Comparison of tropospheric humidity from AIRS, MLS, and theoretical Models

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Introduction

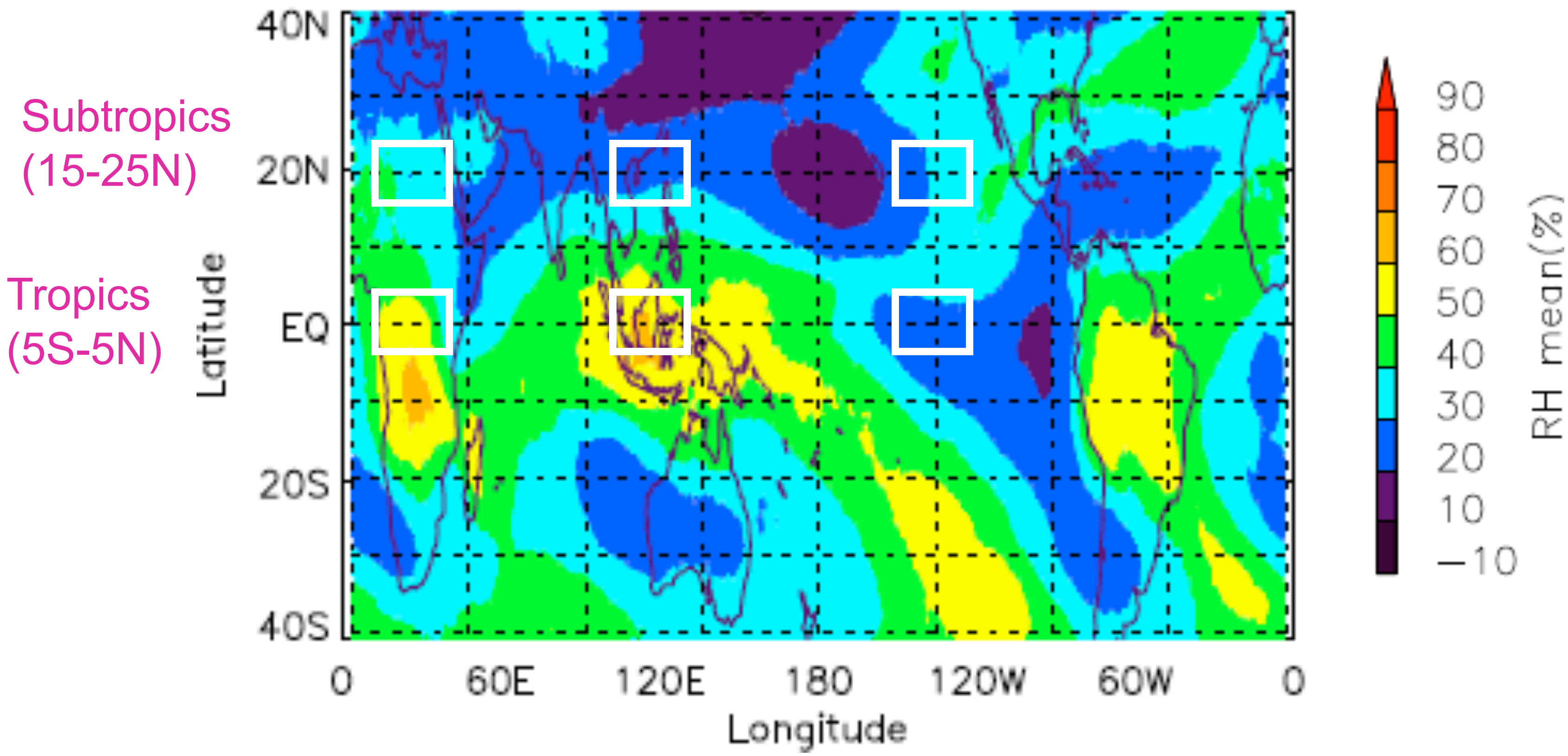
- Climate is sensitive to upper tropospheric humidity, and it is important to know
  - ➢ *distributions* of water vapor in this region, and
  - ➢ *processes* that determine these distributions.

- We examine the probability distribution functions (PDFs) of upper tropospheric relative humidity (RH) for measurements from
  - ➢ Aqua AIRS
  - ➢ Aura MLS
  - ➢ UARS MLS
- Consider spatial variations of PDFs. Focus here on DJF, ~250hPa

- Also compare with theoretical models (generalization of Sherwood et al (2006) model).

Climatological UT Relative Humidity

DJF (2002-2007) 200-250hPa
Mean Relative Humidity (AIRS)



- Subtropics is drier than the Tropics
- But also significant zonal variations

200-250hPa

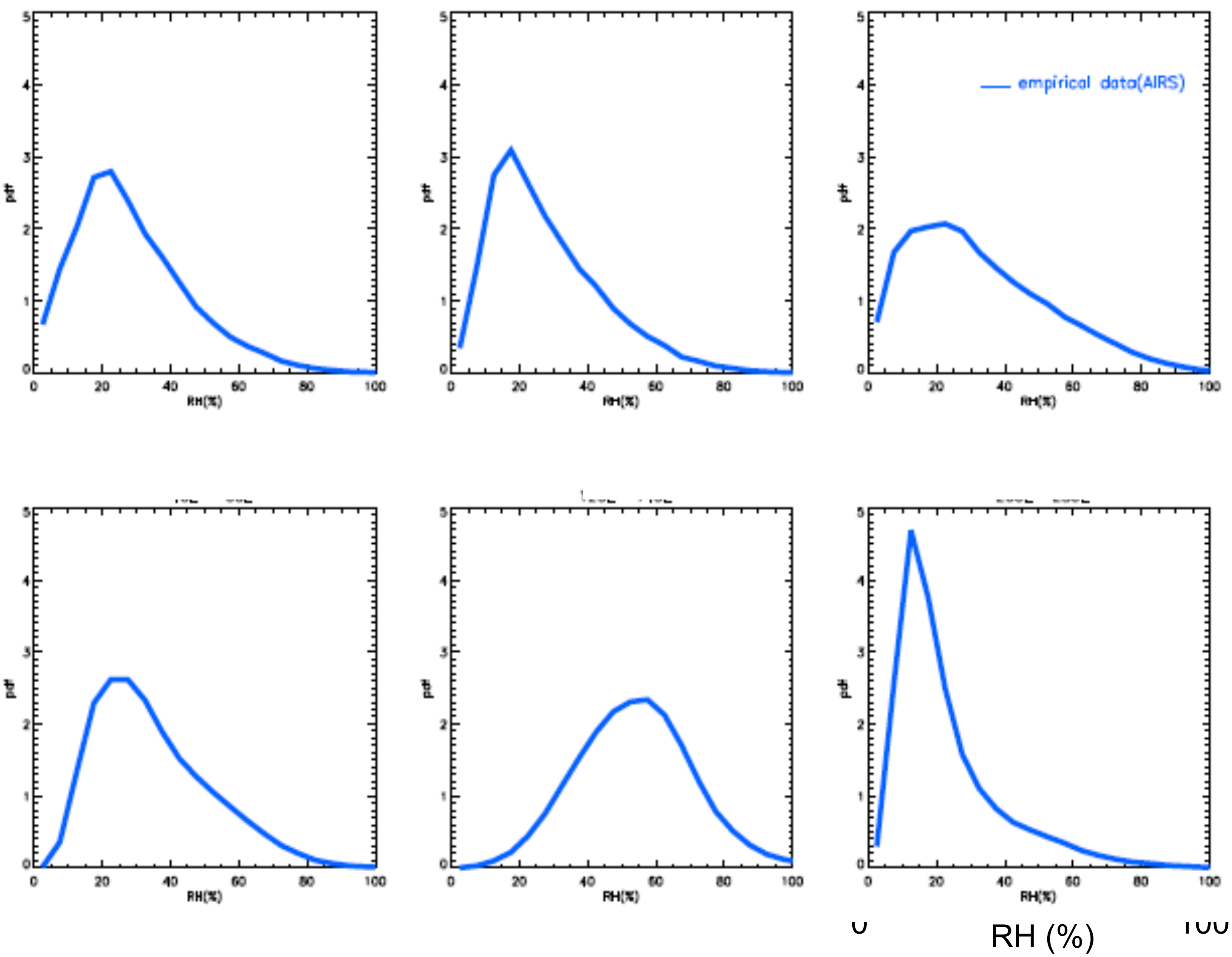
PDFs: AIRS

Large variation in PDFs - peak, spread, skewness, …

40E-60E | 120E-140E | 260E-280E

Subtropics (15-25N)

Tropics (5S-5N)

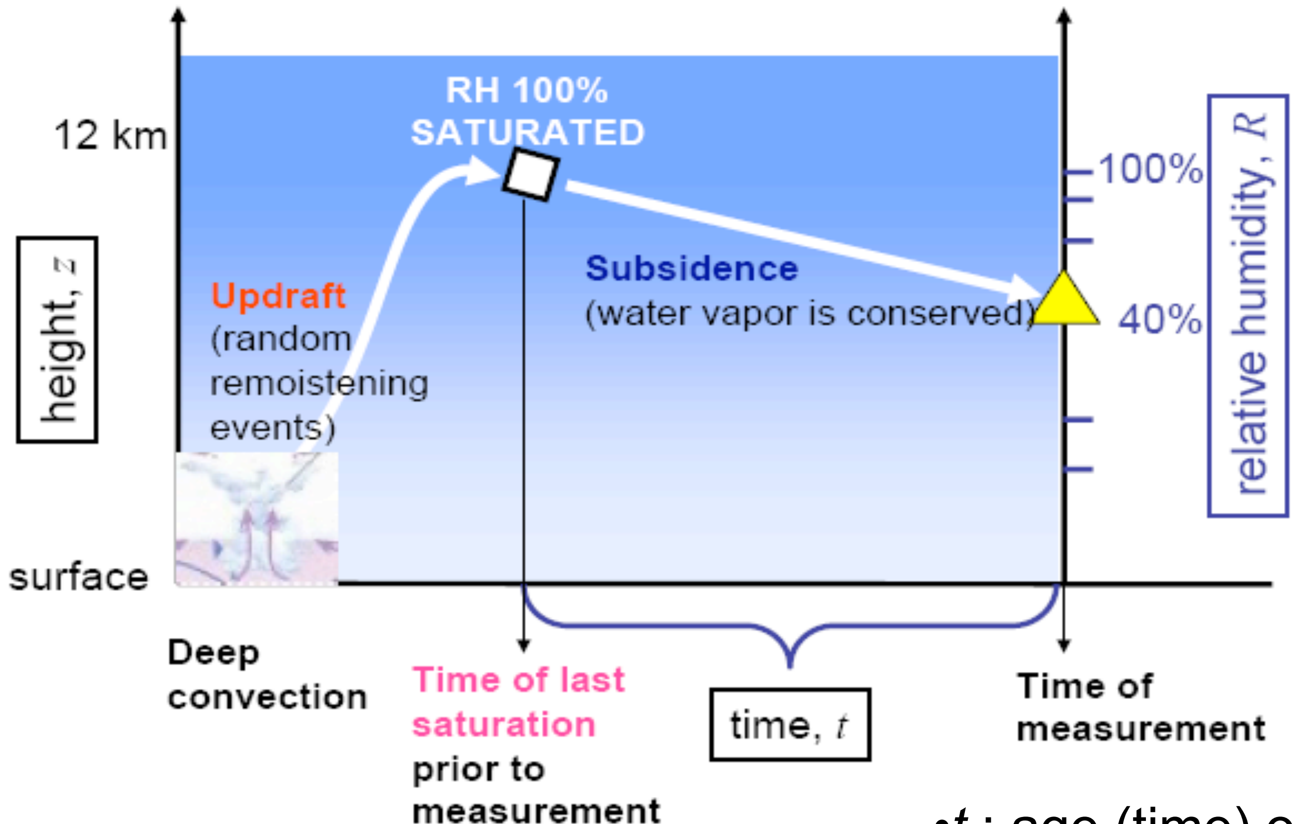


Theoretical Models

Basic Assumption:

• Moistening by random events

•Uniform Subsidence (water is conserved)



•*t* : age (time) of parcel since last saturation

Theoretical Model: Generalized Version

As in the Sherwood et al. (2006) model, given uniform subsidence, RH can be approximated as

$$R(t) \approx exp\left(-\frac{t}{\tau_{Dry}}\right)$$

Time since last saturation is now modeled as random moistening events but includes randomness of these events (*k*).

$$P(t) = \frac{\left(\frac{1}{\tau_{Moist}}\right)^{k} exp\left(-\frac{t}{\tau_{Moist}}\right) t^{k-1}}{\Gamma(k)}$$

Eliminate t from above equations, yields the generalized PDFs of RH as

$$P(R) = \frac{k^k r^k R^{kr-1}}{\Gamma(k)}(-\log R)^{k-1}$$

When k=1 it is the same as sherwood et al.(2006)

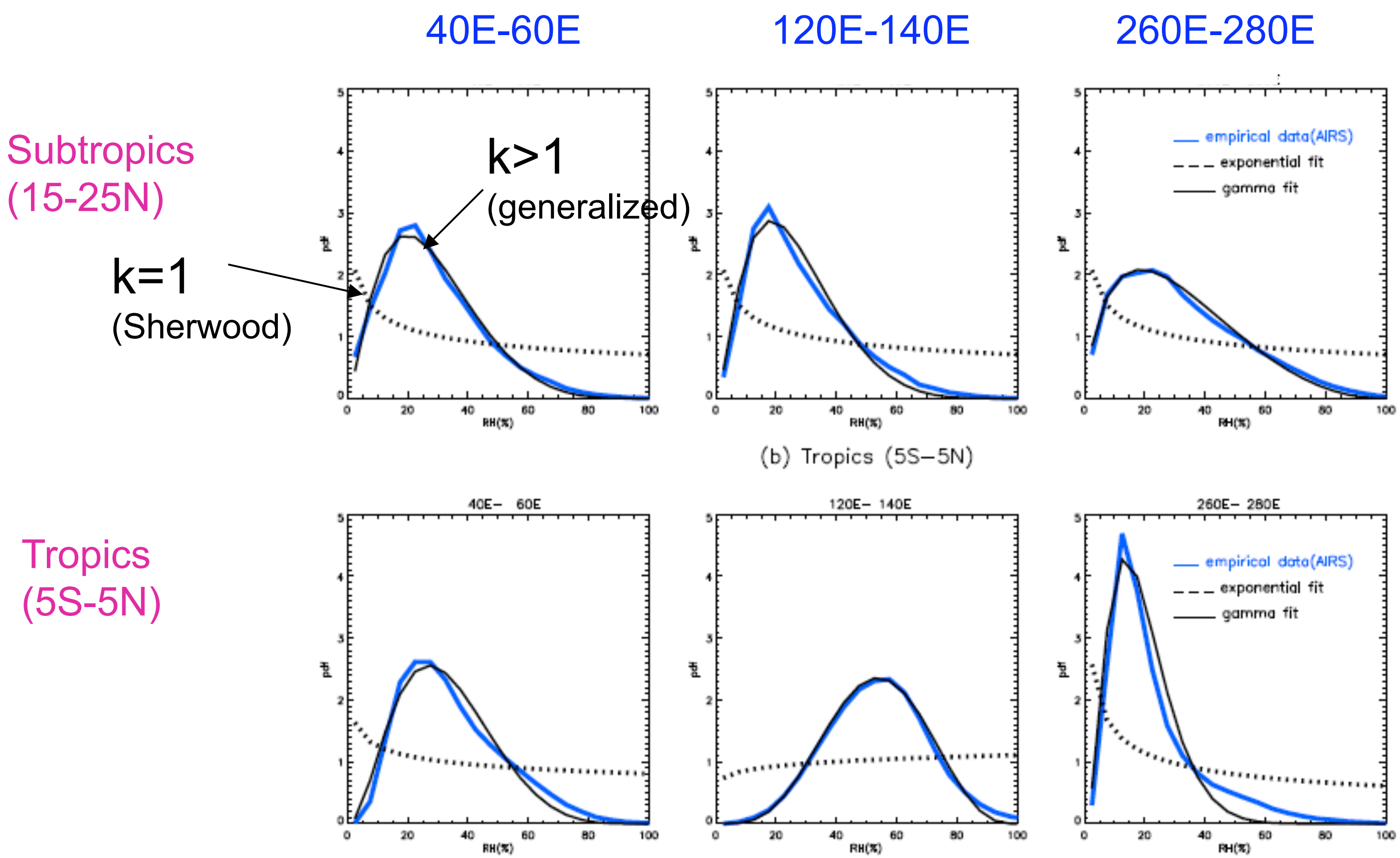
$$P(R) = rR^{r-1}$$

where, $\Gamma(k)$: Gamma function

r: ratio of drying time (τ_{dry}) to moistening time (τ_{moist})
k: measure of randomness of remoistening events

PDFs: Data and Model

How well do the theoretical models fit the observed PDFs?

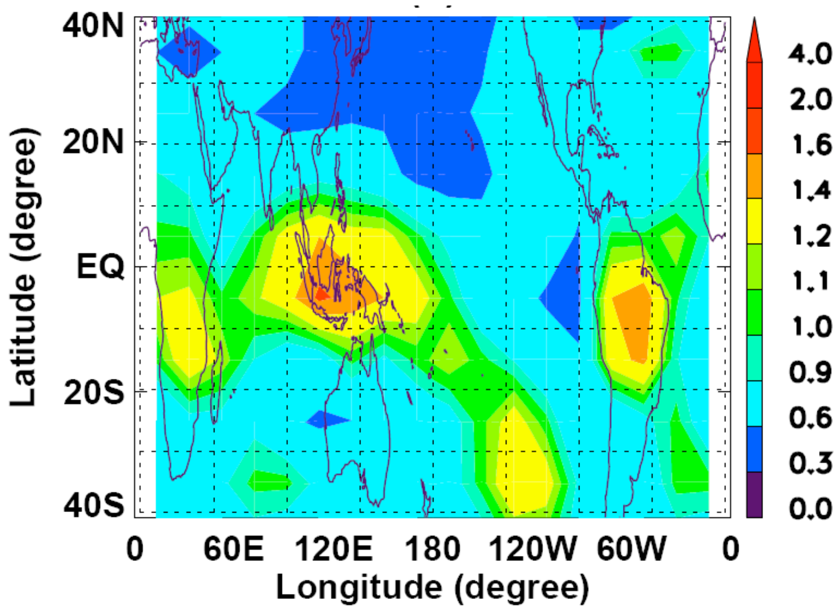


Generalized Model can fit the observed PDFs (peak, spread, skewness), with *r* and *k* varying with location.

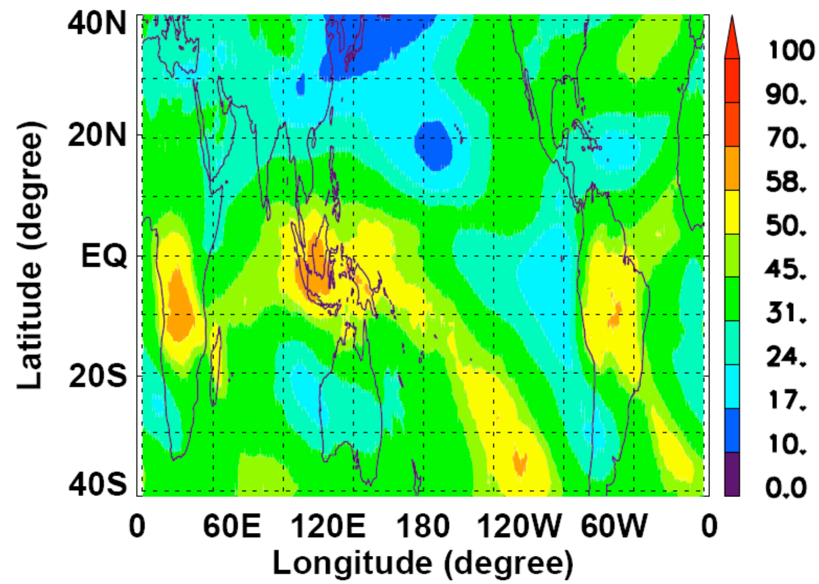
Maps of “r” and “mean RH”

AIRS (2002-2007)

r



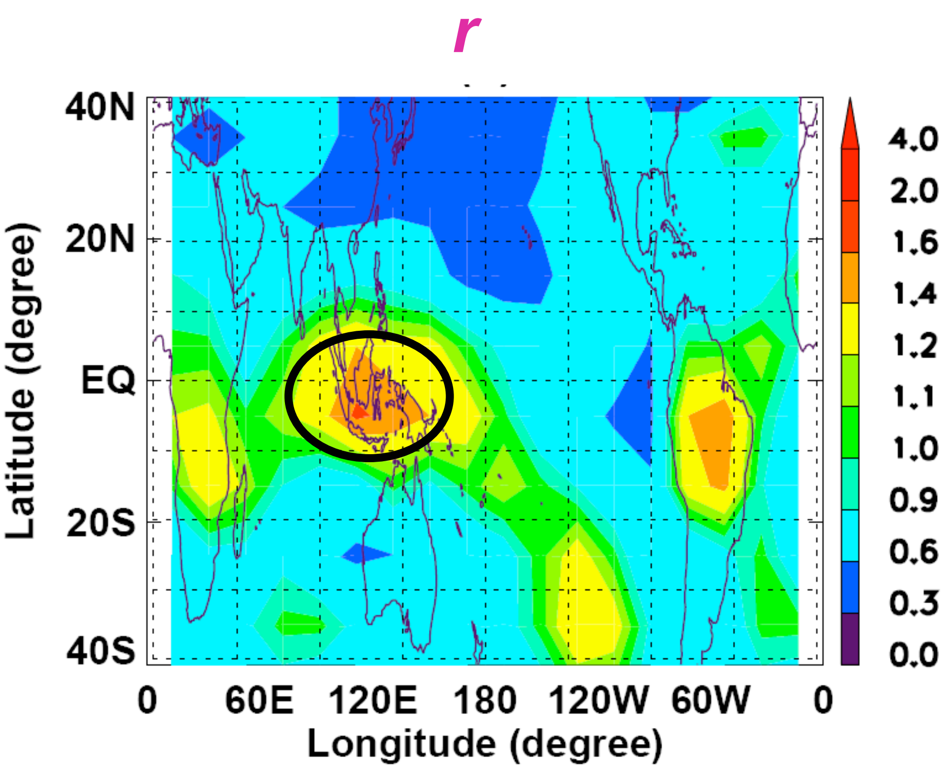
μR

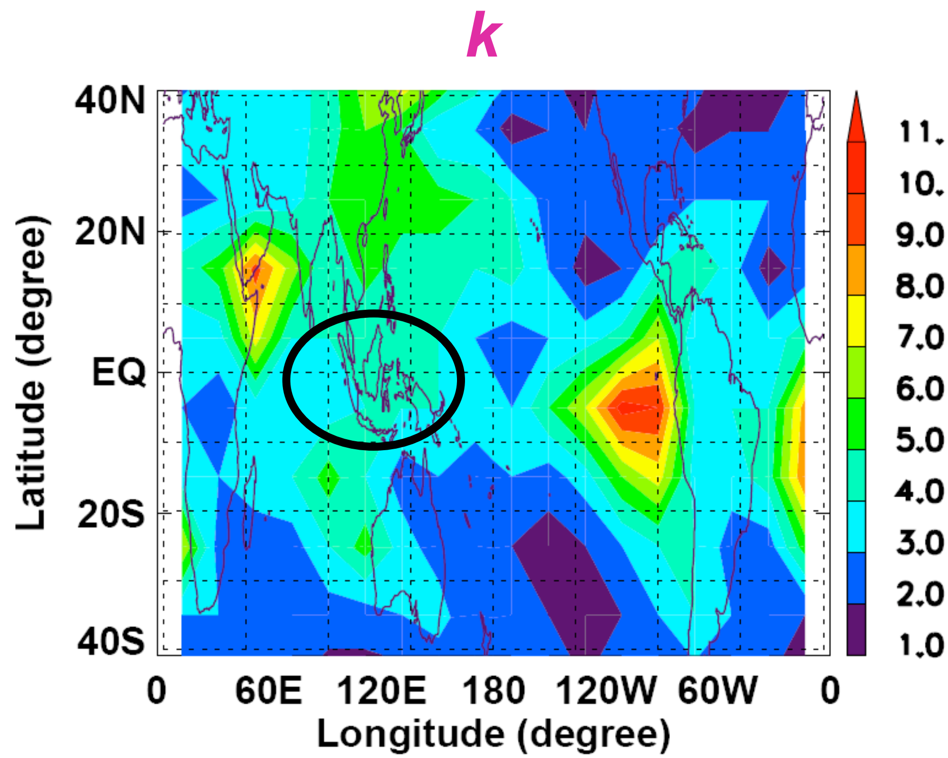


Strong resemblance between maps of ***r*** and **mean RH** (μ_R)

Maps of "r" and "k"

AIRS (2002-2007)





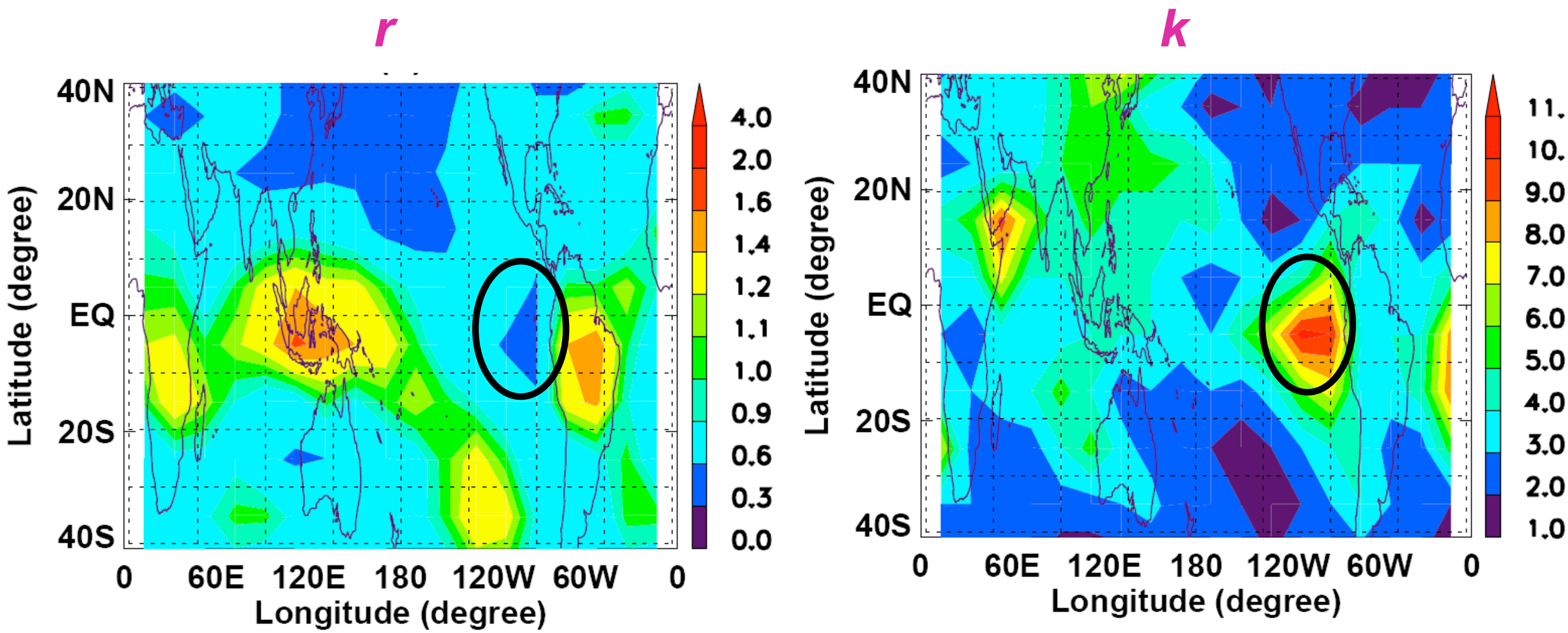
Convective Regions:

- **large *r* (*r*>1) and small *k***

=> Rapid, random remoistening

Maps of "r" and "k"

AIRS (2002-2007)

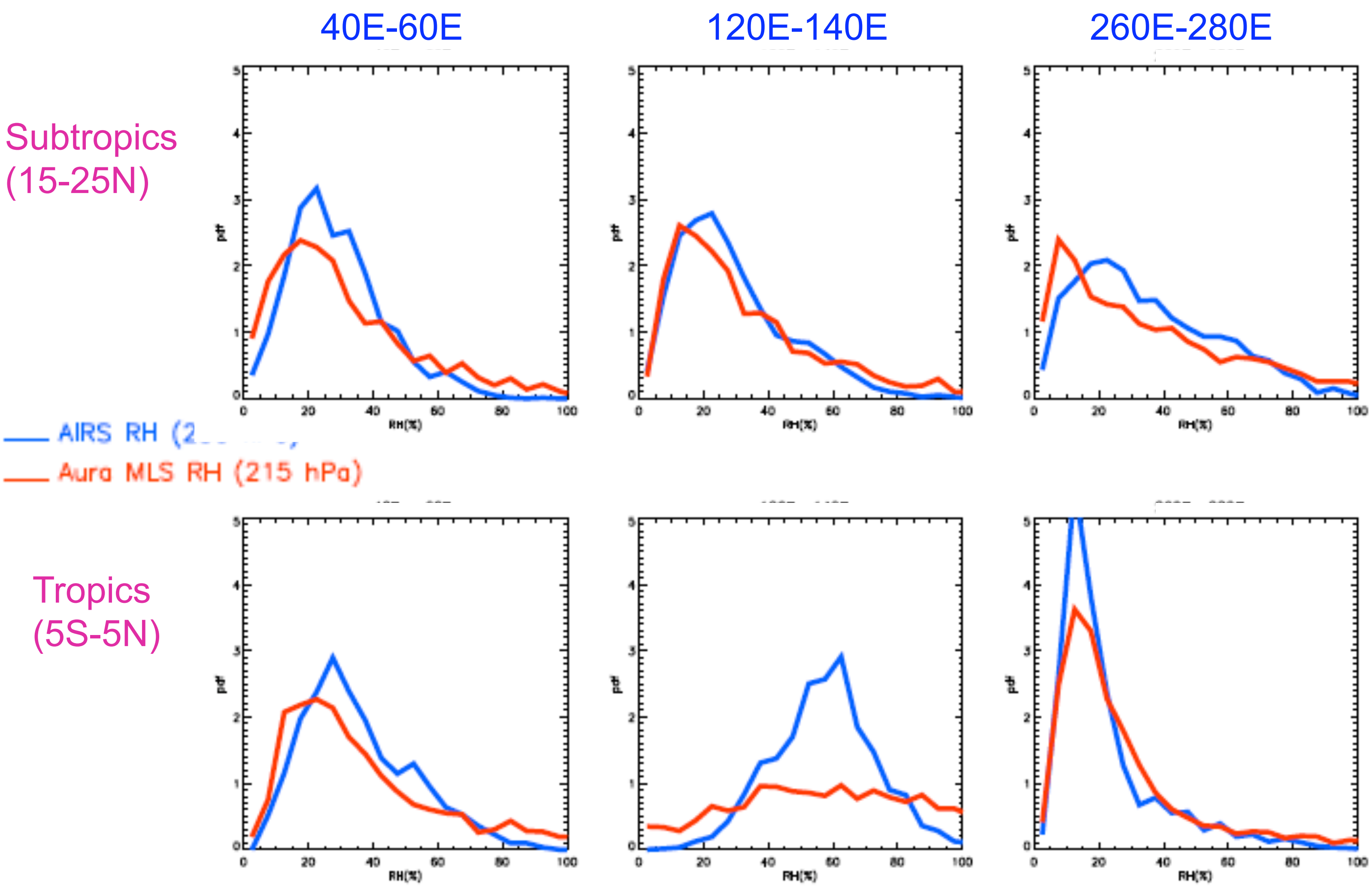


Non-convective Regions:

- **small *r* (*r*<1) and large *k***

=> Slower, more regular remoistening (horizontal transport)

PDFS: AIRS - Aura MLS Comparison



Good agreement between AIRS and Aura MLS, with some exceptions.

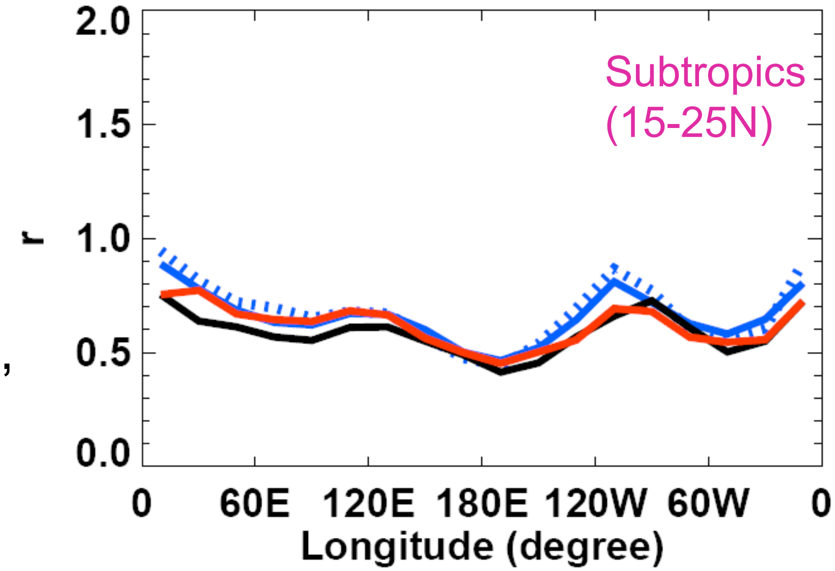
Spatial Variations in r

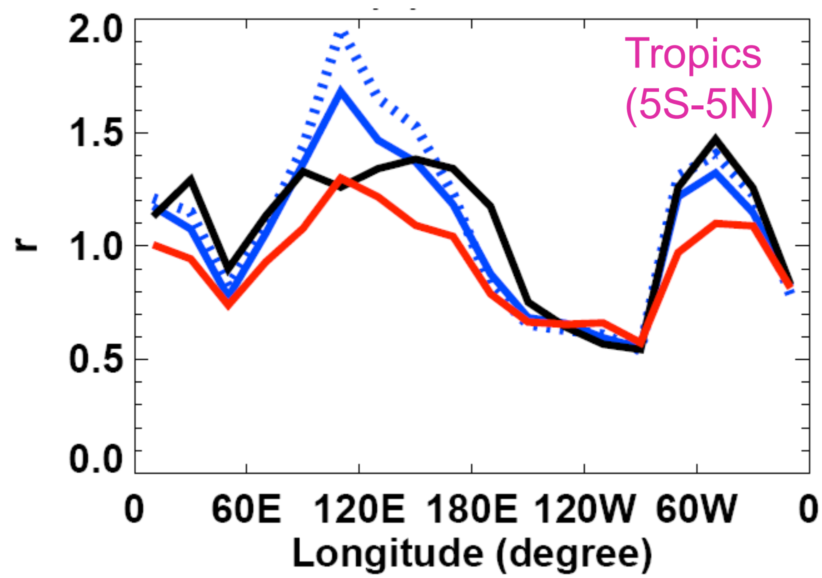
$r = \tau_{dry} / \tau_{moist}$

- Good agreement between different data sets.

- All show
  $r > 1$ in tropical convective regions,
  $r < 1$ in dry regions.

- Expected as larger r implies more rapid remoistening





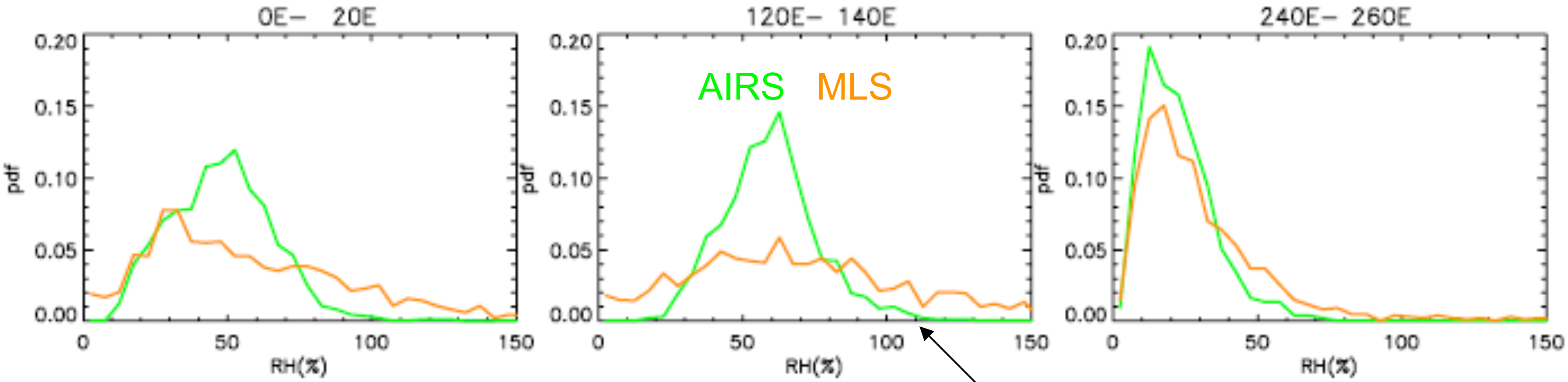
___AIRS (2002-07)

_ _AIRS (2005-07(match with MLS))

___UARS MLS (1992-94)

___Aura MLS (2005-07)

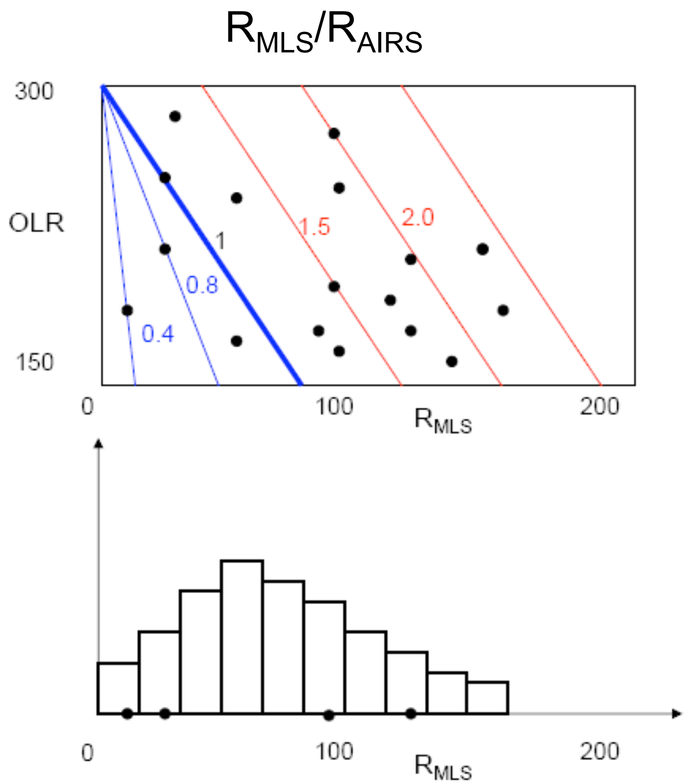
AIRS - Aura MLS bias



Largest difference: Tropical convective regions (5S-5N, 120-140E)

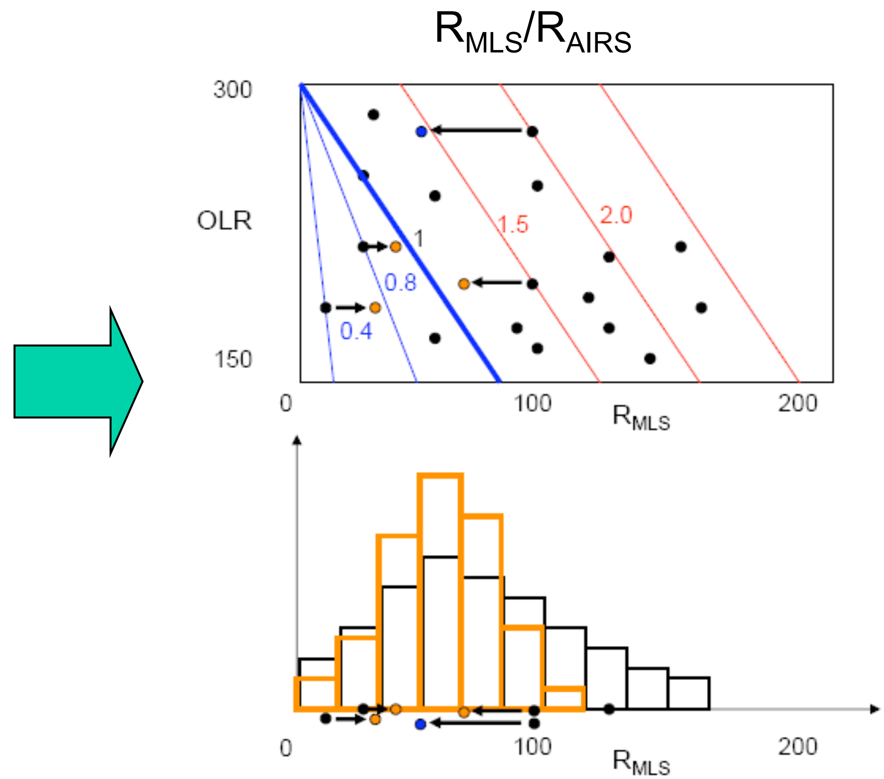
- There are some differences between AIRS and MLS PDFs.
- Differences are not simply a function of RH.
- Is there a simple parameterization of the AIRS-MLS difference?

Bias between data: R_{MLS}/R_{AIRS}



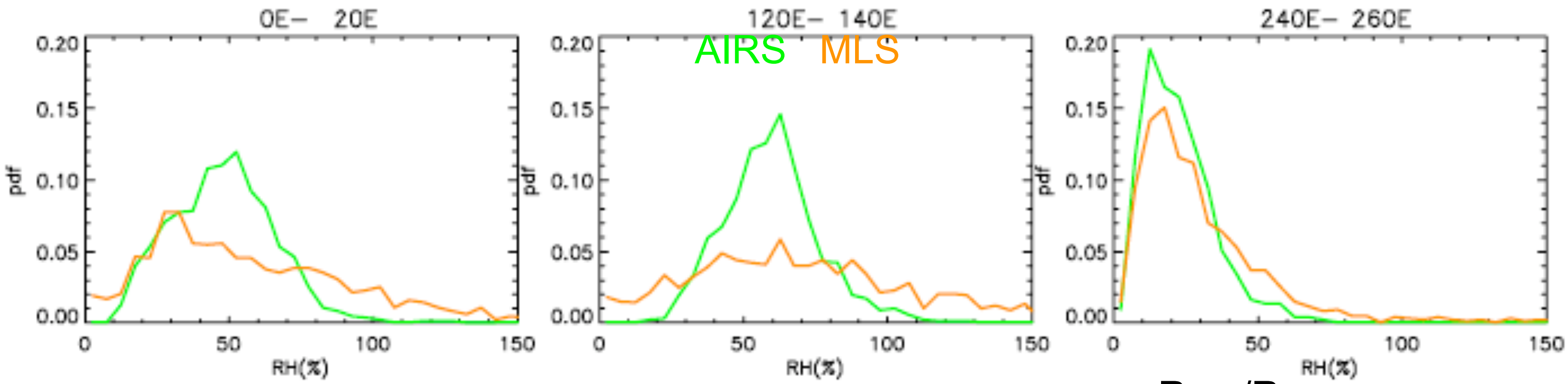
NOAA spatially and temporally interpolated OLR (2005-2006)

PDFs of MLS data



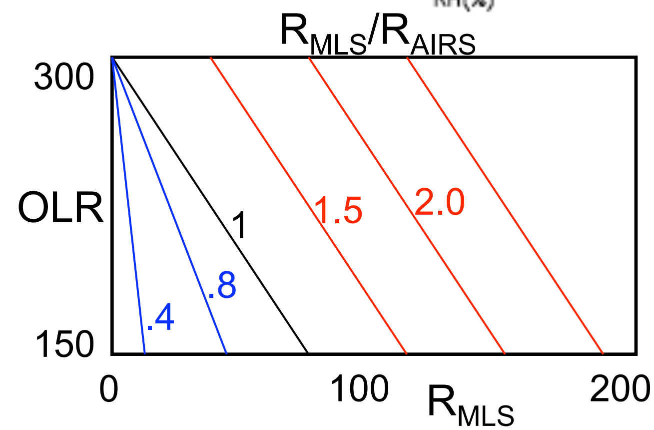
PDFs of MLS data *after transform*

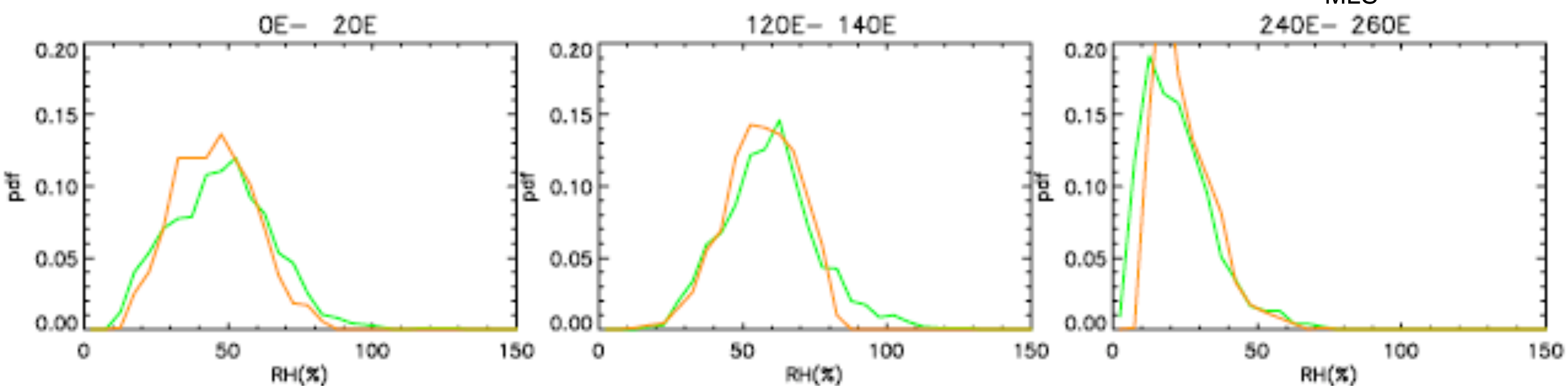
AIRS - Aura MLS bias



Transform MLS Data

$R_{MLS}/R_{AIRS} = f(R_{MLS}, \textbf{OLR})$





Conclusions

- Several robust features (peak, range, skewness) are found in the observed PDFs from all three data-sets (Aura and UARS MLS, AIRS).

- All can be well fit by a generalized version of the Sherwood et al. (2006) theoretical model.

- Consistent spatial variations in "r" (ratio of drying and moistening times) and "k" (randomness of moistening process).

> • Large *r*, small *k* in tropical convective regions
>
> ⟶ rapid, random remoistening
>
> • Small *r*, large *k* in dry regions
>
> ⟶ slow, more regular remoistening

- A more quantitative link between the different physical processes and the parameters *r* and *k* is needed. This would be performed by trajectory-based water vapor simulations.

Theoretical Model: Sherwood et al (2006)

Sherwood et al. (2006) assumed that if parcels uniformly subside, RH can be approximated as

$$R(t) \approx exp\left(-\frac{t}{\tau_{Dry}}\right)$$

Time since last saturation is modeled as time between random moistening events

$$P(t) = \exp(-t/\tau_{\text{moist}})/\tau_{\text{moist}}$$

Eliminate *t* from above equations, yields the PDFs of RH as

$$P(R) = rR^{r-1}$$

where,

$$r = \tau_{\text{dry}}/\tau_{\text{moist}}$$

τ_{dry} is the uniform drying time by subsidence

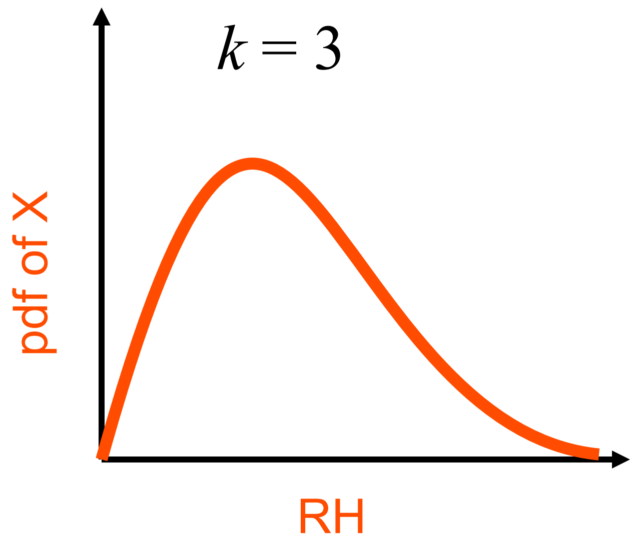
τ_{moist} is the time between remoistening events.

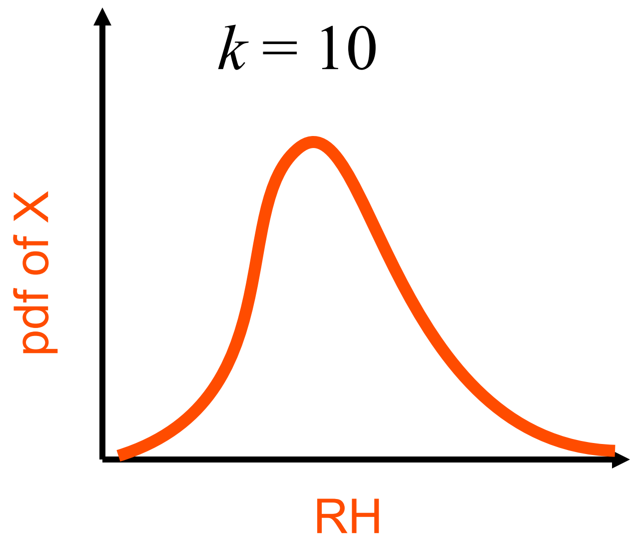
Characteristics of the Gamma PDF

$k = 1$ Gamma PDF= Exponential PDF

$k > 1$

$$k \propto \left(\frac{\text{mean(RH)}}{\text{standard deviation(RH)}} \right)^2$$





k : randomness parameter

Large k => less random moistening events

• Variations in r and k characterize variations in the moistening processes.

• The maps of μ_R and σ_R show a strong resemblance to those of r and k, respectively, i.e., there is **large** $\boldsymbol{\mu_R}$ where $\boldsymbol{r}$ **is large** and **large** $\boldsymbol{\sigma_R}$ where $\boldsymbol{k}$ **is small**.

$r \sim \mu_R$

$k \sim 1/(\sigma_R)^2$