Overview on retrievals from passive sensors

Ralf Bennartz
EES, Vanderbilt University
SSEC, University of Wisconsin

GPM was launched successfully on:

Thu, 27 Feb 2014 18:38:33 UTC

GPM was launched successfully on:

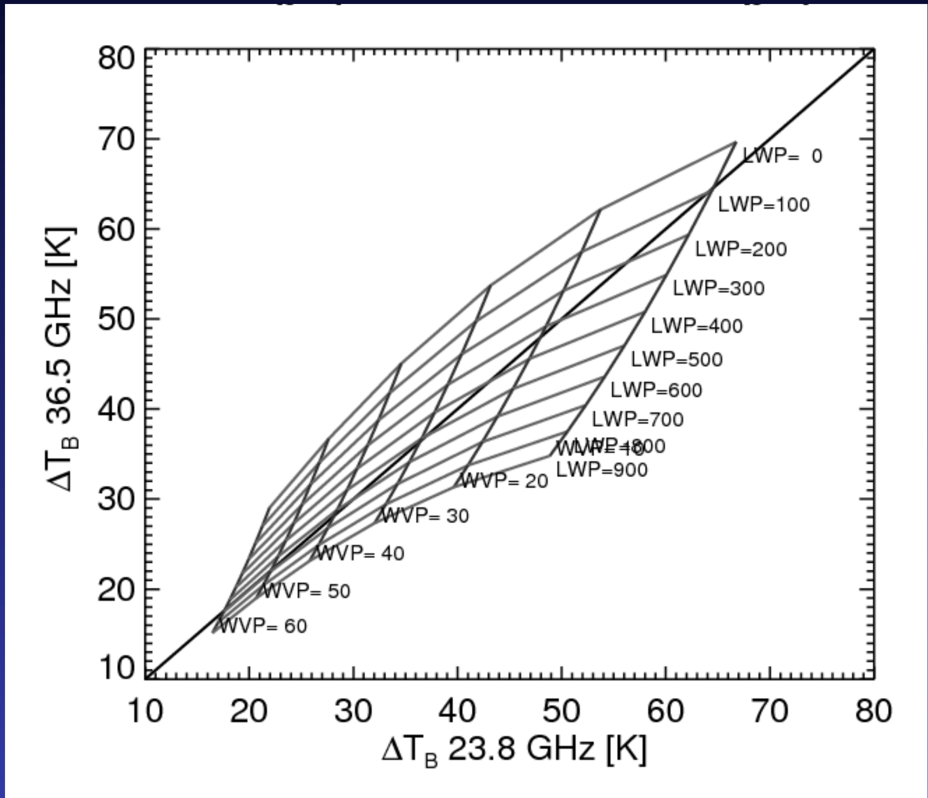
Thu, 27 Feb 2014
18:38:33 UTC

OCO-2 launch planned 1 July

Outline

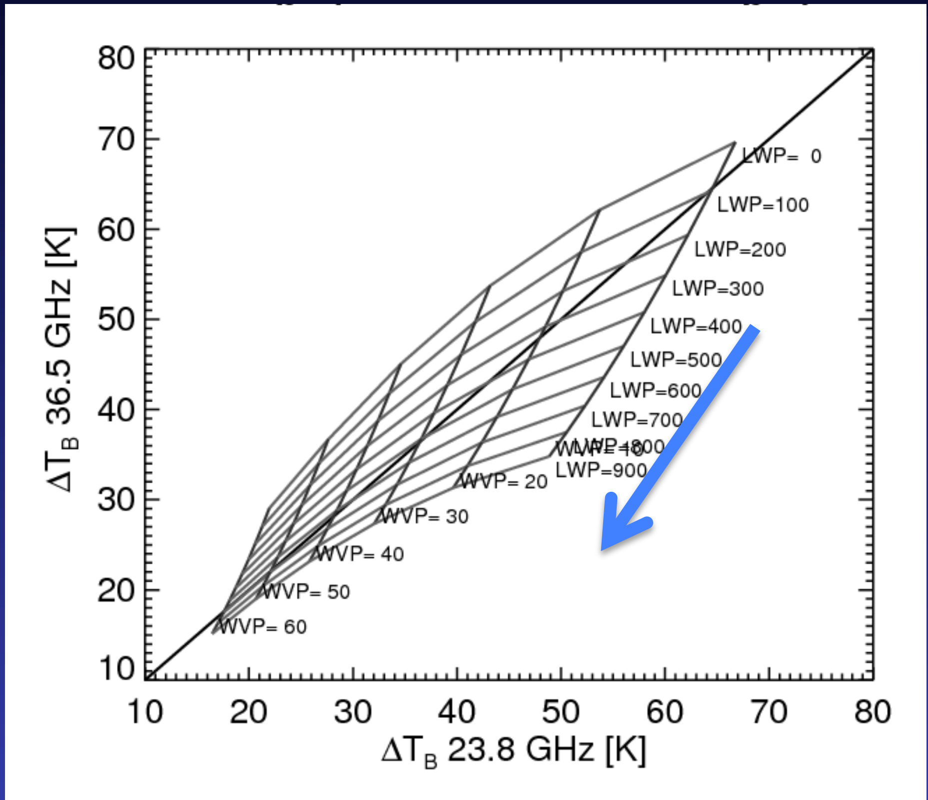
- Microwave
- Visible/Near-IR
- Aggregation
- Conclusions

MW: Principle of retrieval



- Use 2 channels and polarization difference to estimate WVP, LWP
- Also affected by rain water
- Separation of RWP/ LWP critical.

MW: Principle of retrieval

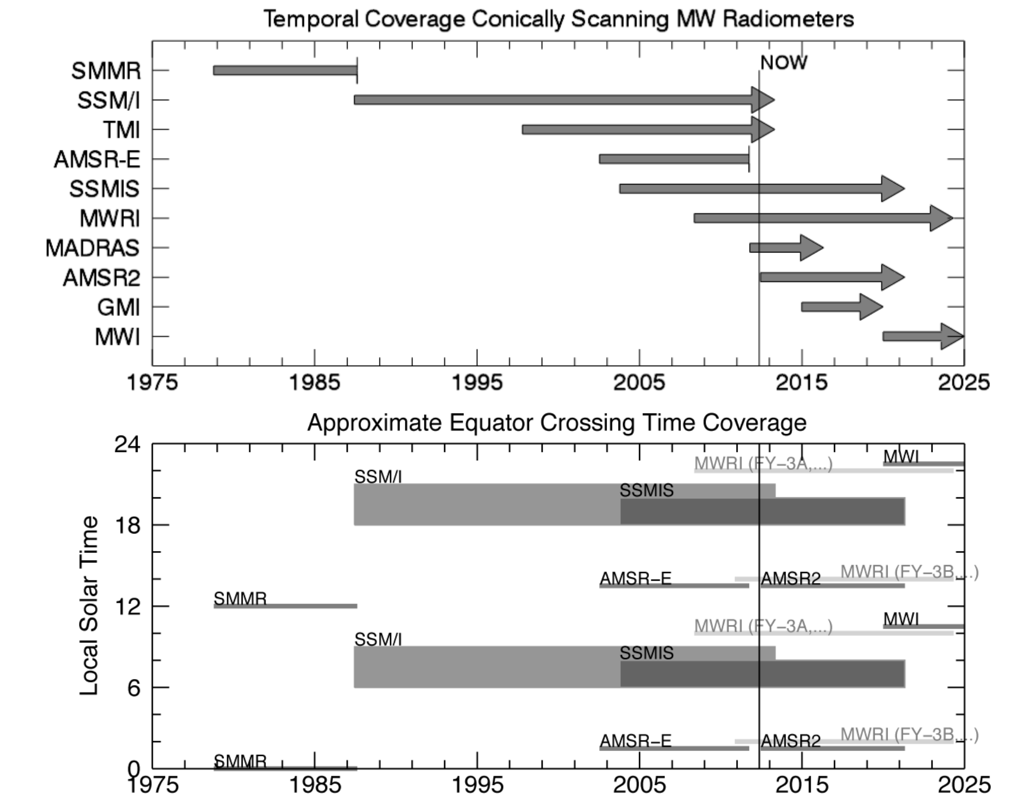


- Use 2 channels and polarization difference to estimate WVP, LWP
- Also affected by rain water, wind, cloud temperature
- Separation of RWP/ LWP critical.

MW Cloud liquid water path climatology

- Based on Wentz SSM/I since 1987, AMSR-E, and TMI
- Monthly diurnal mean liquid water path
- Climatological diurnal cycle
- O' Dell, Wentz, and Bennartz, J Climate, 2008
- Various limitations for high LWP (due to presence of rain), slight biases for low LWP

Data Record

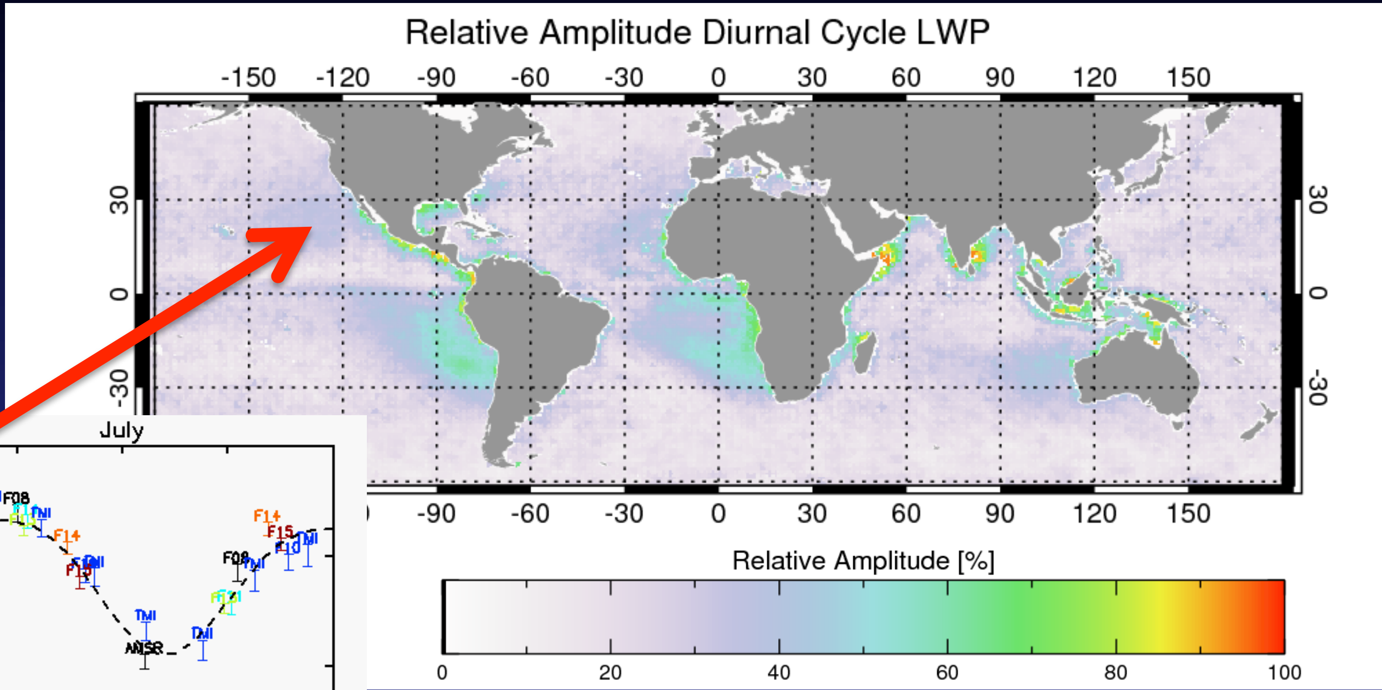


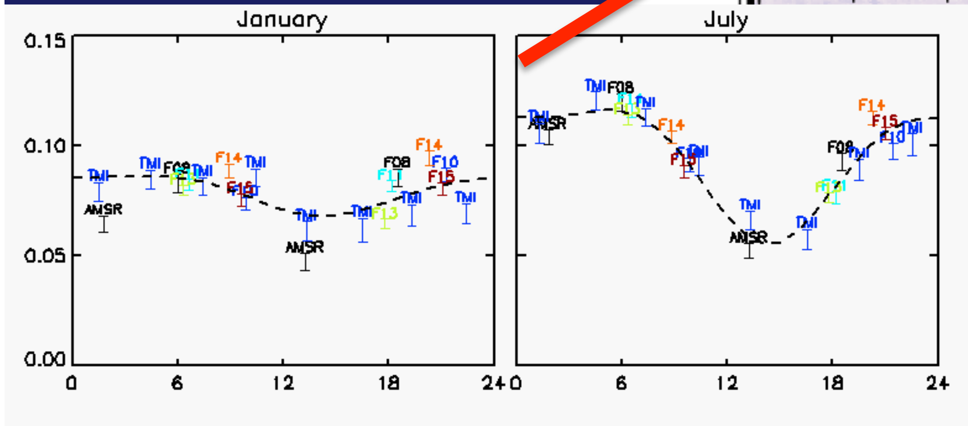
- SSM/I, SSMIS Morning/Evening Coverage since 1987
- TRMM/GPM crisscrossing in LEXT since 1997 resp 2014
- AMSR-E/AMSR-2 13:30 LEXT
- MWI on EUMETSAT/ EPS-SG early afternoon orbit

MW cloud liquid water path climatology

- Based on Wentz SSM/I since 1987, AMSR-E, and TMI
- Monthly diurnal mean liquid water path
- Climatological diurnal cycle
- O'Dell, Wentz, and Bennartz, J Climate, 2008
- Ongoing NASA Measures project (2013-2018)

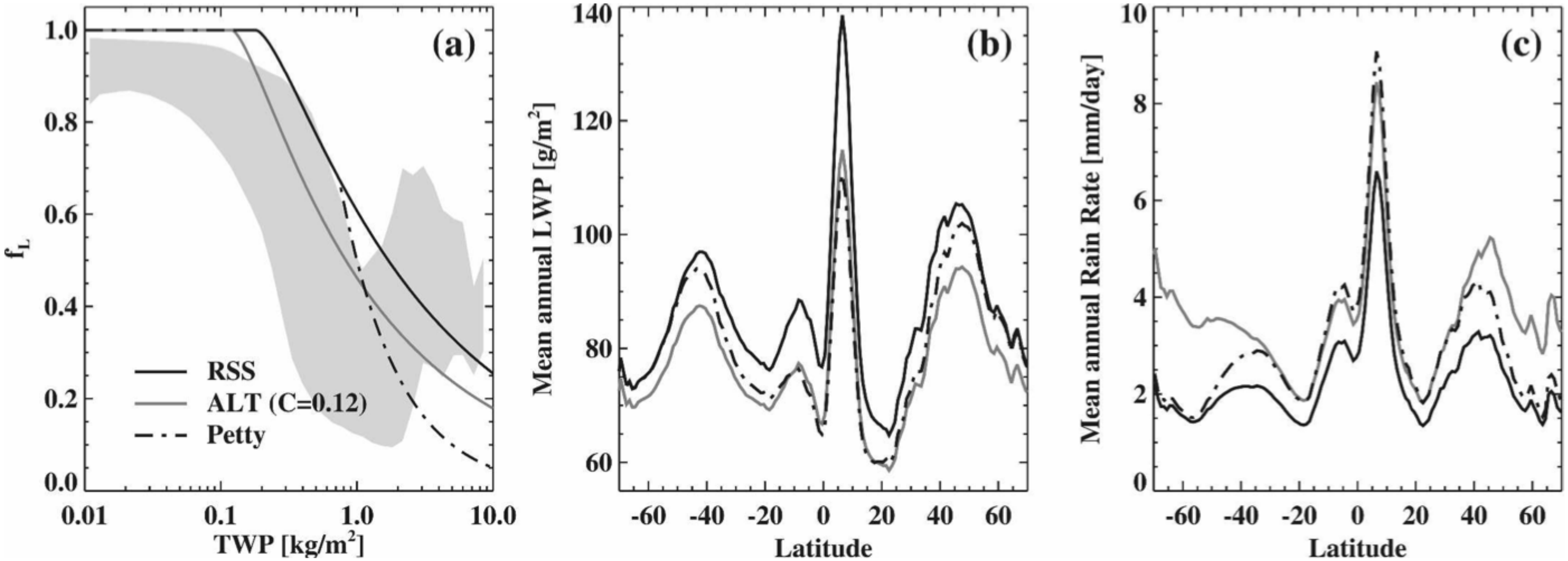
The diurnal cycle of LWP



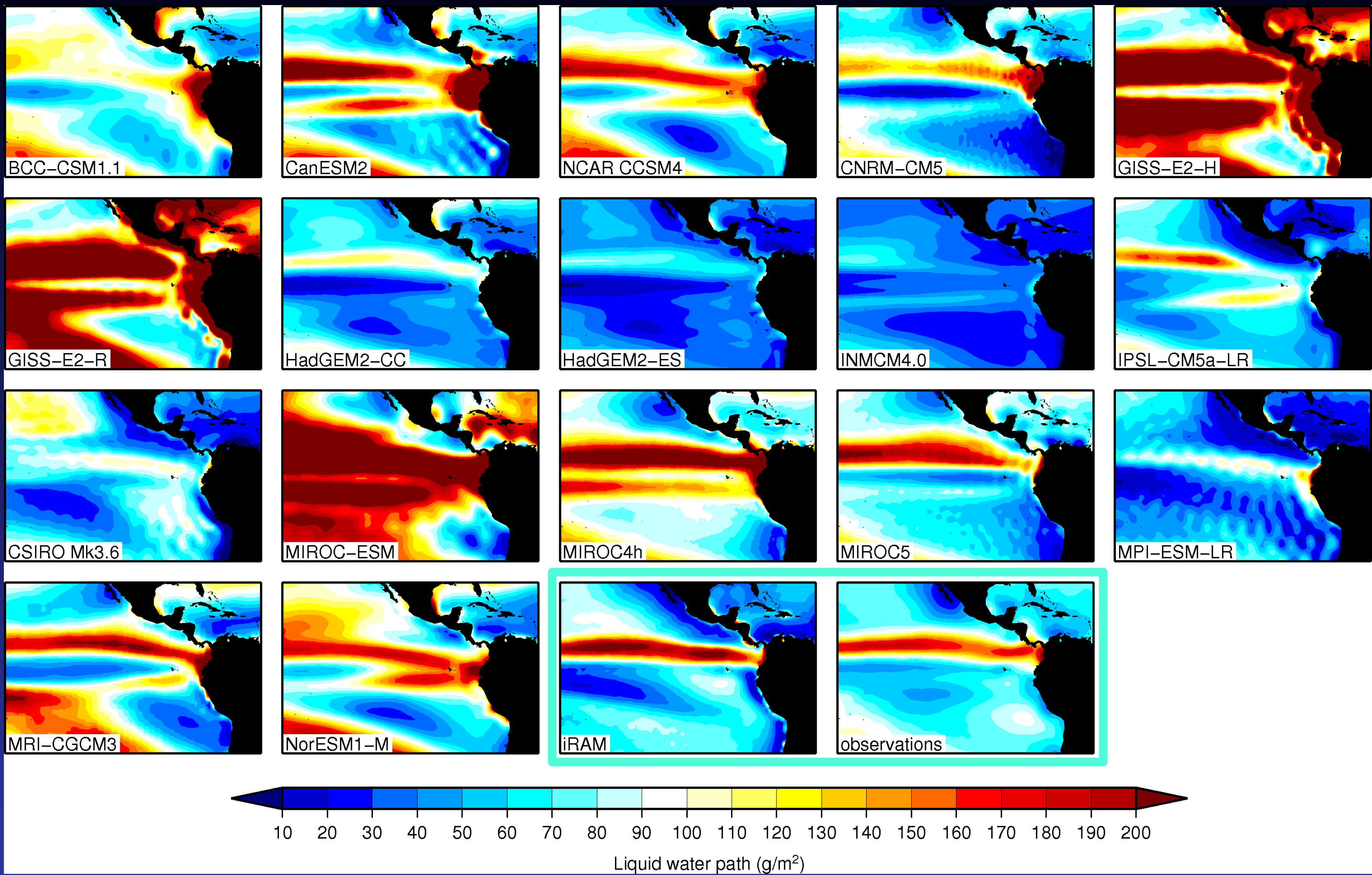


Long-term satellite studies of LWP must account for the diurnal cycle. Otherwise, satellite drifts will lead to an aliasing of the diurnal cycle onto trends of LWP.

Separation of rain from cloud water

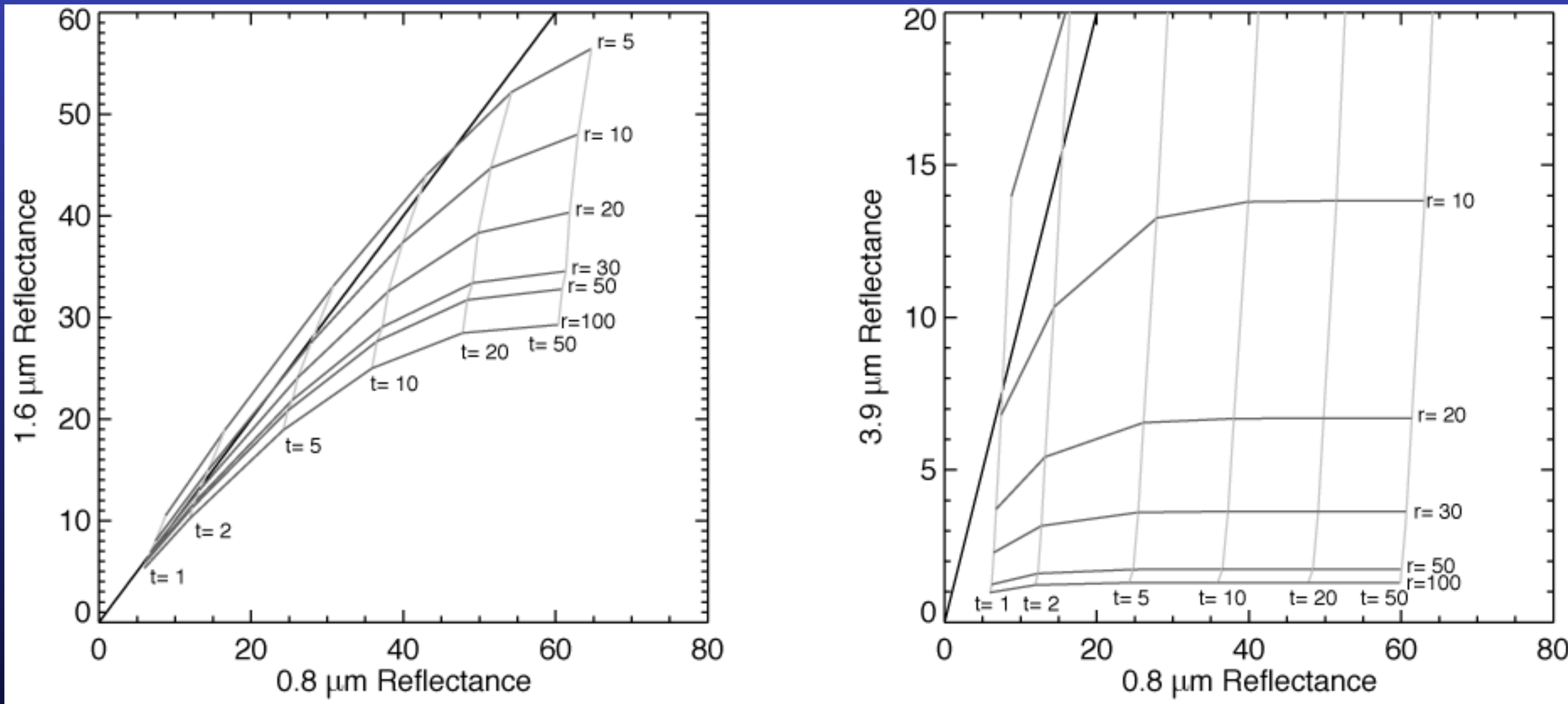


Liquid water path, observations versus IPCC AR-5 (CMIP-5)

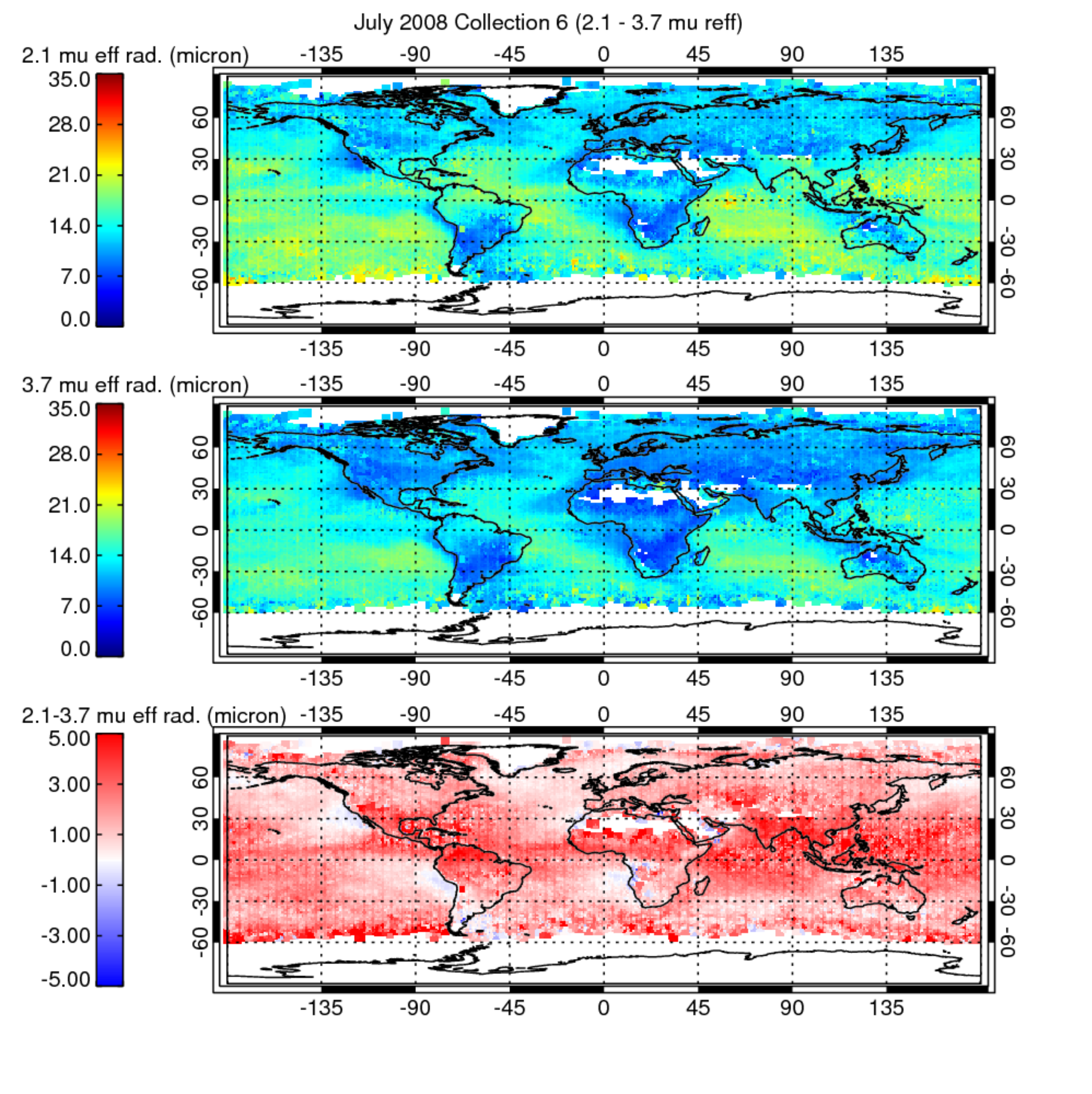


Lauer et al. (2012)

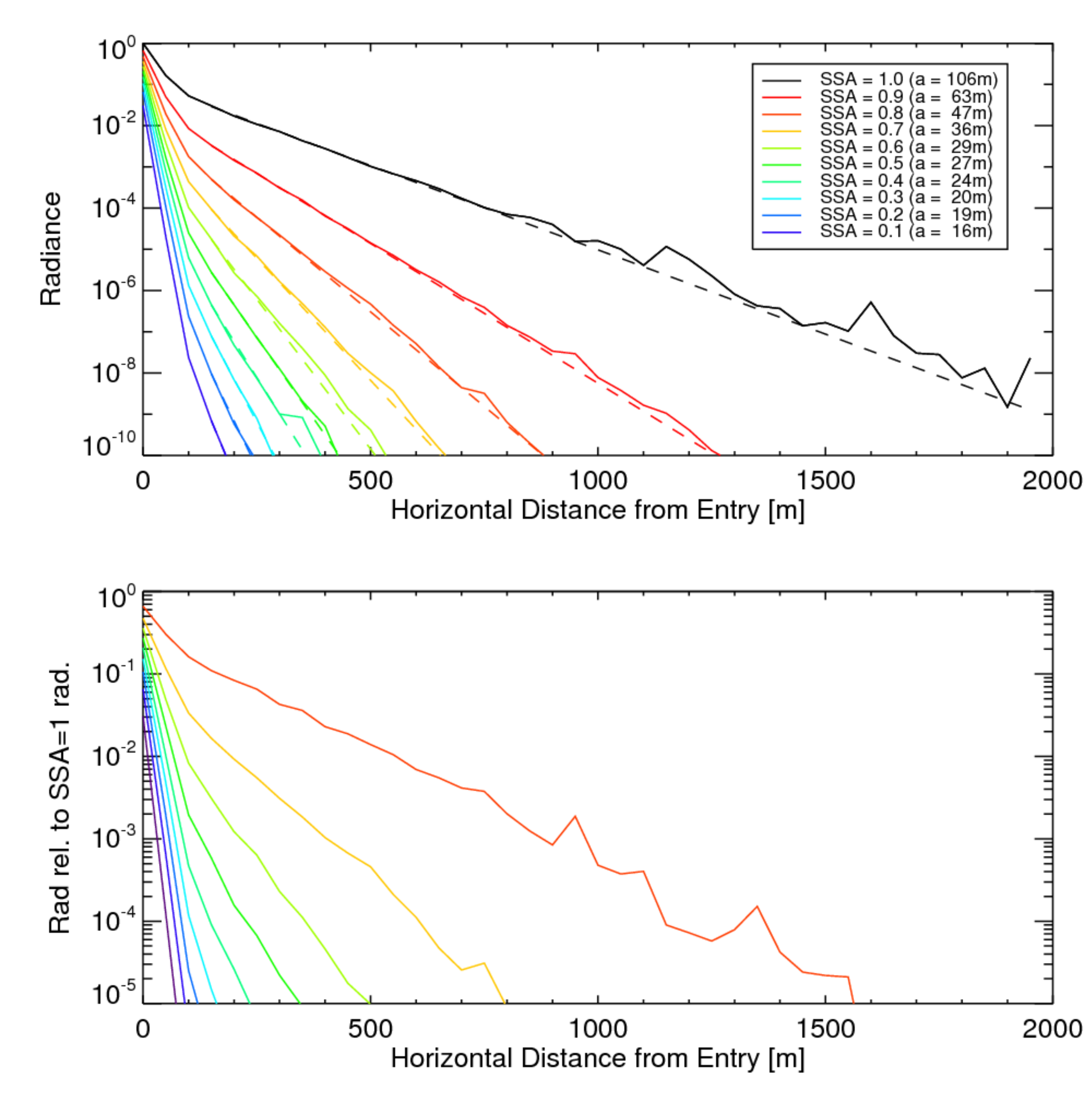
Nakajima-King retrieval



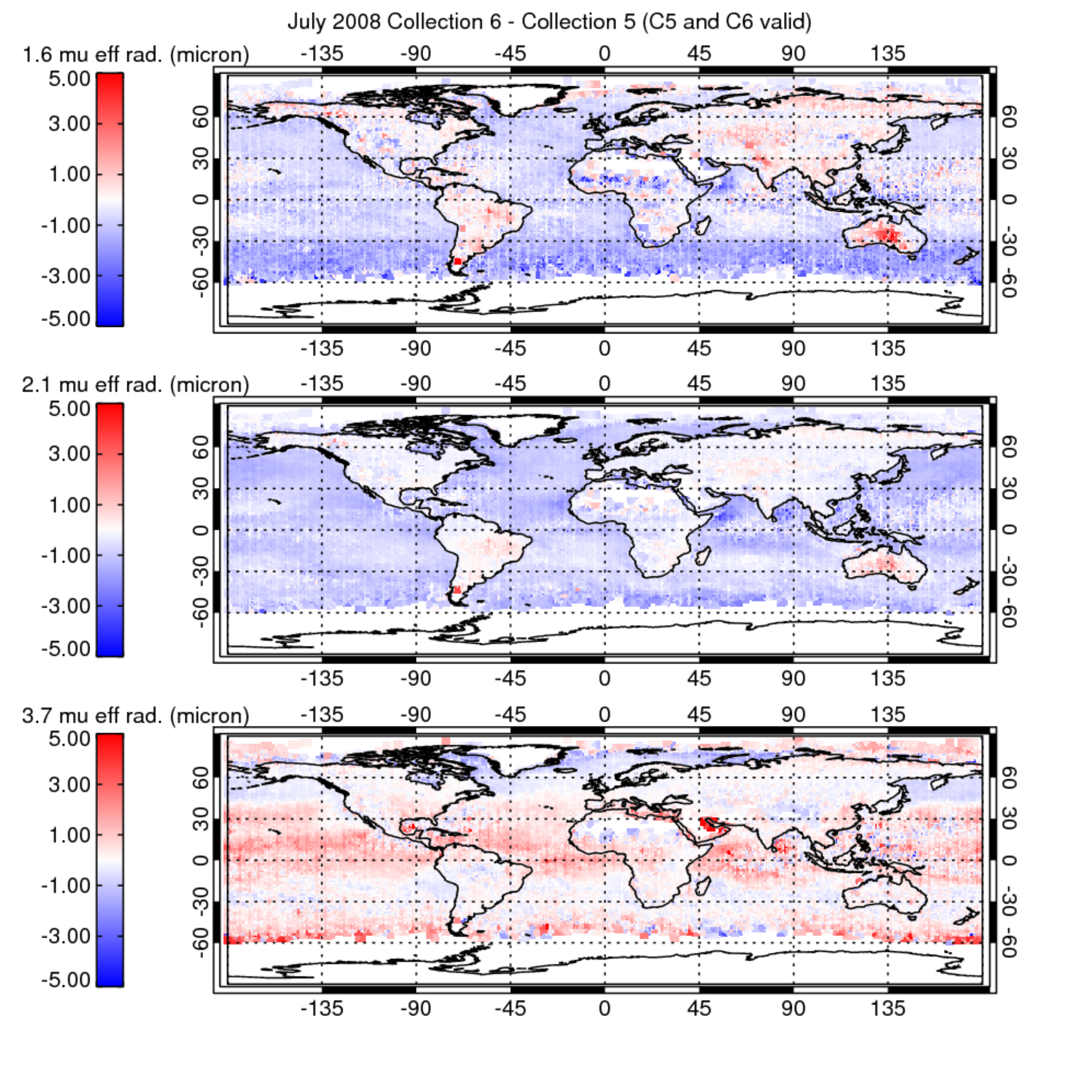
Effective Radius Collection 6 – Collection 5



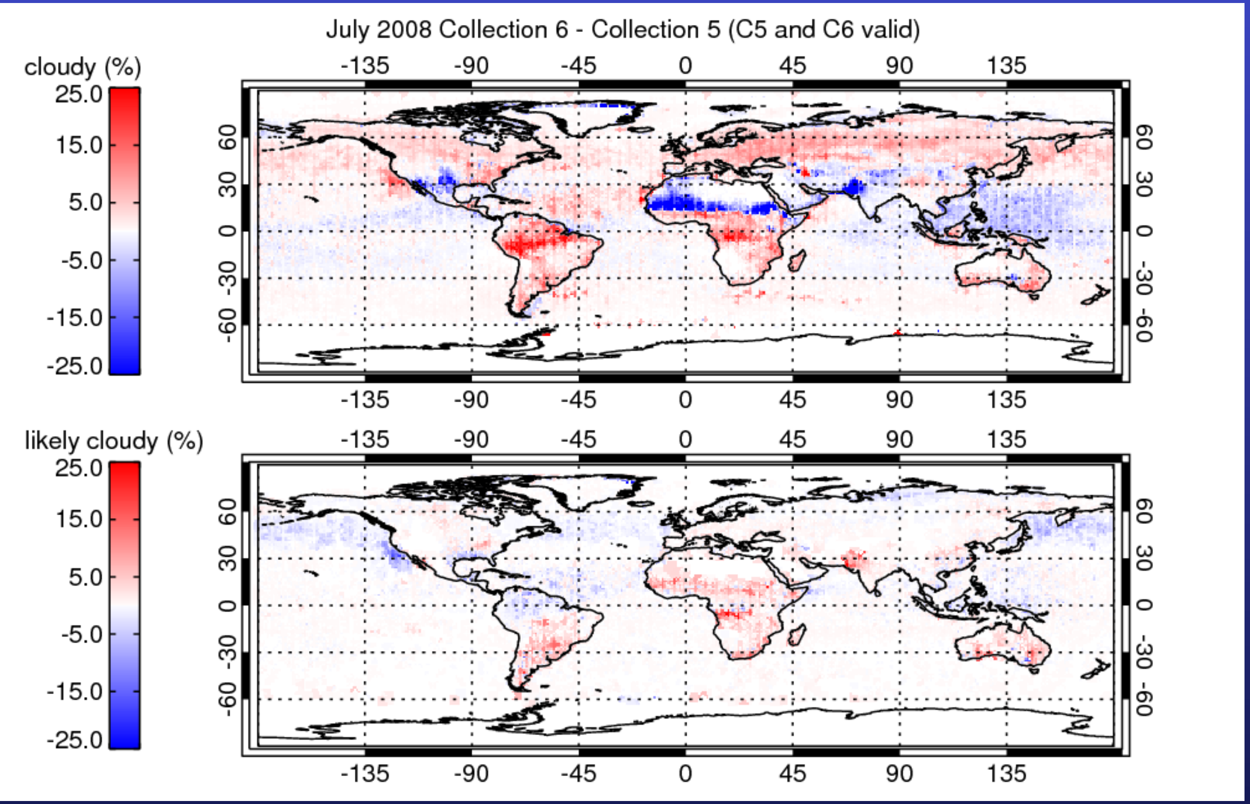
Horizontal photon transport



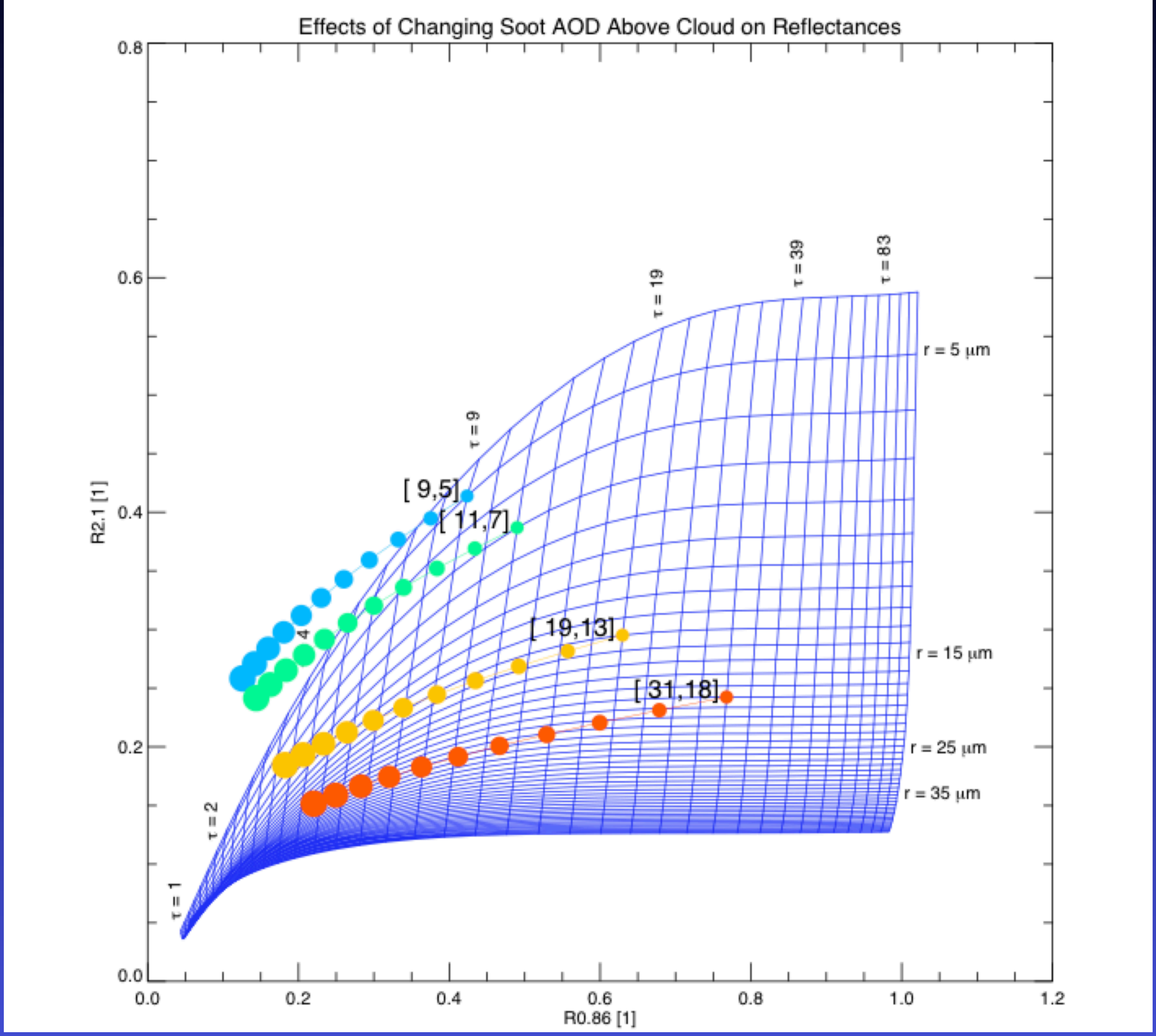
Effective Radius Collection 6 – Collection 5



Cloud fraction Collection 6 – Collection 5



Absorbing aerosol above cloud



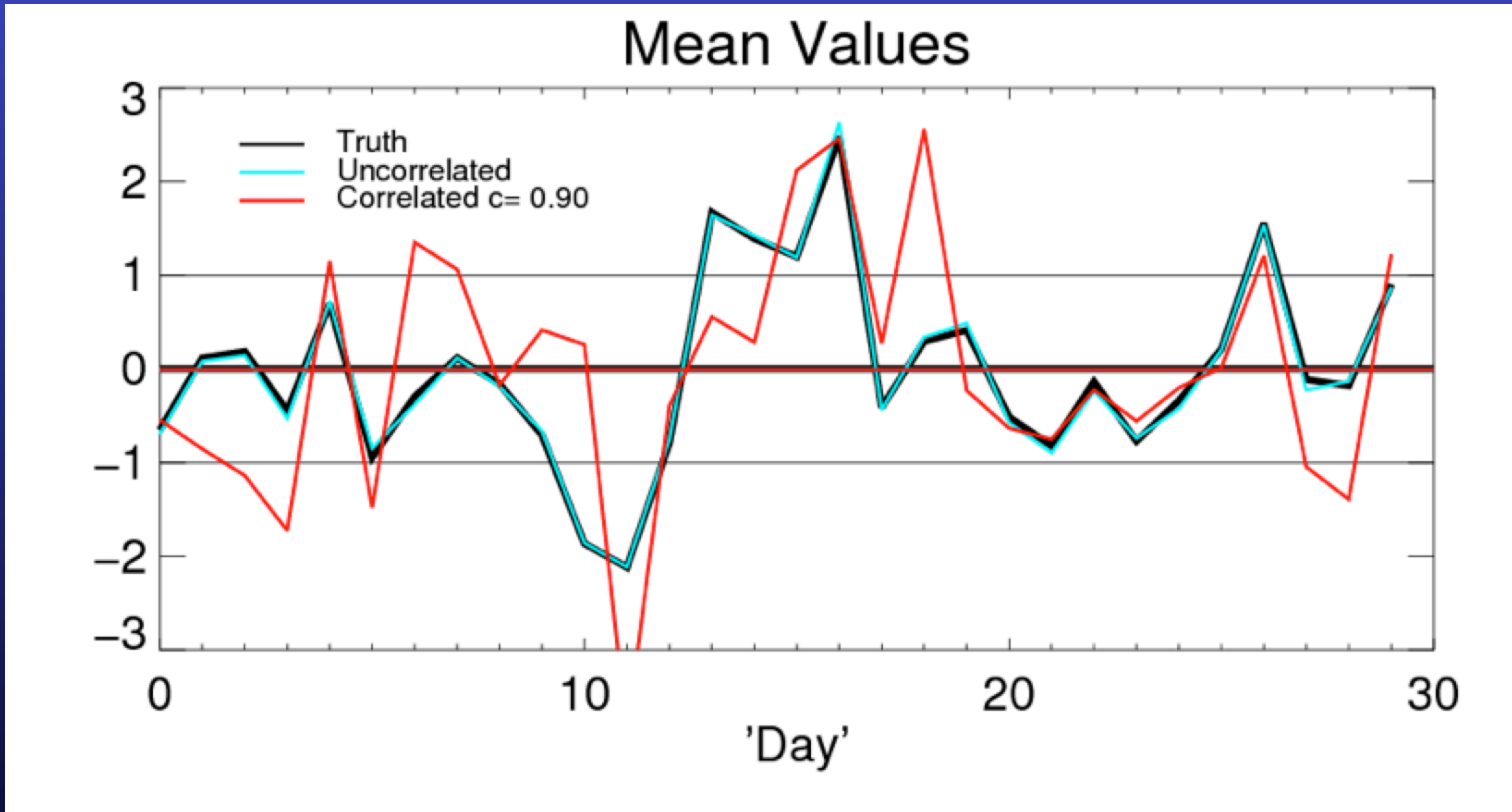
Aggregation/Error propagation

1. What is the best estimate for the mean state of a variable x?

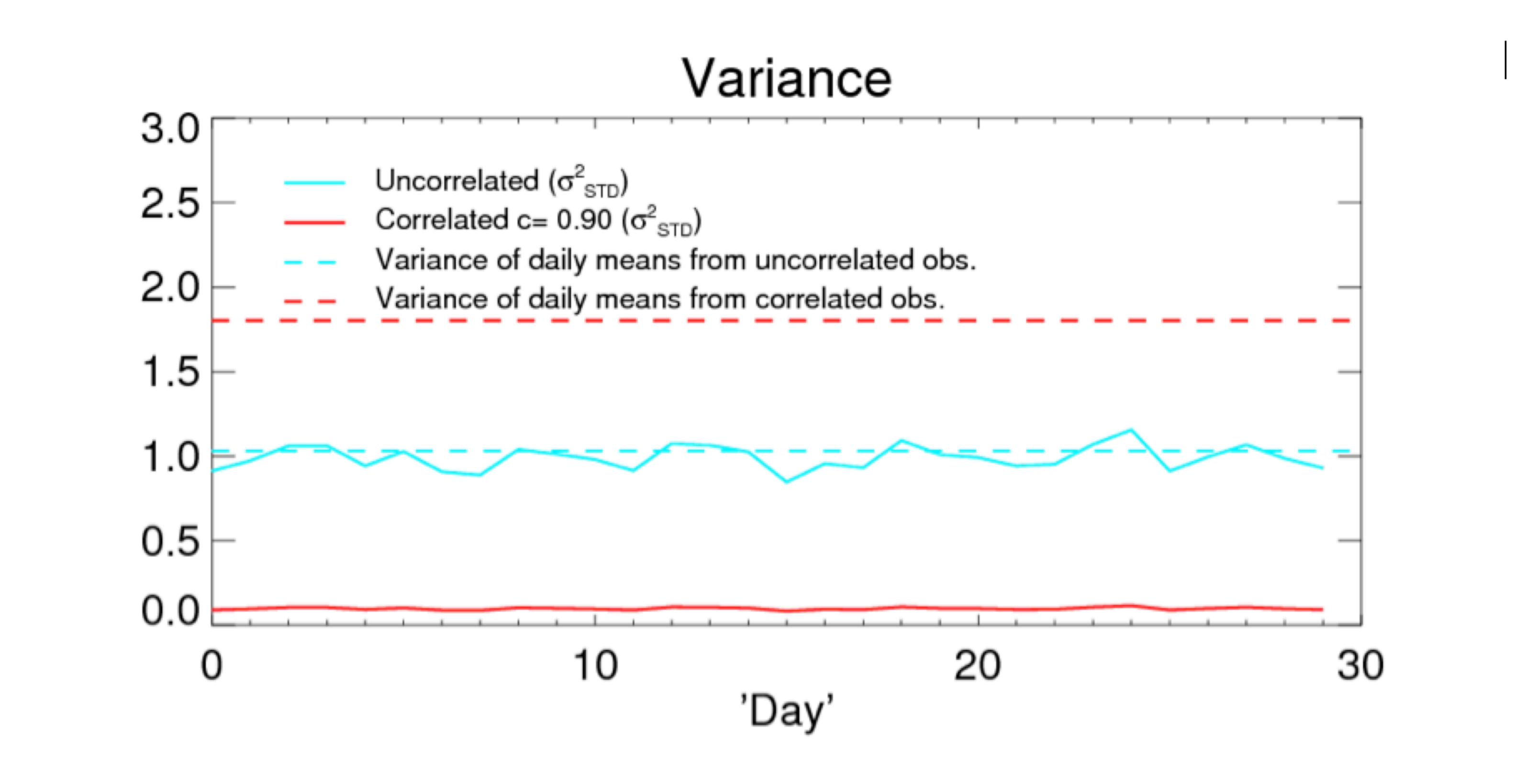
2. Given the uncertainty of the individual observations (described by **S**) and the temporal and spatial variability of the observed variable, what is the uncertainty associated with our estimate of x?

3. What is the true variance of x in time and space, i.e., what would be the variability of the observed variable, if the observing system was error-free?

Aggregation/Error propagation



Aggregation/Error propagation



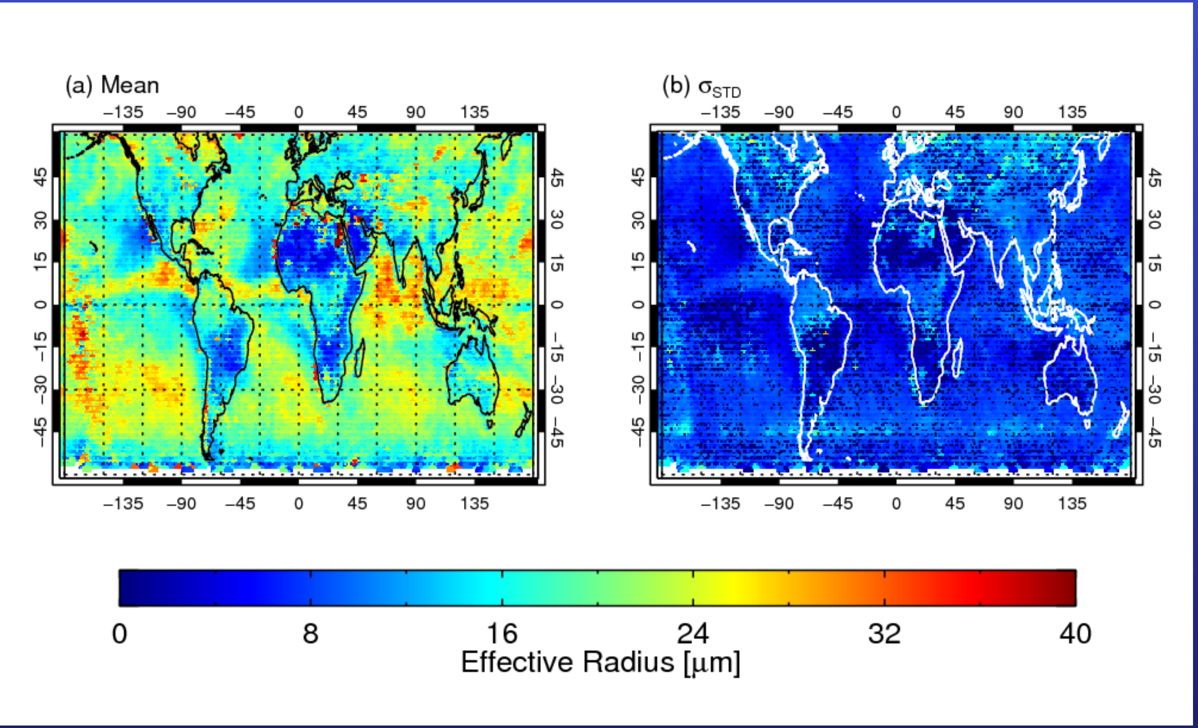
Aggregation/Error propagation

- Correlated L2-errors will reduce variability around the estimate of the mean value compared to uncorrelated errors of the same magnitude.

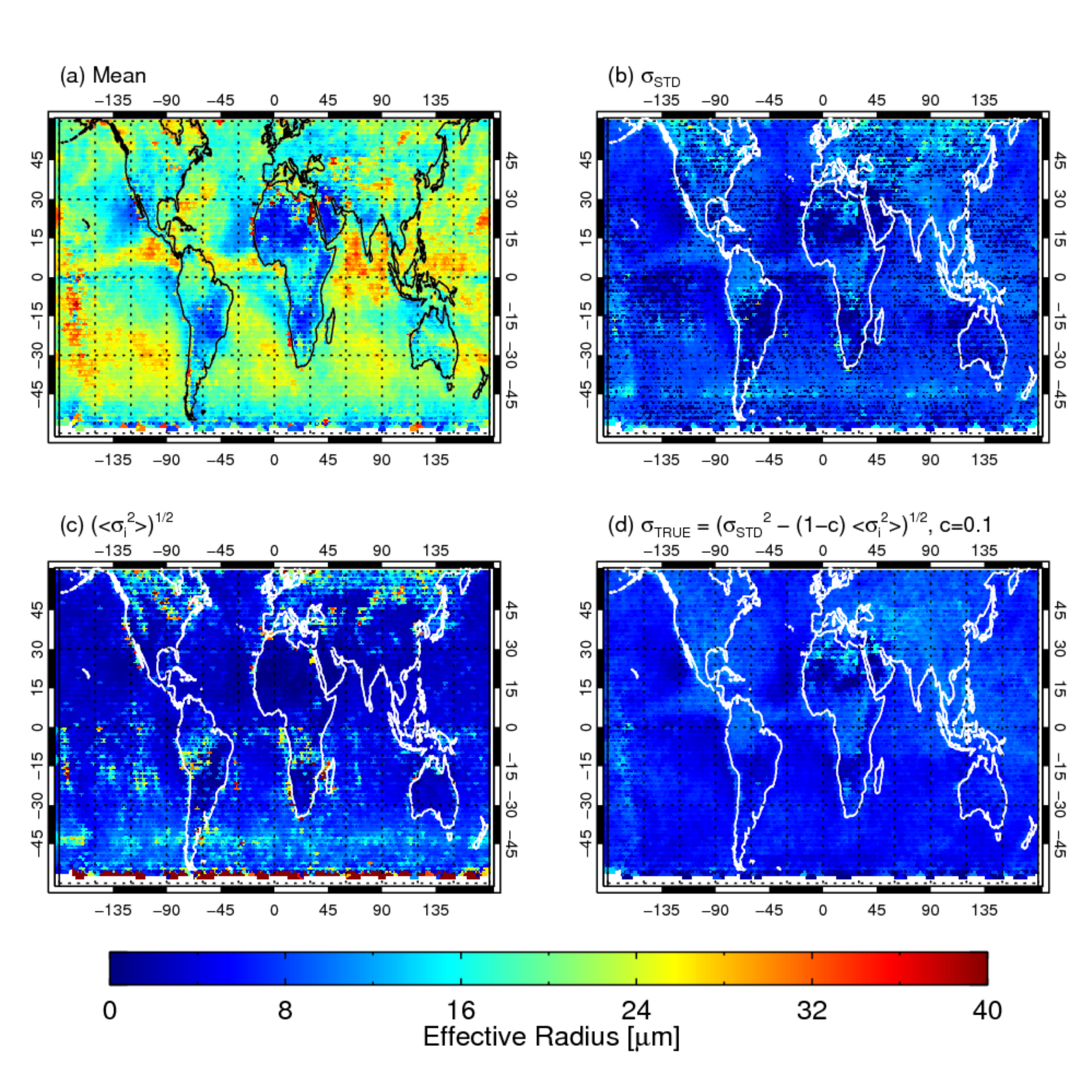
- However, the estimate of the mean value can be further apart from the true mean.

- If correlated errors occur only within a ‘day’ and errors between different ‘days’ are uncorrelated, the day-to -day variability will be higher in the correlated dataset.

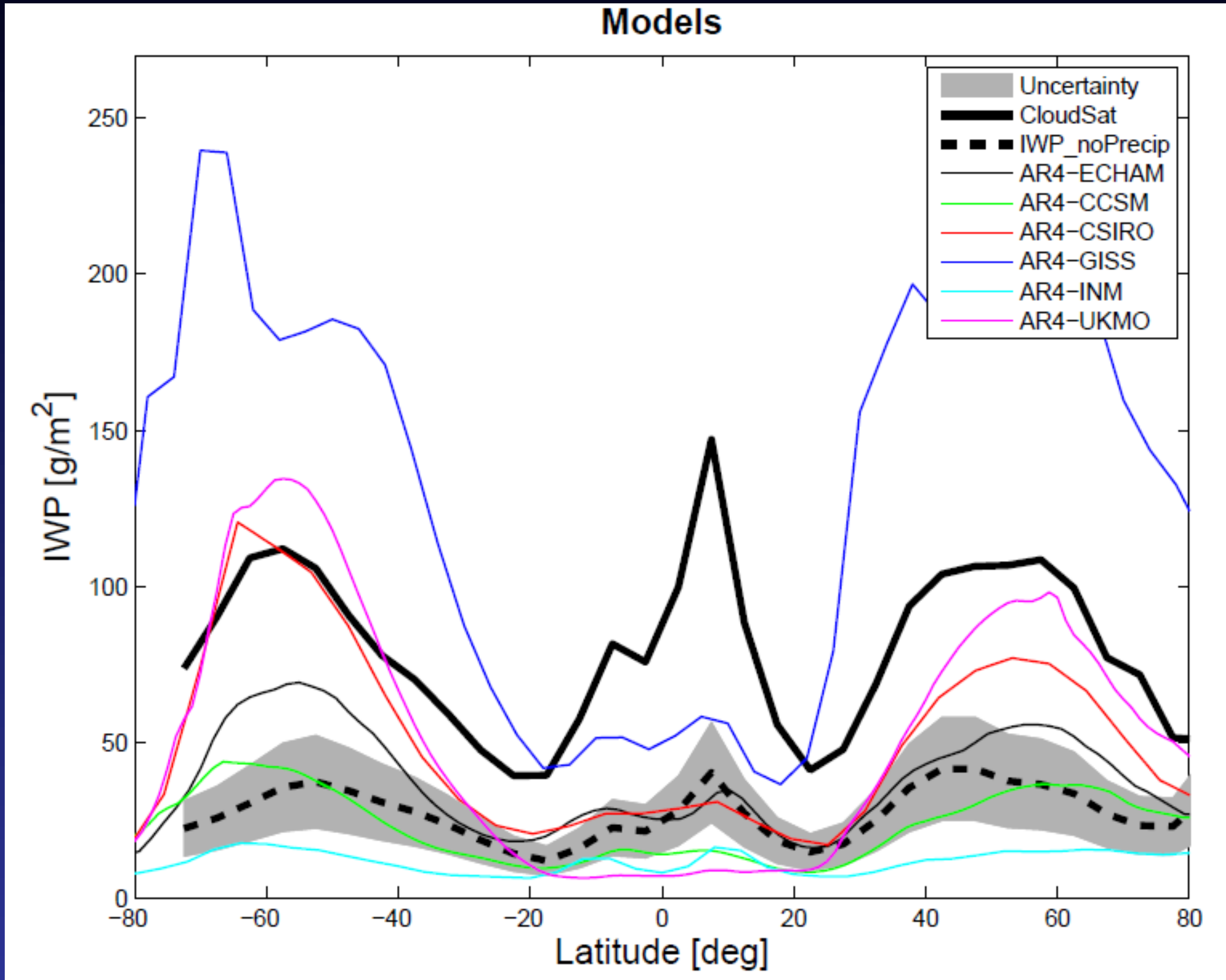
Aggregation/Error propagation



Aggregation/Error propagation



Ice water path



(Eliasson et al, 2011)

Climate datasets

- Legacy: If we want to observe climate, we need to have long-term records. Polar orbiting imagers and passive microwave conical scanners most important.
- Transparency: We need to keep track of what is being done in each processing step. From calibration to level 3 gridding.
- Dynamics: Move away from static datasets. Need to be able to re-process entire time-series.
- Uncertainty estimates: Need to better convey uncertainty estimates