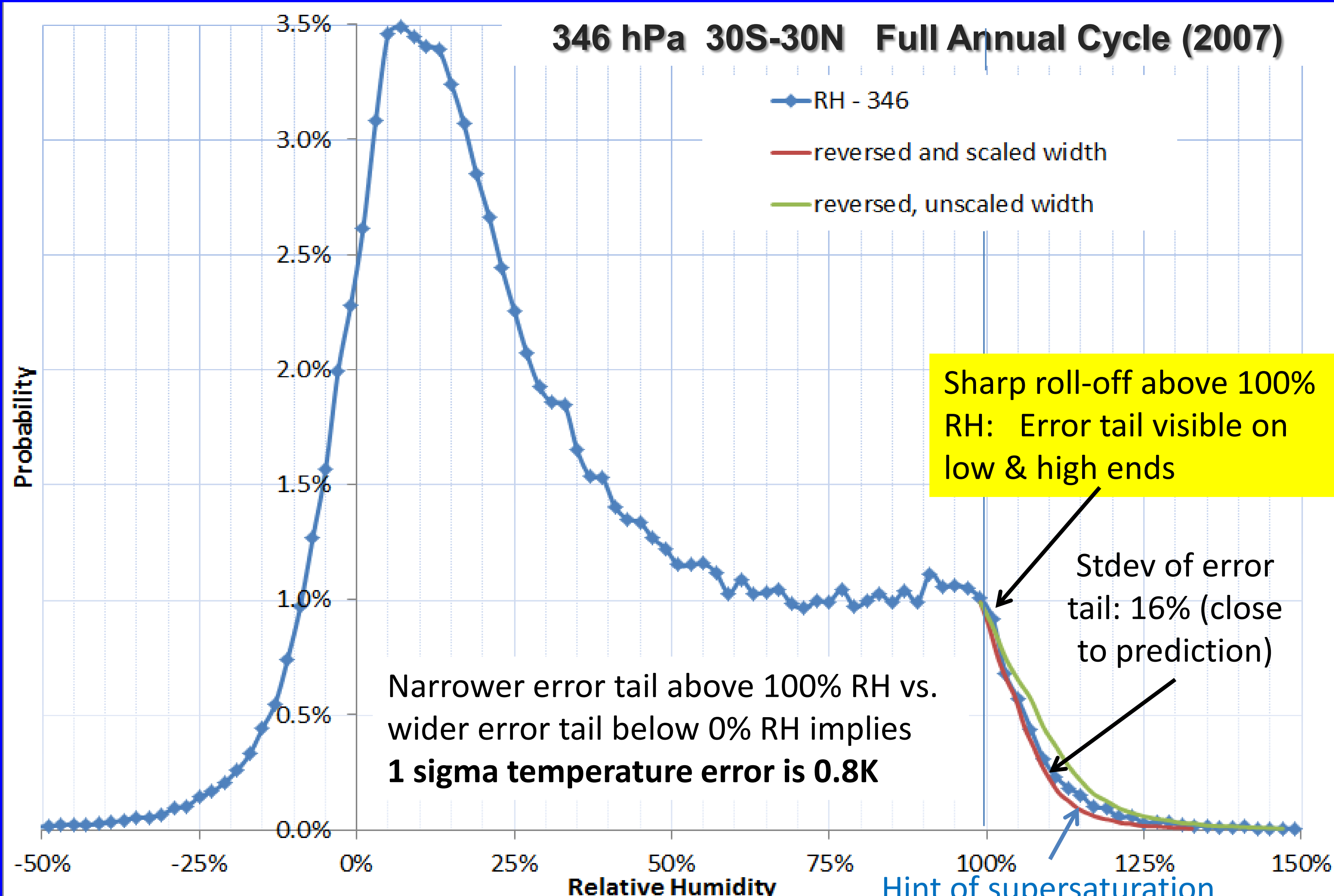
where L is the latent heat and $B_s = a_1 TP \,/\, a_2 e_s$.

Figure shows predicted low latitude, 1-sigma errors vs. altitude & relative humidity



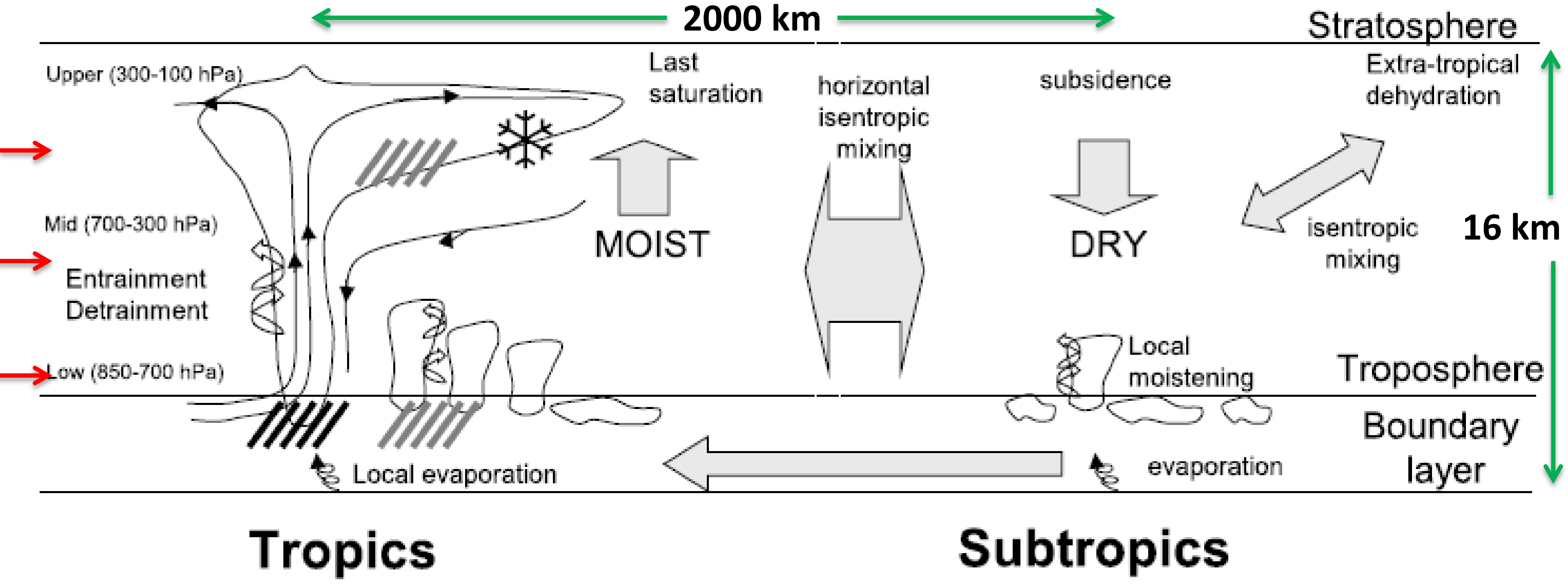
Kursinski et al., 17

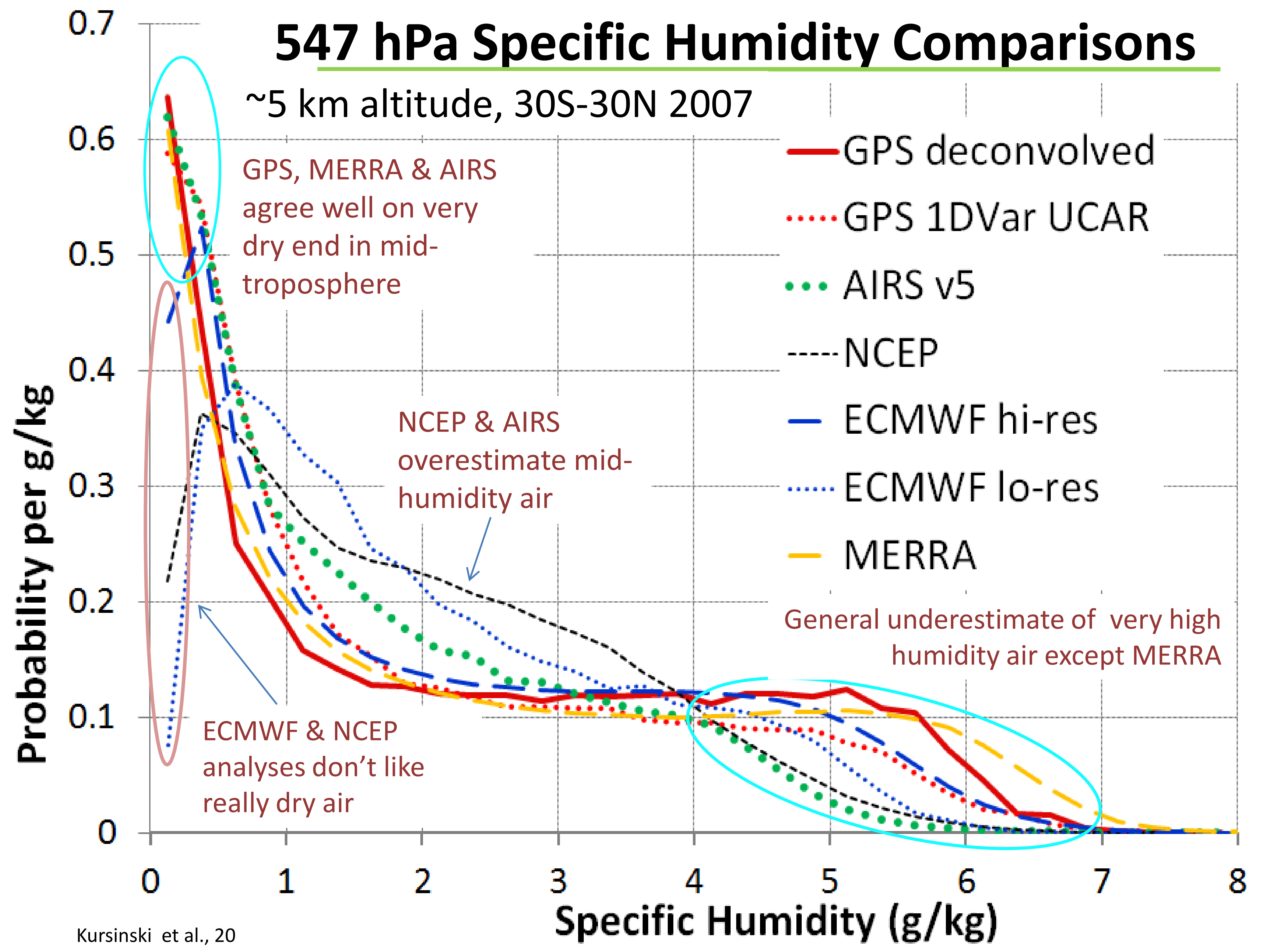
Relative Humidity Histogram 346 hPa



Low Latitude Moisture

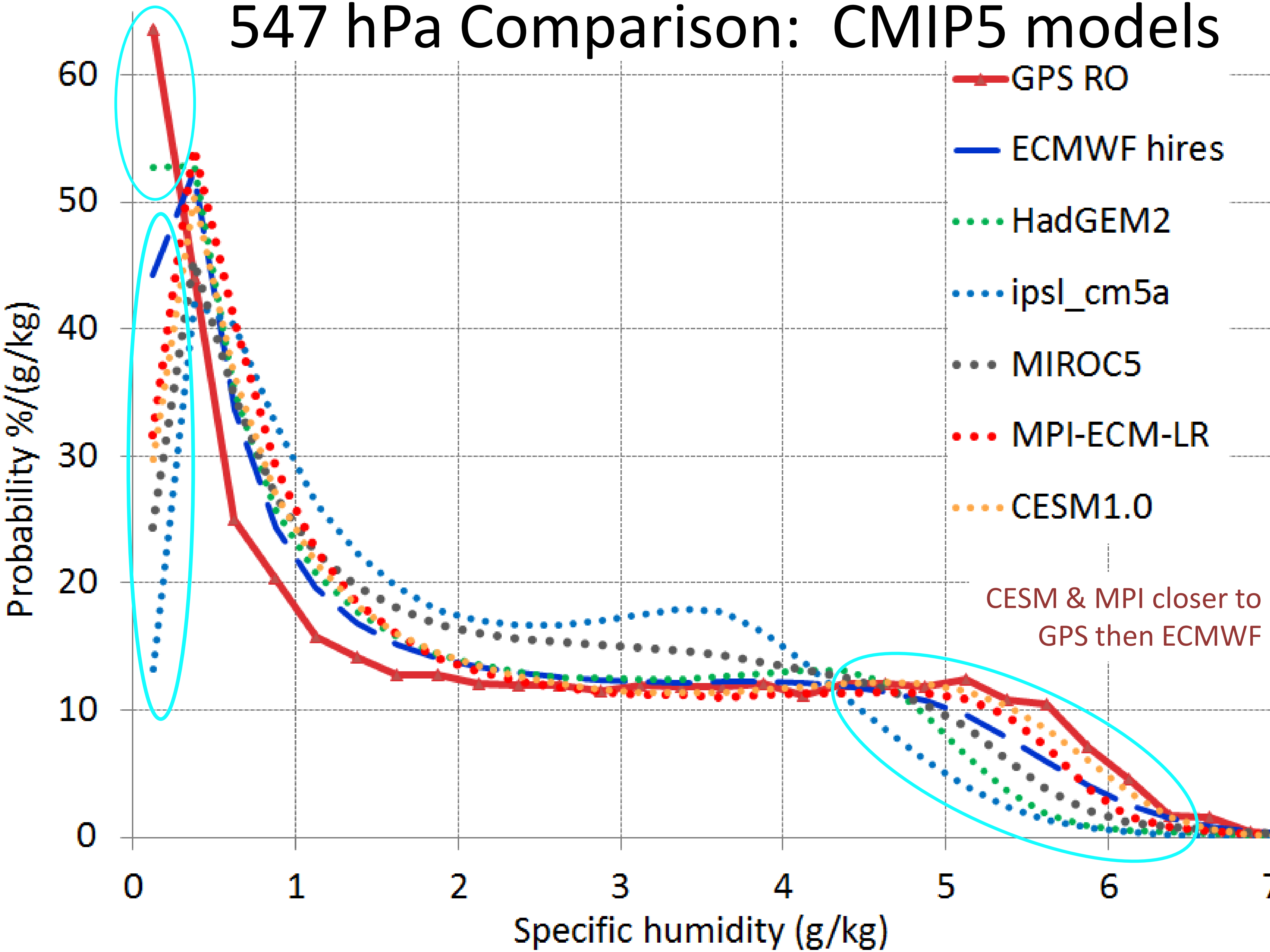
- Convection creates extremes, stretching the H_2O vapor distribution
- Mixing & diffusion compress distribution toward its center
- Specific humidity is conserved in the absence of sources & sinks => ***tracer***
- Relative humidity important for conversion between vapor & condensed phases => ***clouds & precipitation***





547 hPa Specific Humidity Comparisons
~5 km altitude, 30S-30N 2007
GPS deconvolved
GPS 1DVar UCAR
AIRS v5
NCEP
ECMWF hi-res
ECMWF lo-res
MERRA
GPS, MERRA & AIRS agree well on very dry end in mid-troposphere
NCEP & AIRS overestimate mid-humidity air
ECMWF & NCEP analyses don't like really dry air
General underestimate of very high humidity air except MERRA
Probability per g/kg
Specific Humidity (g/kg)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
1
2
3
4
5
6
7
8
Kursinski et al., 20

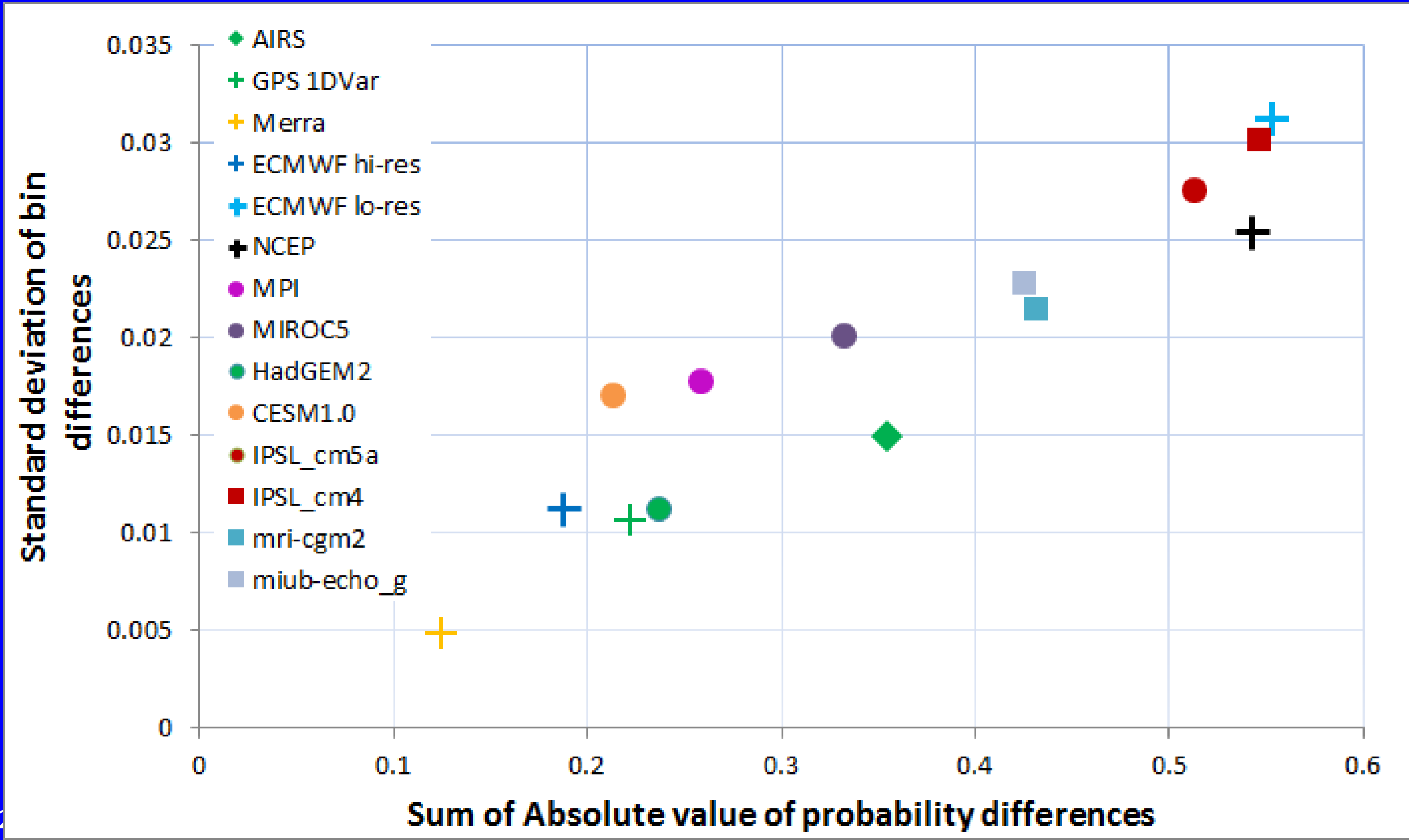
547 hPa Comparison: CMIP5 models



Performance Comparison 547 hPa

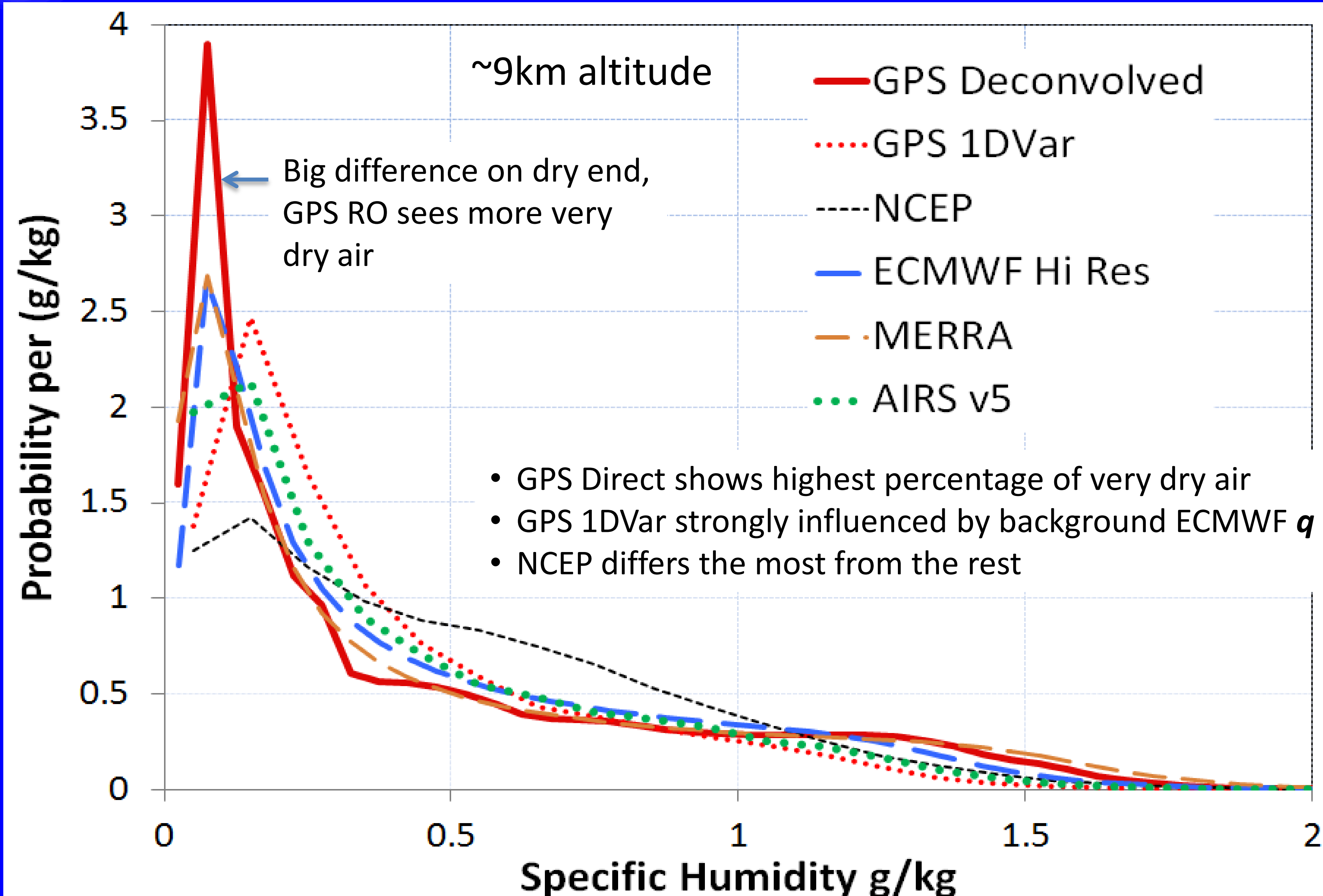
To summarize comparisons, use two metrics:

- X-axis: Sum histogram's absolute probability differences
- Y-axis: Std dev of histogram differences vs. GPS

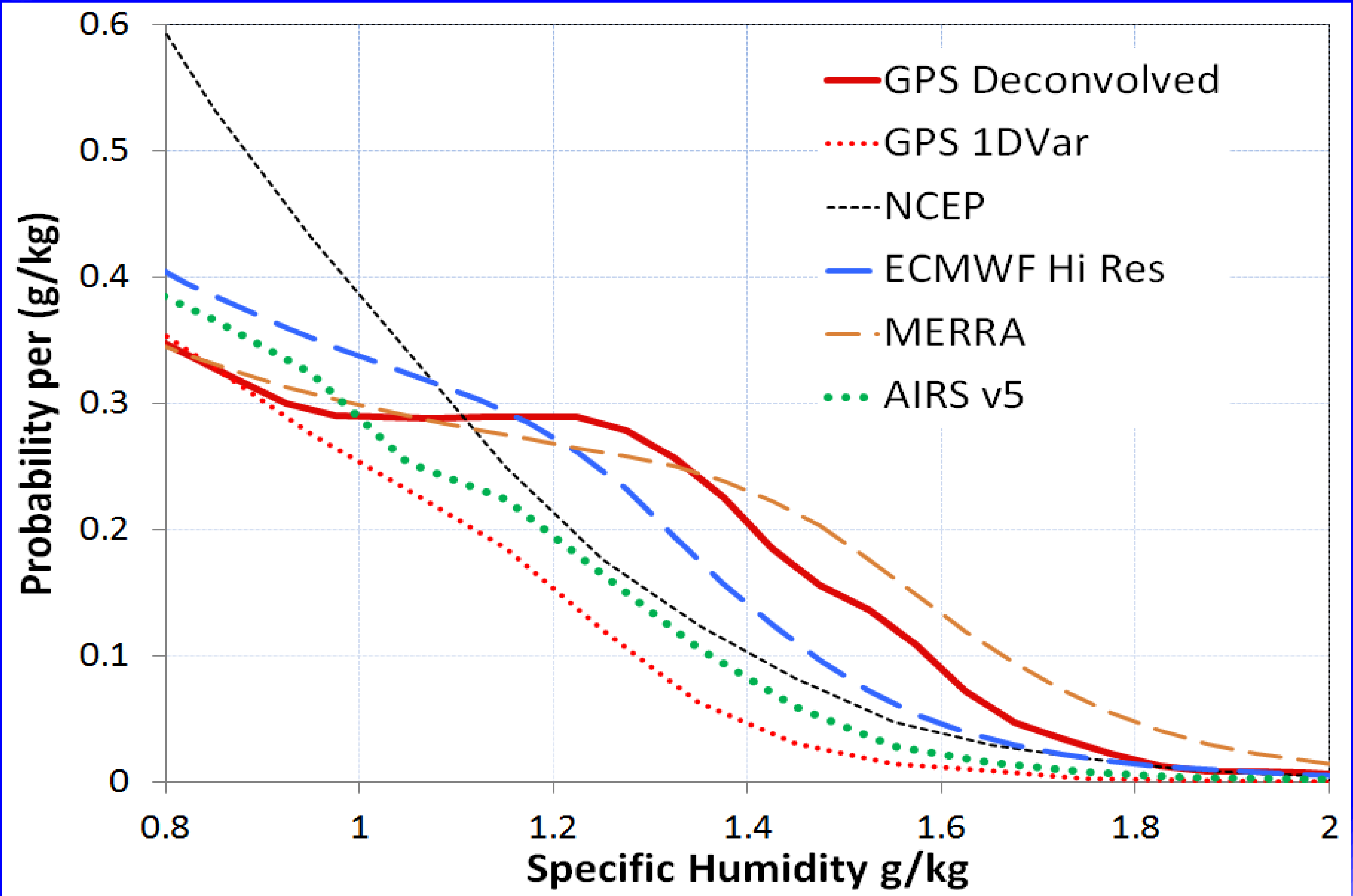


Kursinski et al., 2

0.05 g/kg res. **346 hPa** Specific Humidity 30S-30N 2007



346 hPa Low Latitude Comparison (2007)



Comparison of Estimates of Low Latitude Humidity Means

Specific humidity: 30S-30N annual averages

- Means

	GPS	AIRS v5	ECWMF lo-res	ECMWF hi-res	MERRA	NCEP	Sat-Adv
346 mb	0.44	0.397	0.448	0.448	0.48	0.496	0.456
547 mb	2.22	2.12	2.29	2.14	2.43	1.98	2.51

- Fractional Differences Relative to GPS RO

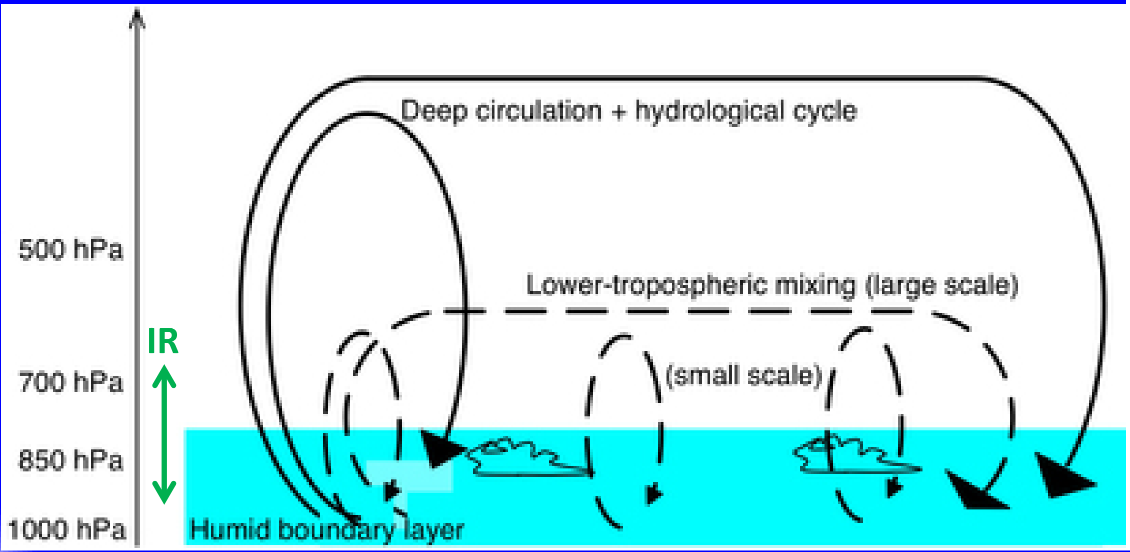
	GPS	AIRS v5	ECWMF lo-res	ECMWF hi-res	MERRA	NCEP	Sat-Adv
346 mb	0.0%	-9.1%	2.5%	2.5%	**9.0%**	13.5%	4.3%
547 mb	0.0%	-4.6%	3.2%	-3.6%	**9.5%**	-10.8%	13.1%

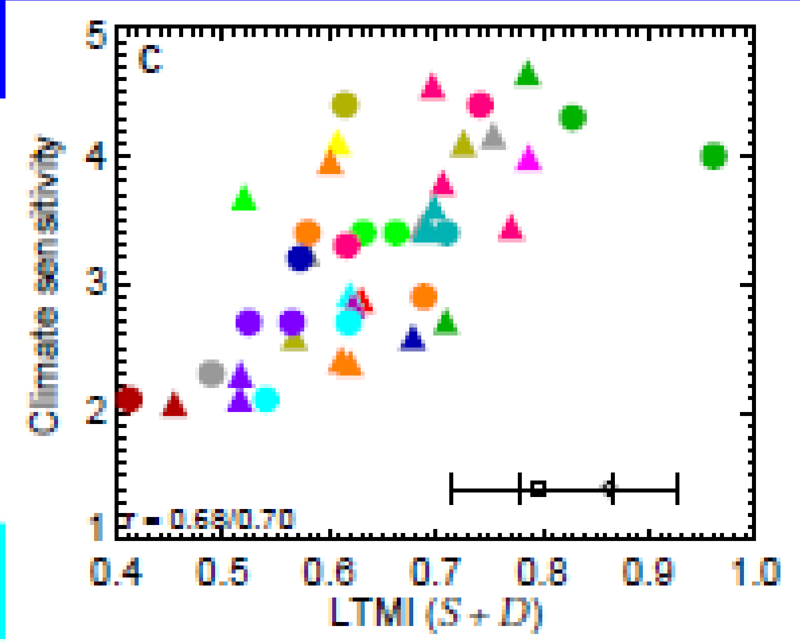
- Lots more going on than is captured in the means
  - MERRA histogram shapes closest to GPS but biased high in terms of mean

Kursinski et al., 25

Sherwood et al. (2014) Reduction in Climate Uncertainty?

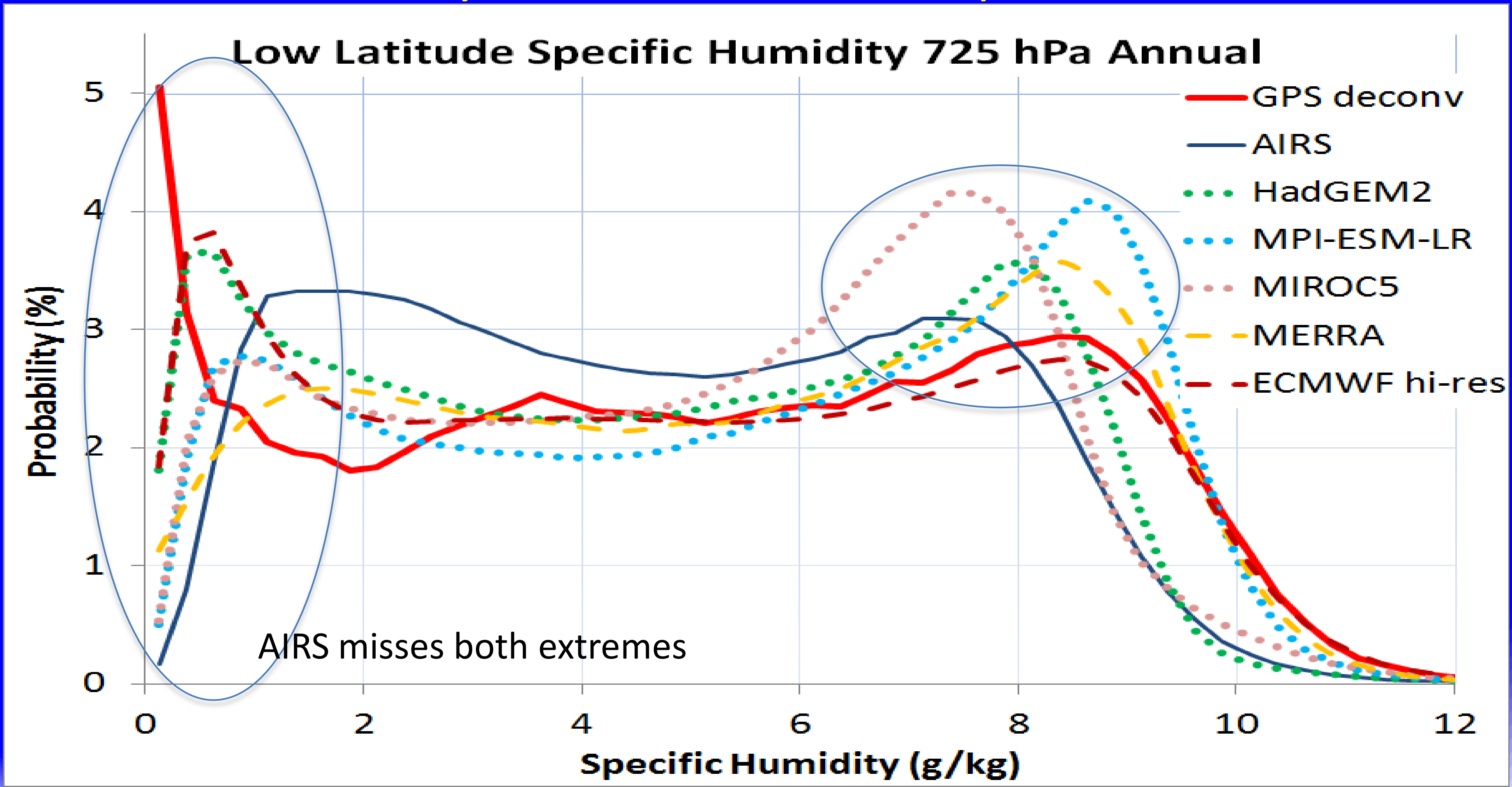
- As climate warms, models indicate stronger mixing => dehydrates BL
  - ⇒ Reduces low cloud cover => lowers albedo => more SW absorption
- Increase in mixing & dehydration of low-cloud layer in warmer climate proportional to mixing strength in present climate
- Evaluated model mixing against "observations" (= MERRA analyses)
  - ⇒ High climate sensitivity **>** 3°C for CO_2 doubling.



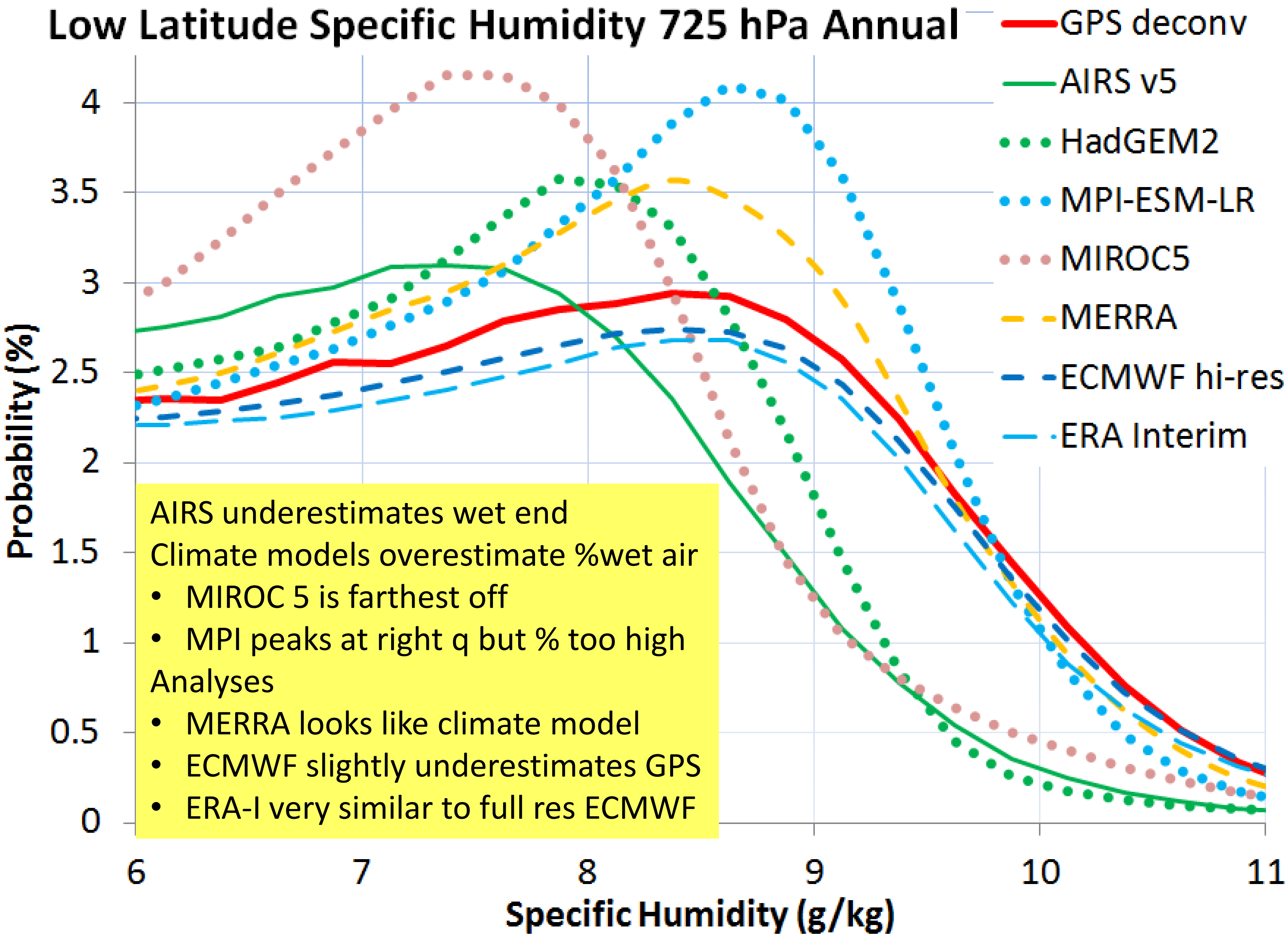


Climate Model & Analysis Comparison 725 mb

- Model peak ***q*** on wet end is a bit small except in MPI
- Modeled % of wet air near the peak is too high
- MERRA % too high; ECMWF slightly too low
- Models & analyses miss driest subtropical air



725 hPa Comparison: 30S-30N Wet End



AIRS underestimates wet end

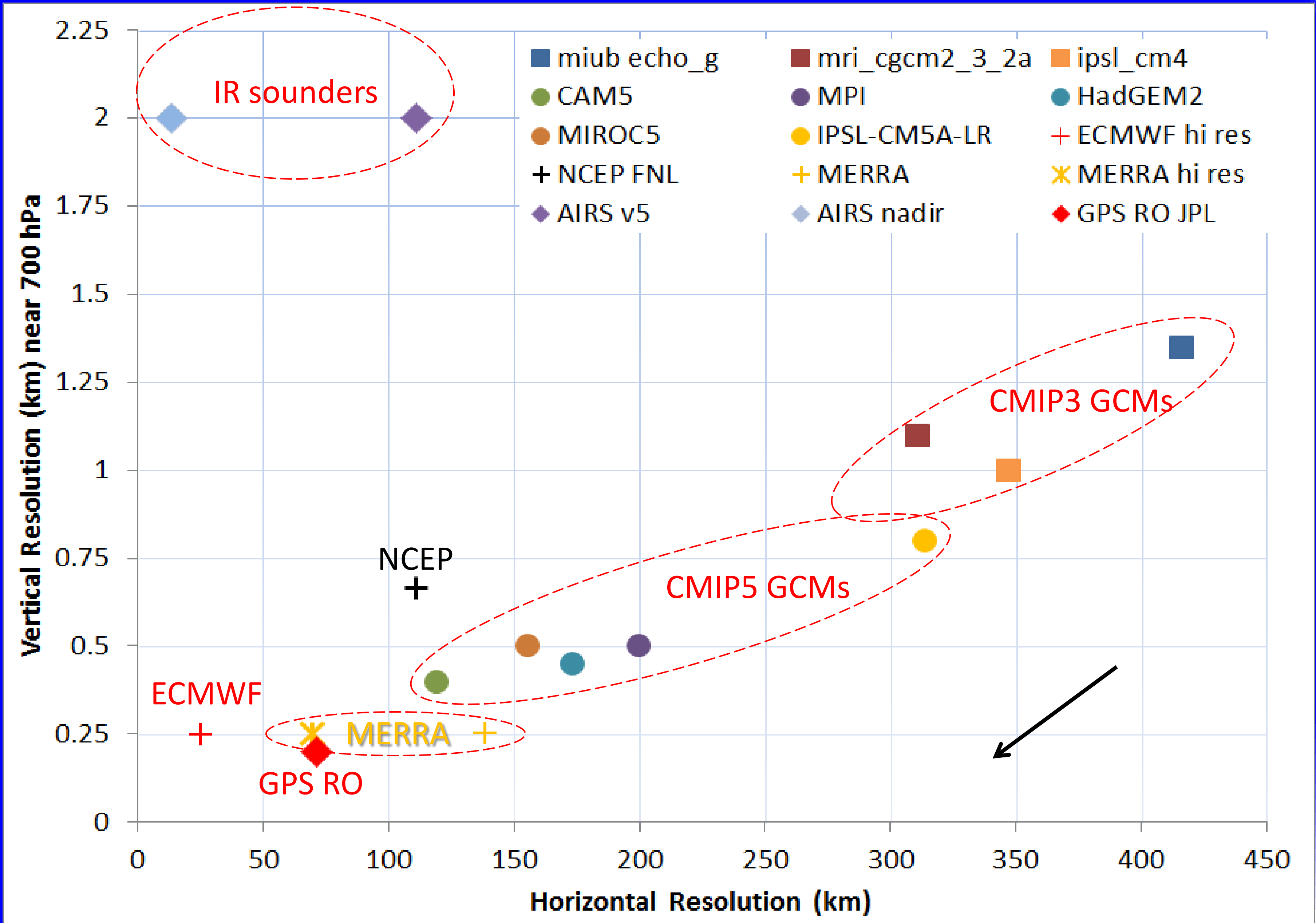
Climate models overestimate %wet air

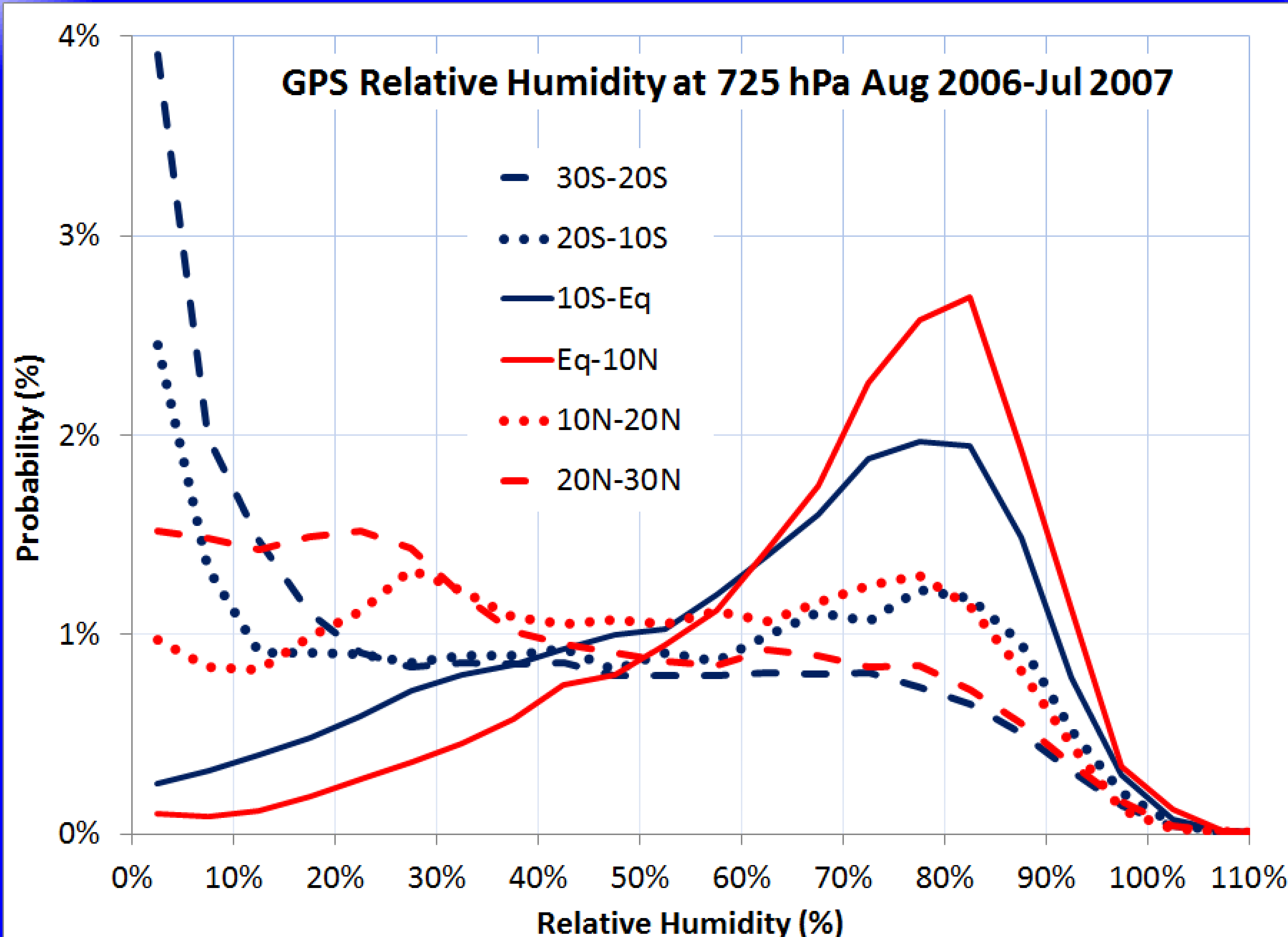
- MIROC 5 is farthest off
- MPI peaks at right q but % too high

Analyses

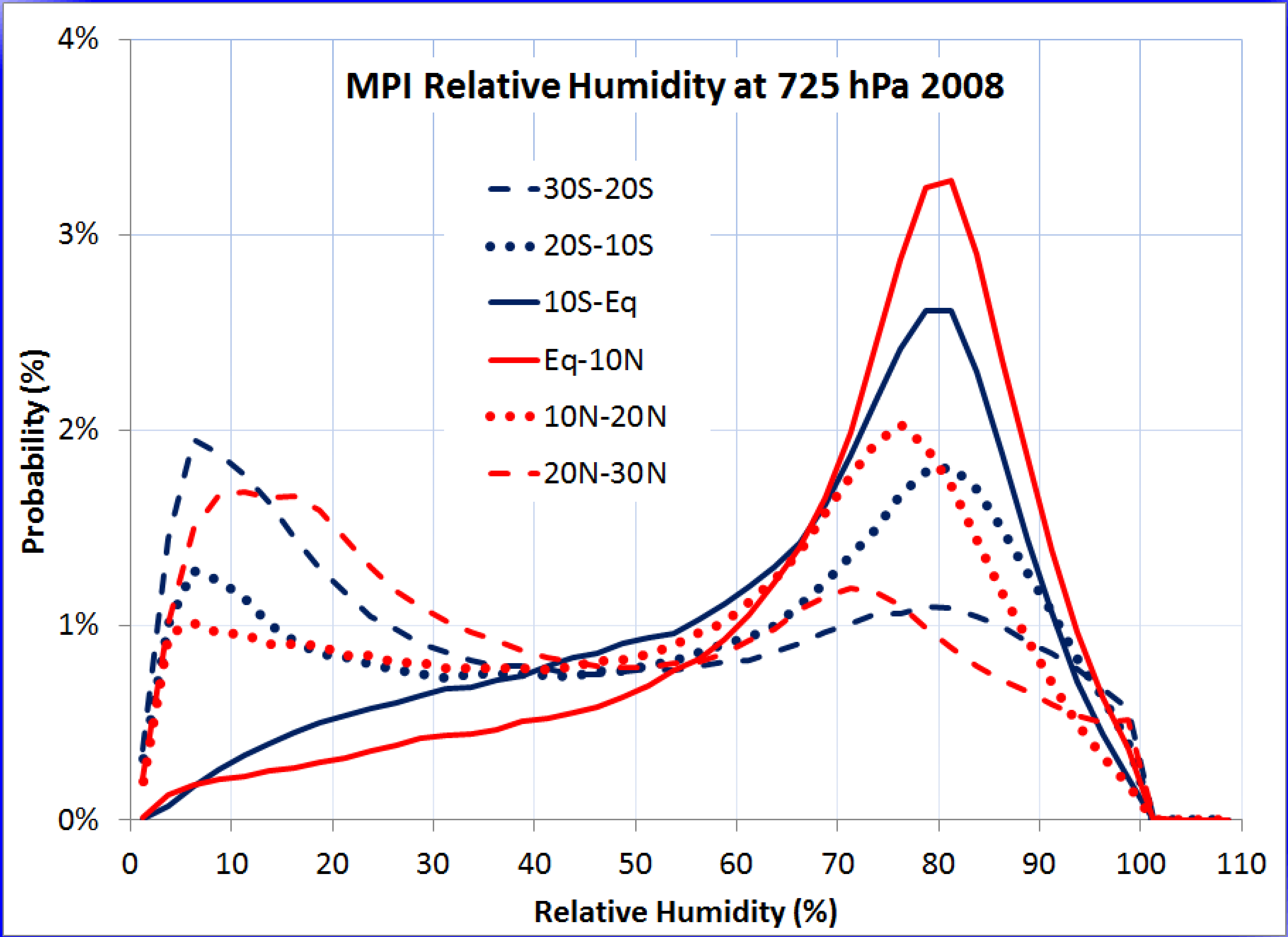
- MERRA looks like climate model
- ECMWF slightly underestimates GPS
- ERA-I very similar to full res ECMWF

Vertical & Horizontal Resolution Near 725 hPa





GPS Relative Humidity at 725 hPa Aug 2006-Jul 2007
4%
3%
2%
1%
0%
Probability (%)
30S-20S
20S-10S
10S-Eq
Eq-10N
10N-20N
20N-30N
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
110%
Relative Humidity (%)



MPI Relative Humidity at 725 hPa 2008
30S-20S
20S-10S
10S-Eq
Eq-10N
10N-20N
20N-30N
Probability (%)
4%
3%
2%
1%
0%
0
10
20
30
40
50
60
70
80
90
100
110
Relative Humidity (%)

Summary & Conclusions: GPS

- GPS RO moisture Information
  - extends to at least 346 hPa at low latitudes
  - Only to ~5 km in winter hemisphere
  - Zonal means can go still higher
  - Low bias: 0.03 g/kg
- GPS generally sees highest amounts of dry and wet moisture extremes of observations, analyses and climate models
  - Exception: MERRA sees more extremely wet air in mid & upper troposphere (must be coming from MERRA model)
- Initially surprising

  ⇒GPS limb sounder has lower horizontal res. than passive sensors

  ⇒ More horizontal averaging & smoothing

  ⇒ Less ability to see extremes (but clearly false conclusion)
- Implication: Very high vert. res., precision & all-weather sampling are more important than higher horiz. res. but poorer vert. res. & limited cloud penetration
  - NOTE: Really want **both**

Summary & Conclusions: GPS

- Further suggests GPS RO horizontal res. is not as poor as we have been stating
  - More like 70 km?
  - Need a study to better determine this
- The GPS RO information is missing in the moisture analyses
  - Need to dramatically increase GNSS RO occ sampling to have more impact on the moisture analyses
  - eventually dominating certain portions of moisture analysis information content
- ATOMMS: Dynamic range and accuracy will be much better than GNSS RO for upper troposphere, winter and middle atmosphere water vapor

Summary & Conclusions: AIRS

AIRS (& passive IR in general?)

- Dry bias on the wet end of distribution at all tropospheric levels
  - Despite cloud clearing
  - IR can't penetrate into & below clouds where wettest air is

  $\Rightarrow$Sampling bias
- In mid-troposphere AIRS sees very dry air similar to GPS
  - Good: Confirms these results
- Underestimates dry air near BL top
  - Presumably due to limited vertical resolution
- Biases make it challenging to use IR for climatological applications

Summary & Conclusions: Analyses

- Use full resolution analyses!
  - Low resolution products substantially compress the histograms
  - Leads to erroneous implications about processes
  - Maybe be adversely impacting 1DVar results?
- ERA-Interim & full resolution ECMWF analyses are quite similar
  - indicates that resolution is not the dominant variable
- MERRA look good statistically in free troposphere but some problems near the BL top
- Analyses are *generally* better than GCMs (no surprise) but ≠ observations
  - 80% to 95% of the information in analyses comes from the forecasts (not the observations)

Climate Model Comparison Summary

- NCAR & MPI are closest to GPS
- Assessing the realism of climate models is challenging & complex.
  - Different figures of merit seem to produce different conclusions
    - Biajun Tian found MIROC5 is best in terms of double ITCZ
    - MIROC5 is clearly not best in terms of moisture histograms

    $\Rightarrow$ "Right" for the wrong reasons
  - Different figures of merit are good in terms of deeper understanding
  - Appears that people working in this area are going to be employed for a long time

Climate Model Comparison Summary

- GPS contains unique information about water vapor for constraining processes at work climate model realism
- Appears to be critical for characterizing and reducing model prediction uncertainty