

# Assimilating cloud and precipitation: benefits and uncertainties

Alan Geer

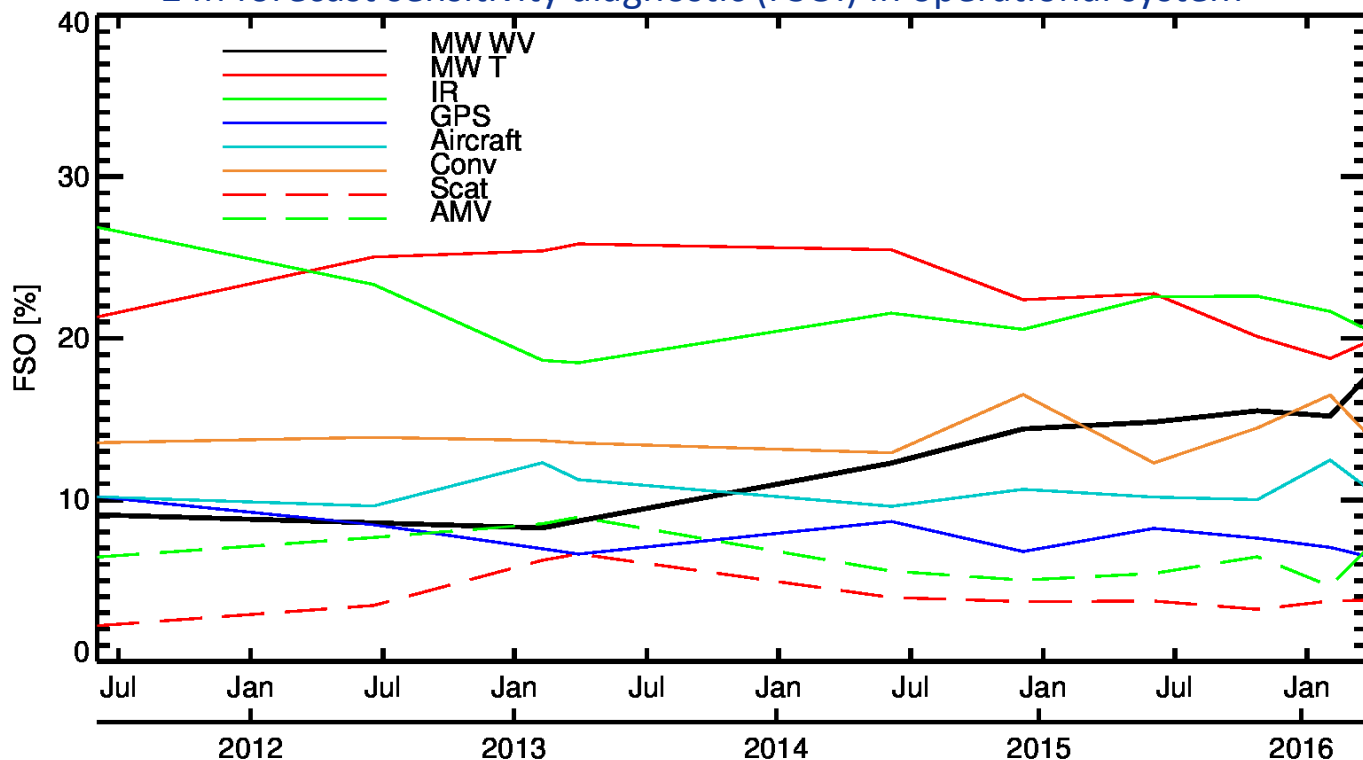
Thanks to: Katrin Lonitz, Peter Lean, Richard Forbes, Cristina Lupu, Massimo Bonavita, Mats Hamrud, Philippe Chambon, Fabrizio Baordo, Masahiro Kazumori, Heather Lawrence, Carla Cardinali, Niels Bormann and Stephen English

# Benefits

# Development of all-sky microwave assimilation at ECMWF

Within the operational system (9km resolution with incremental 4D-Var and flow-dependent covariances from EDA)

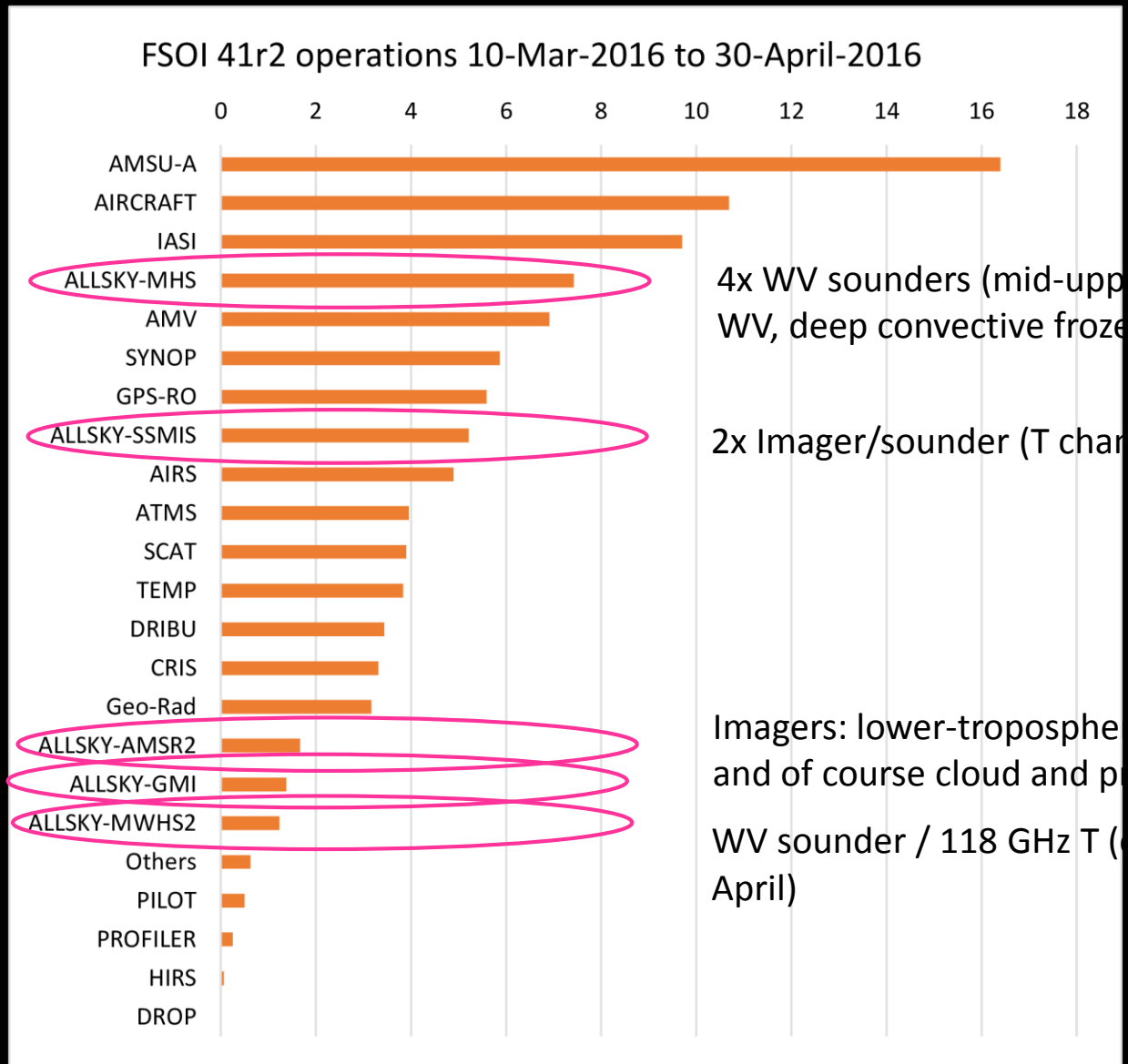
24h forecast sensitivity diagnostic (FSOI) in operational system



Microwave “water vapour” observations have doubled in impact since 2012 as we rolled out the all-sky approach to WV sounders

They now provide similar forecast benefits to conventional, IR or microwave temperature sounding data

# Impact by observing system





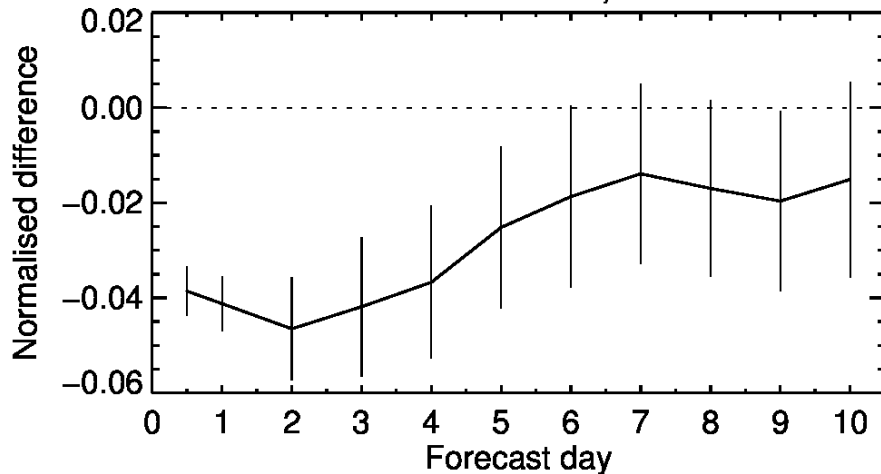
# All-sky microwave assimilation: synoptic impact to day 6

## Change in hemispheric RMSE in 500hPa geopotential

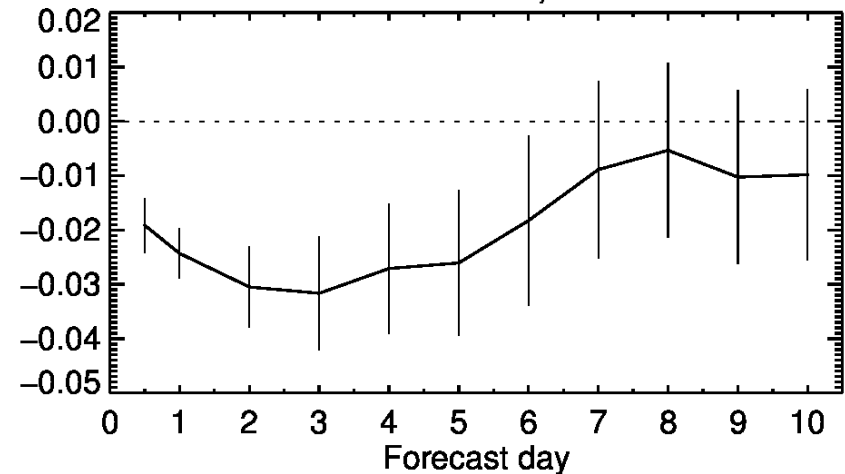
26-Feb-2015 to 24-Aug-2015 from 340 to 359 samples. Verified against own-analysis.

Confidence range 95% with Sidak correction for 4 independent tests.

Z: SH  $-90^{\circ}$  to  $-20^{\circ}$ , 500hPa



Z: NH  $20^{\circ}$  to  $90^{\circ}$ , 500hPa



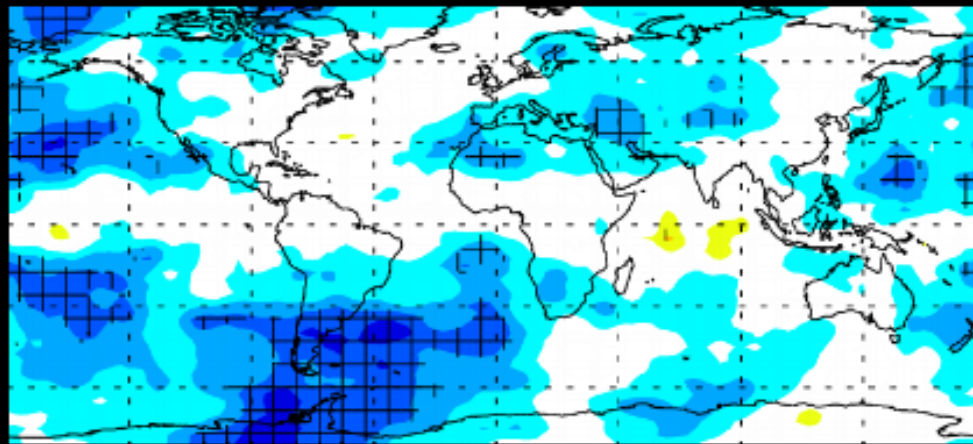
— All-sky GMI, AMSR2, MHS and SSMIS – No allsky control

# All-sky microwave assimilation

Change in RMS 500hPa geopotential error, adding all-sky instruments in full observing system

Average of 6 months verification. Cross-hatching = 95% significance

Early-range impact is mostly oceanic  
over land with the flow



# All-sky microwave assimilation principles

- “All-sky”

- Clear, cloudy and precipitating scenes are assimilated together, directly as radiances
  - So far mainly WV-sensitive, not T-sensitive channels (no AMSU-A/ATMS)
- Cloud and precipitation-capable observation operator: RTTOV-SCATT
- 4D-Var assimilation: forecast model provides TL and adjoint moist physics

- Direct information content:

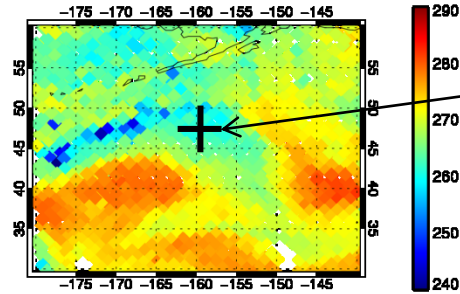
- Water vapour, surface properties (surface windspeed)
- Cloud water, rain (low frequencies)
- Cloud ice, frozen precipitation (higher frequencies)

- Indirect information content (through 4D-Var “tracing” or ensemble correlations):

- Dynamical state of the atmosphere (mass, temperature, winds)

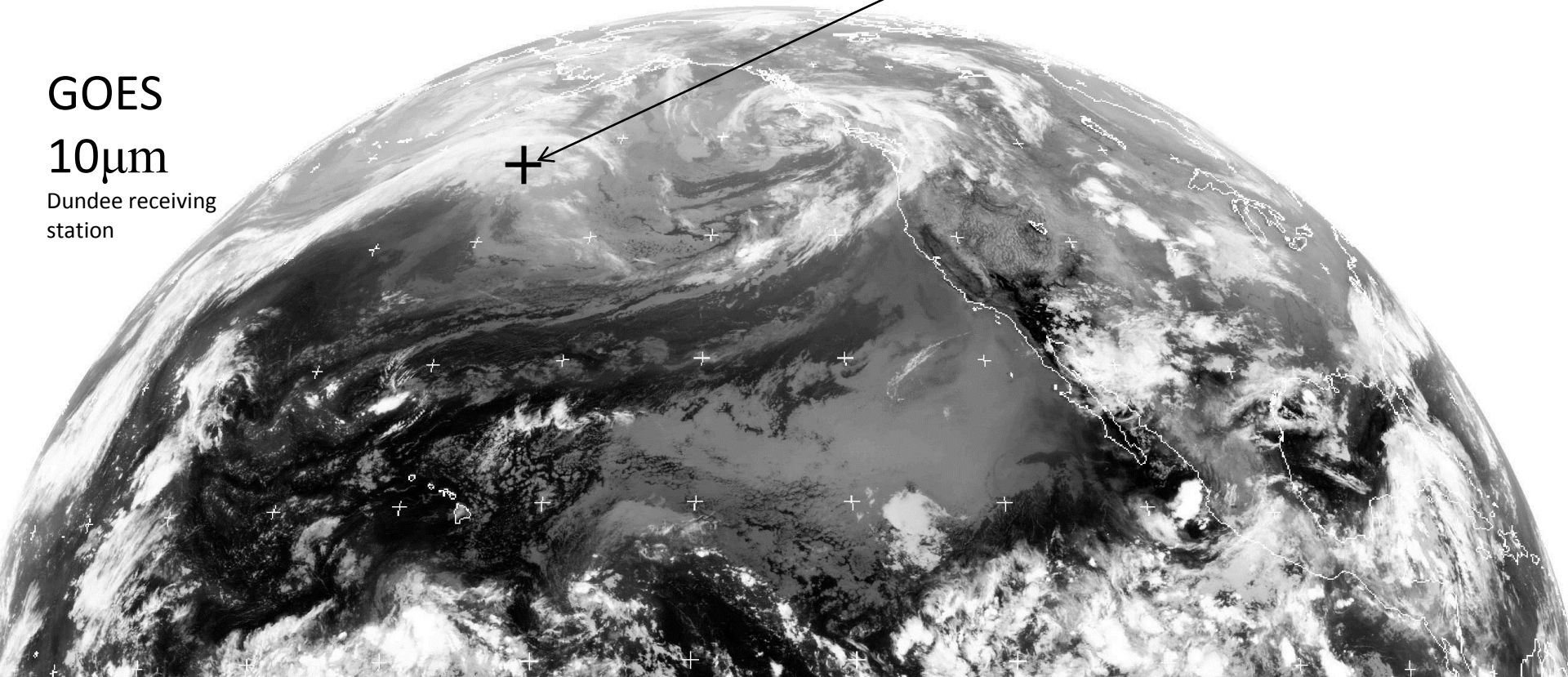
# Frontal cloud and precipitation: single-observation example at 190 GHz

Metop-B MHS  
190 GHz

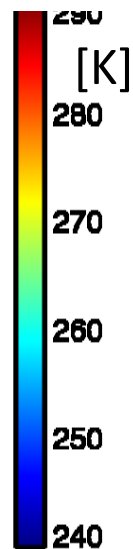
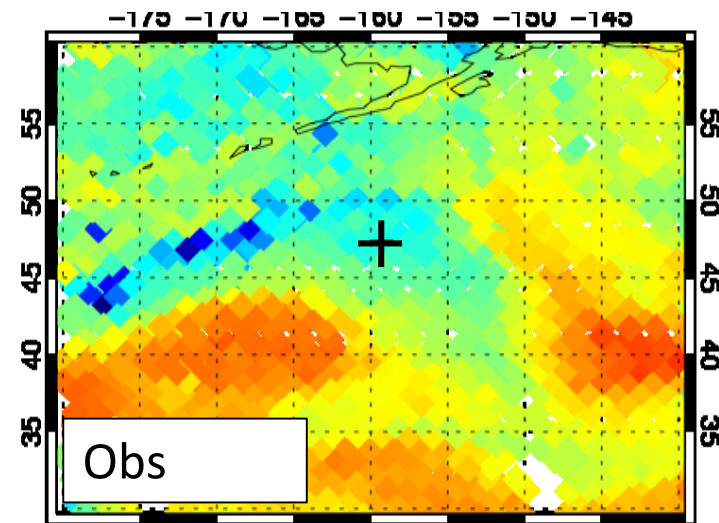
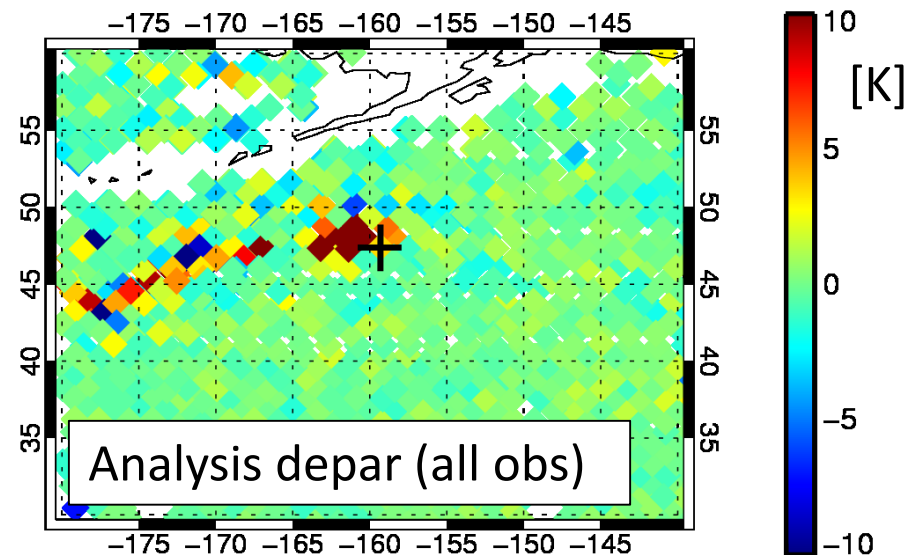
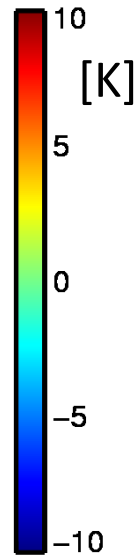
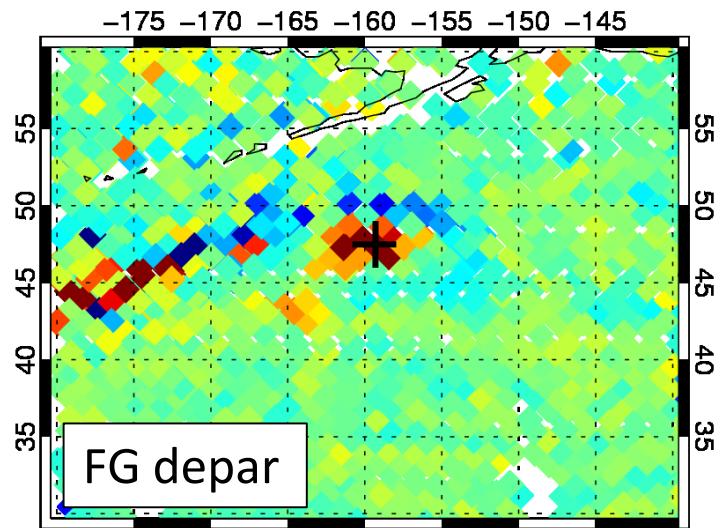


08Z, 15 Aug 2013  
47°N 159°W

GOES  
10μm  
Dundee receiving  
station

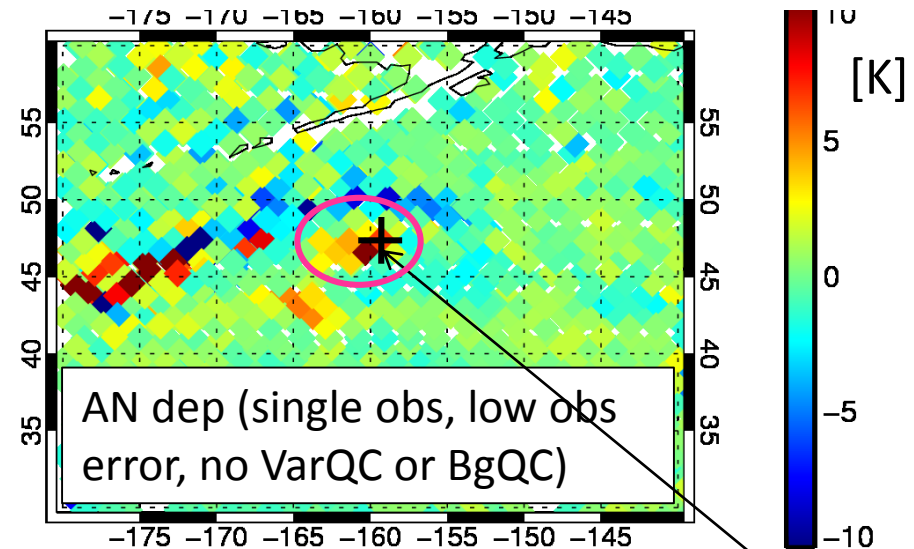
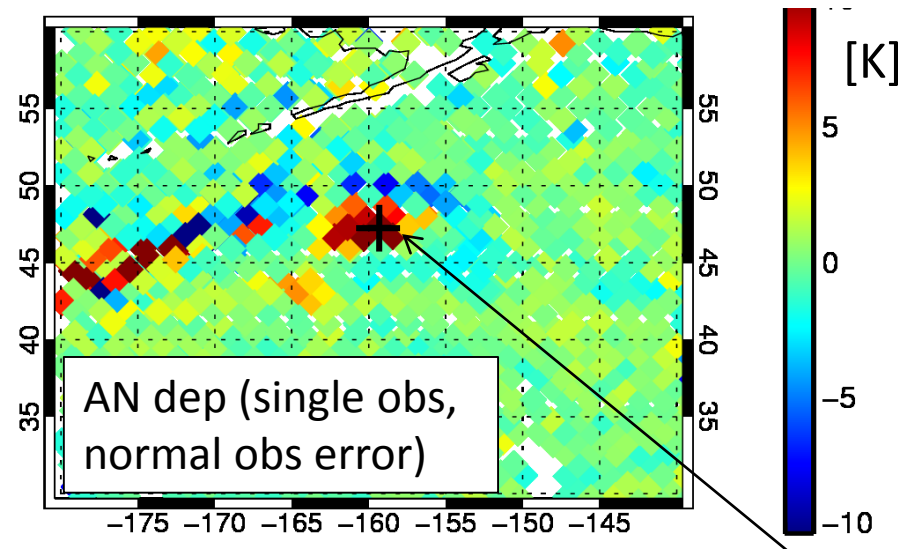
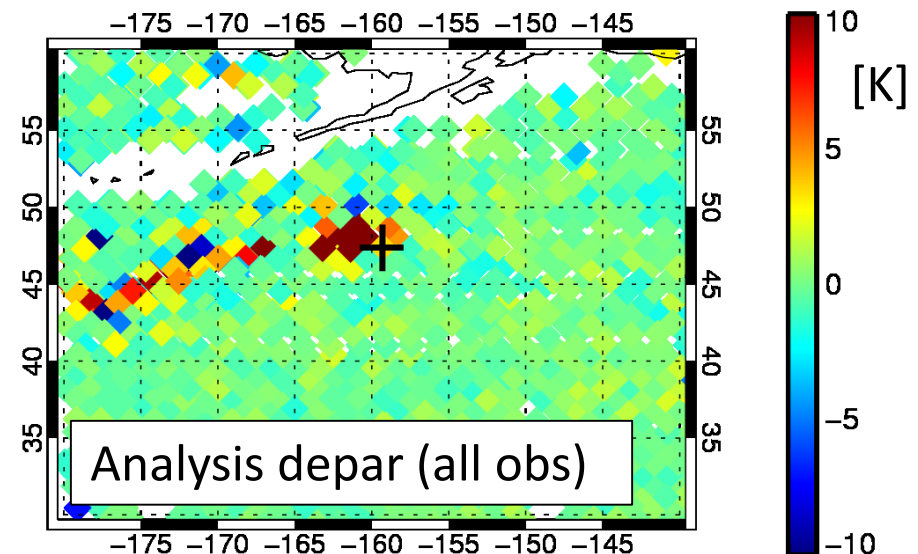
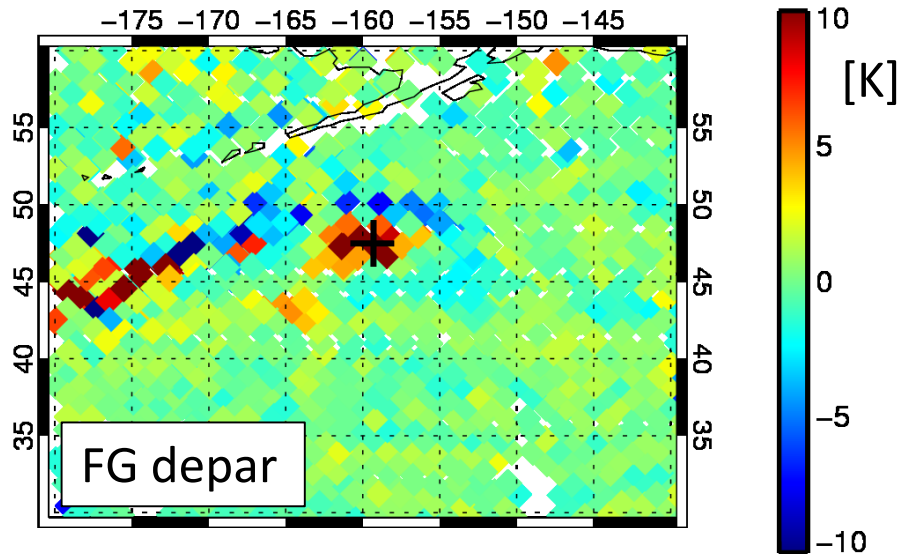


# Frontal cloud and precipitation – all observations





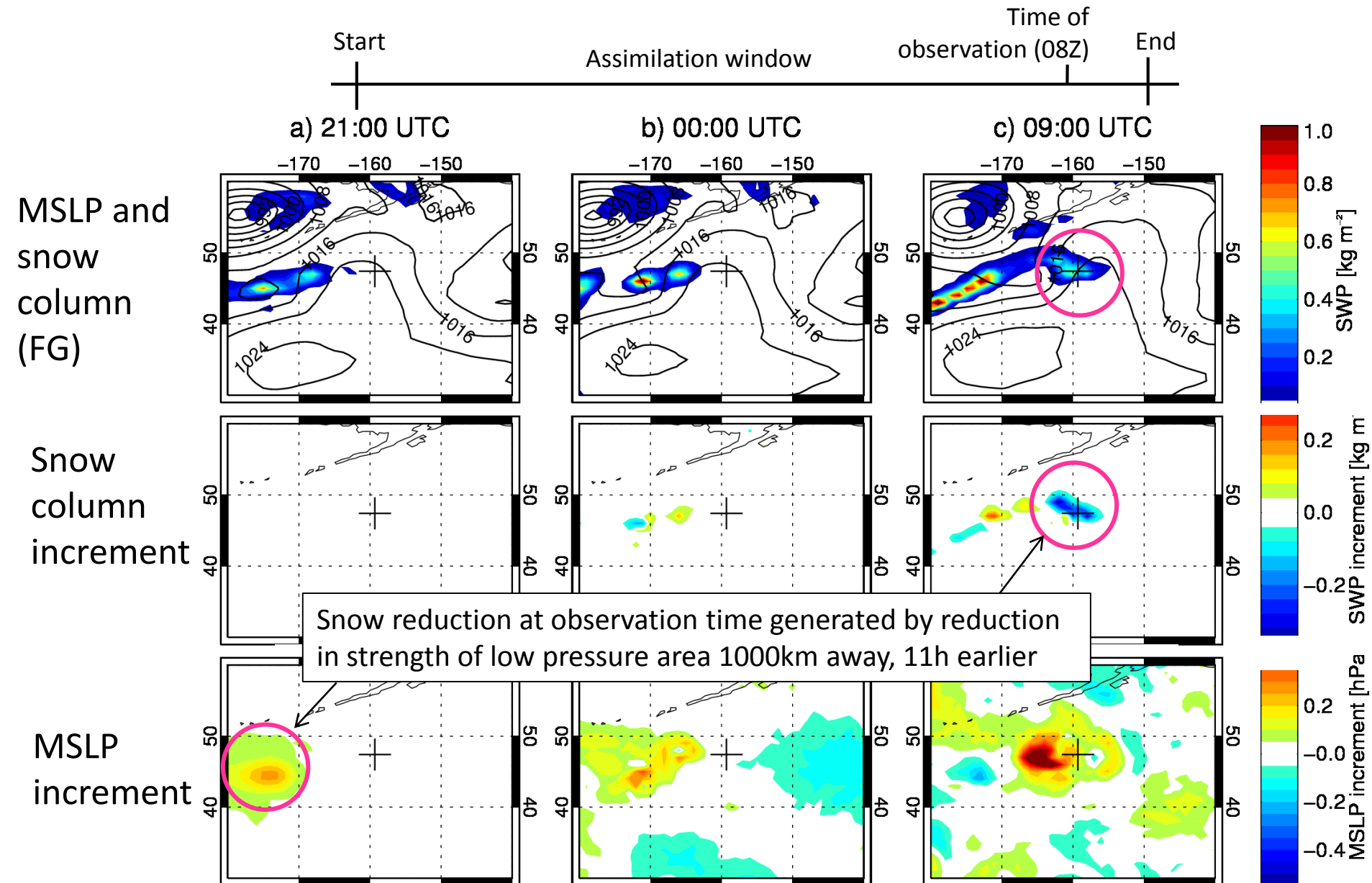
# Frontal cloud and precipitation – single all-sky obs



25% error reduction (honest!)

80% error reduction.  
Locally better than full observing system

# Frontal cloud and precipitation – 190 GHz



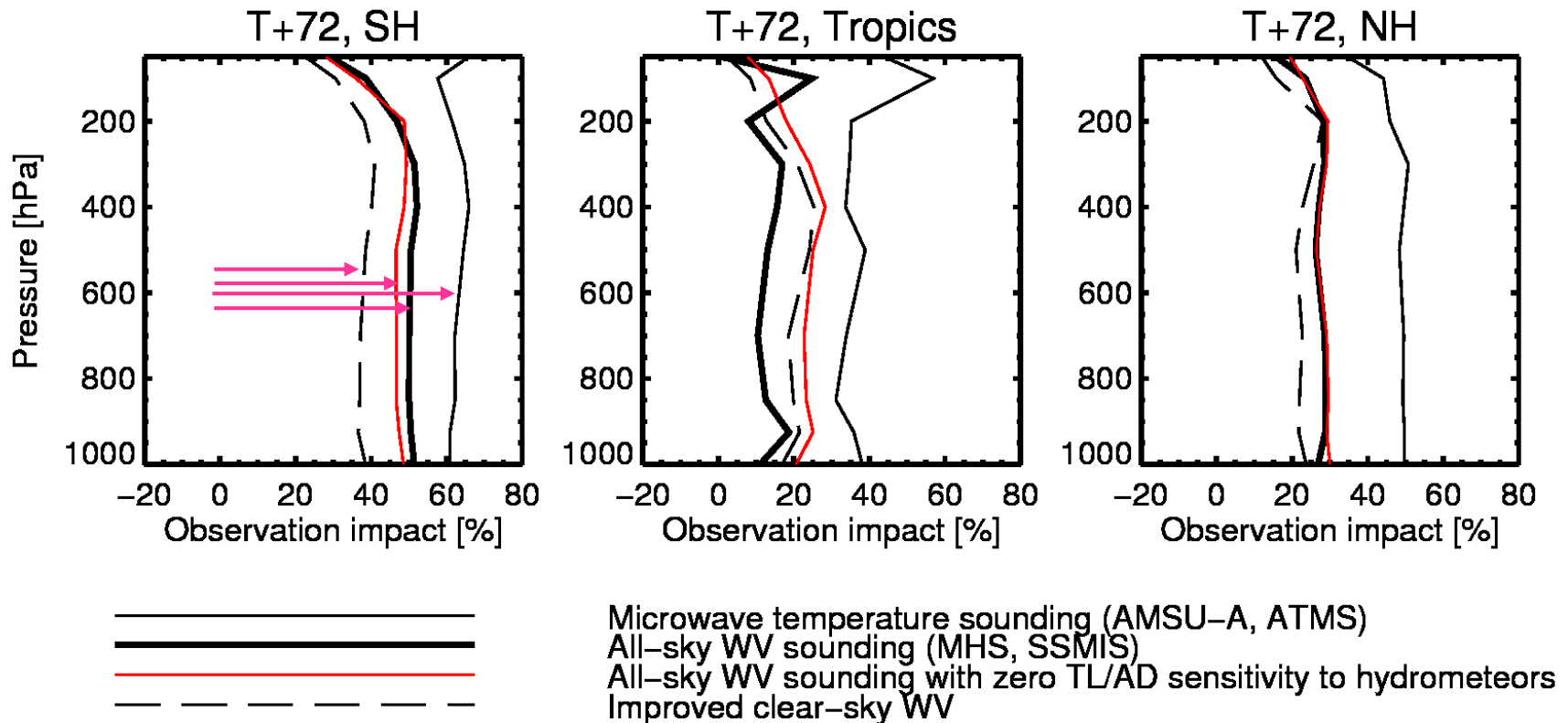
# Does benefit come from WV in cloud, or cloud and precip itself?

Single-observation type impact on T+72 vector wind as % of full observing system (see ECMWF tech. memo. 741, 2014)

Ambitious target: match the impact of microwave T-sounding (7xAMSU-A + ATMS): 60%

Going from clear-sky scenes to all-sky scenes, no TL/AD hydrometeors: from 35% to 46% impact

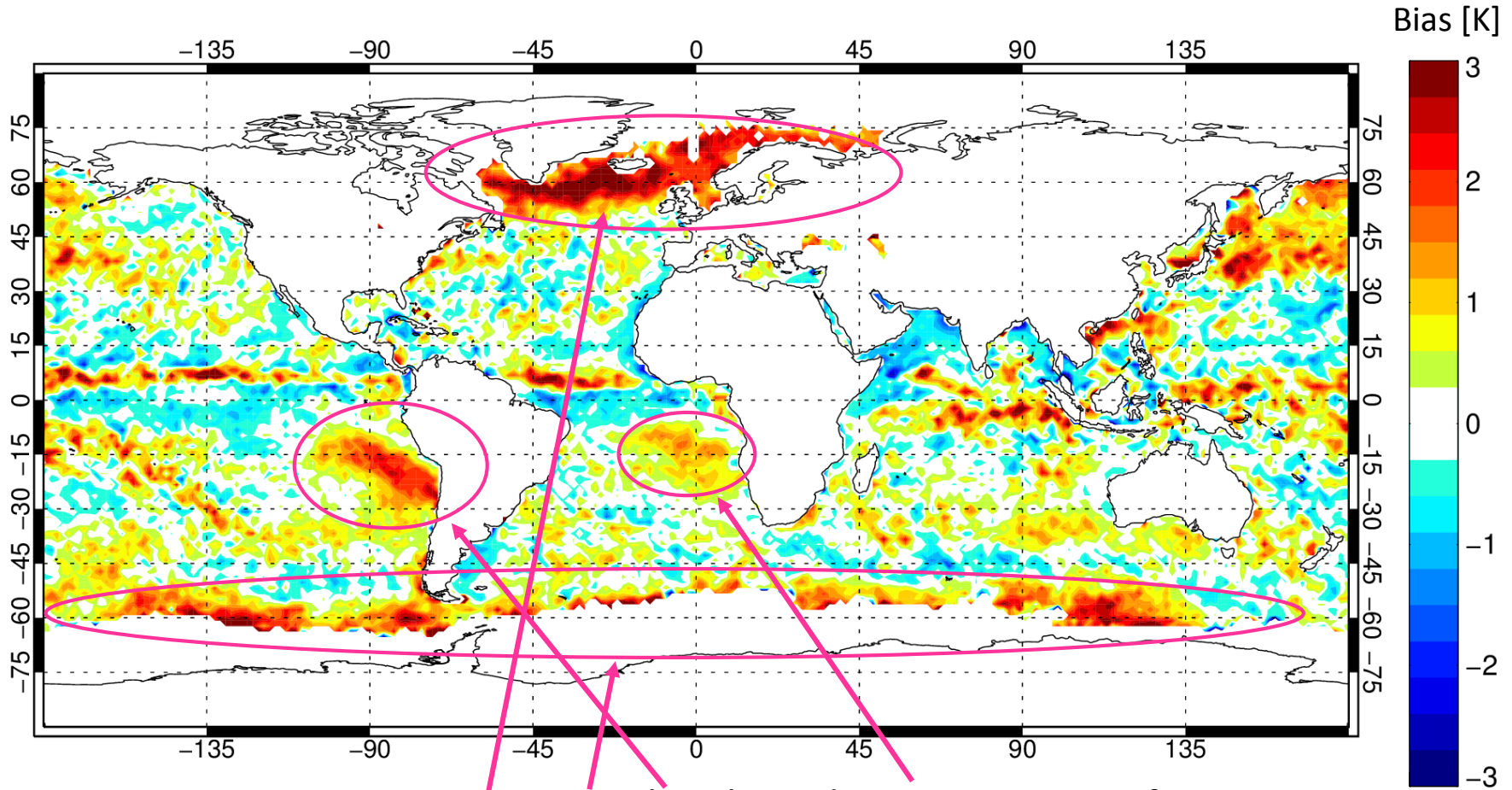
Value of cloud and precipitation itself: from 46% to 50% impact





# Monthly mean biases at 37 GHz (sensitive to cloud, water vapour and rain)

SSMIS channel 37v, December 2014 – all data over ocean, including observations usually removed by QC

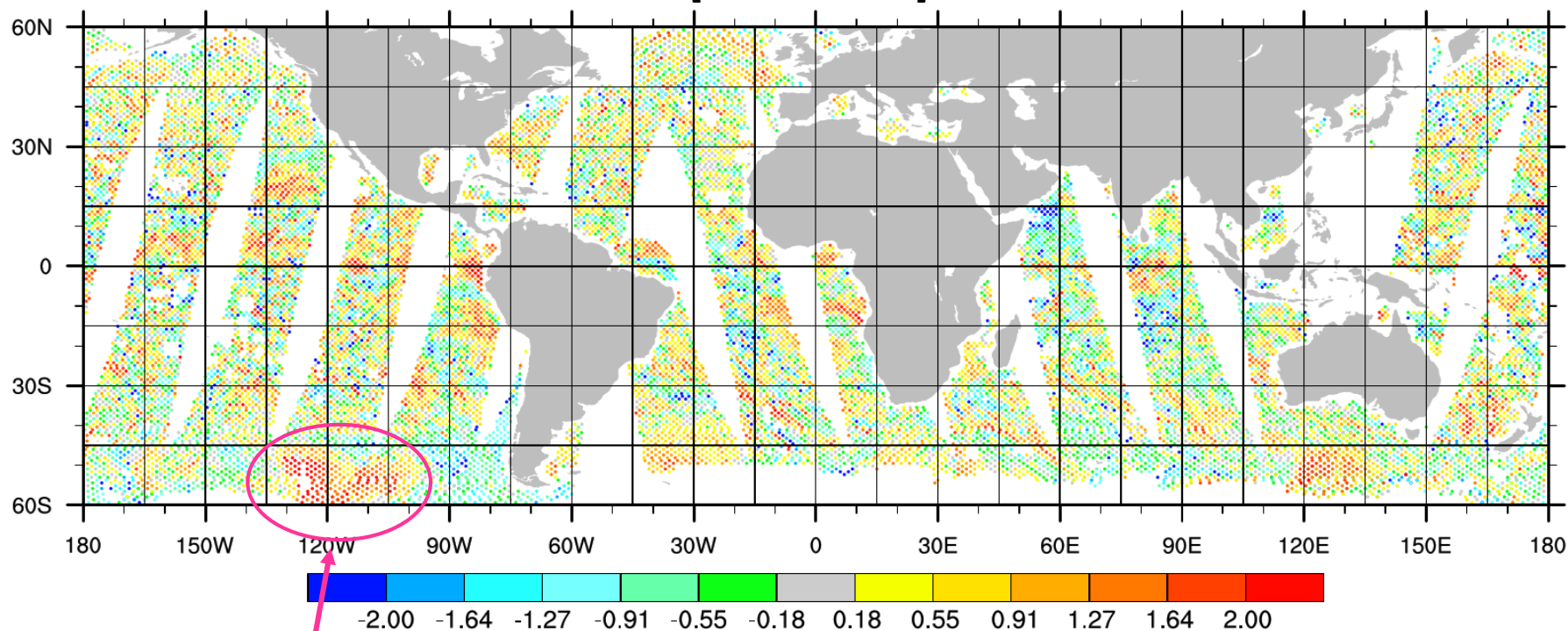


Lack of supercooled liquid water in cold air outbreaks  
Diurnal cycle and water content of marine stratocumulus (Kazumori et al., QJ, 2015)

# Cold air outbreaks

Thanks to Katrin Lonitz and Richard Forbes

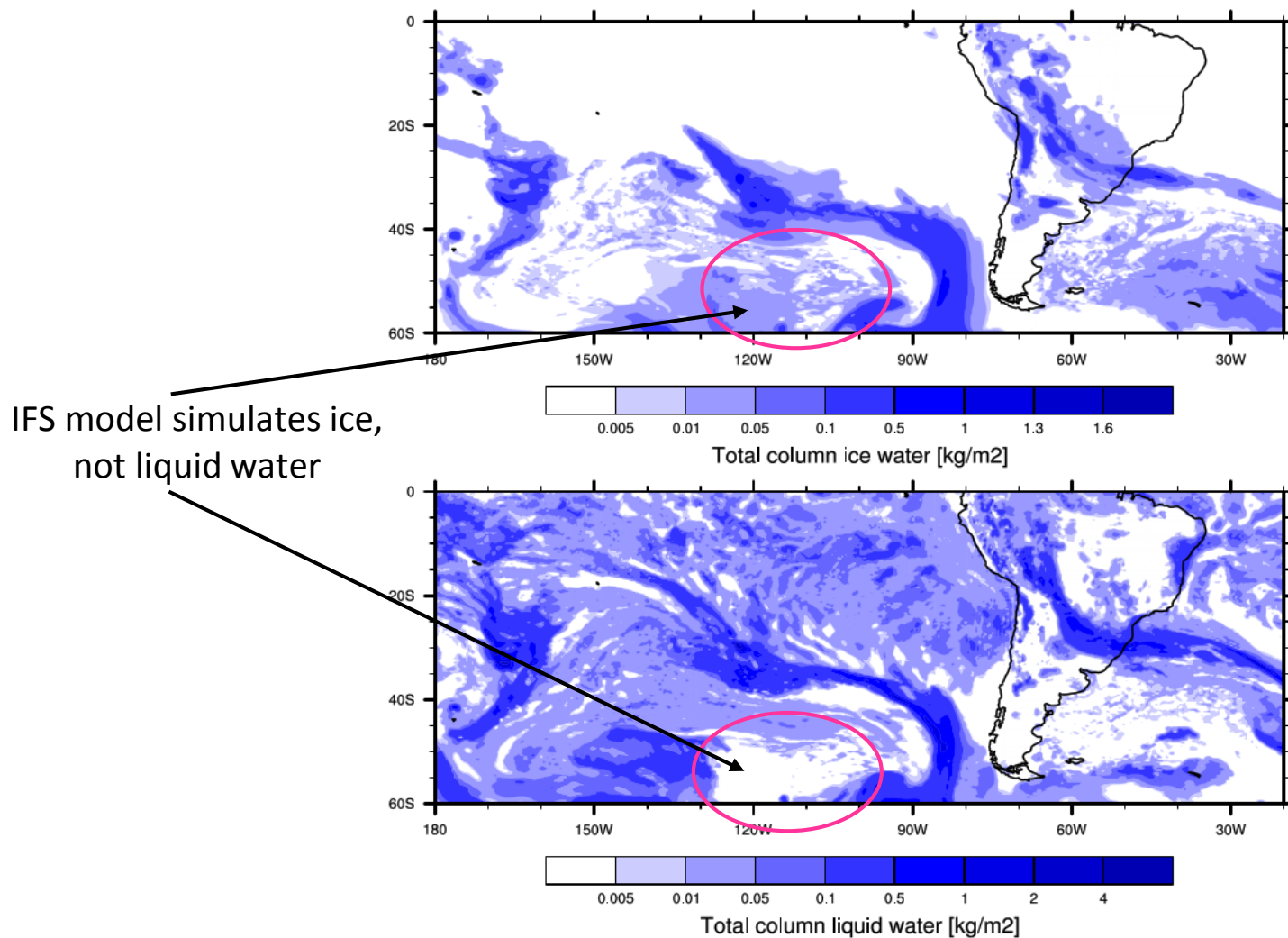
12Z 24<sup>th</sup> August, 2013, 37v FG departure  
[normalised]



Cold air outbreak with large +ve FG departures  
(missing liquid water cloud?)

# Cold air outbreaks

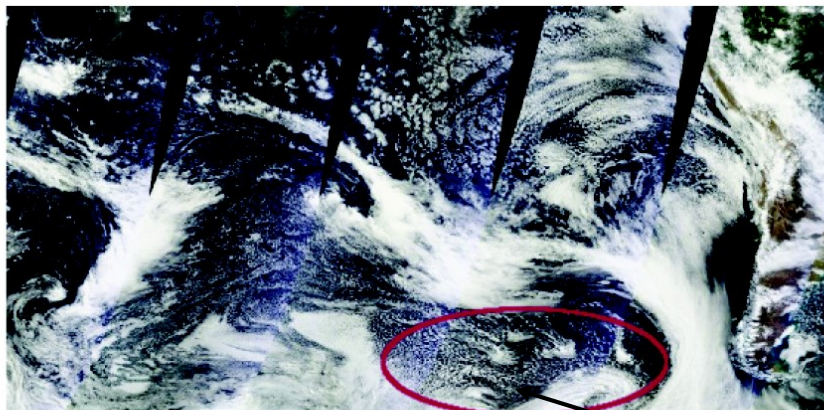
Thanks to Katrin Lonitz and Richard Forbes



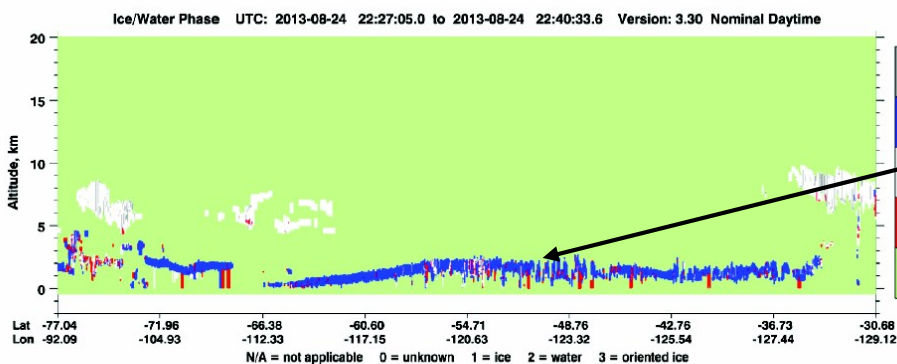


# Cold air outbreaks

Thanks to Katrin Lonitz and Richard Forbes



Composite MODIS image on 24 August 2013 at 08 Z. The whole area shown spans from  $180^{\circ}$ W to  $60^{\circ}$ W and from the equator to  $60^{\circ}$ S.



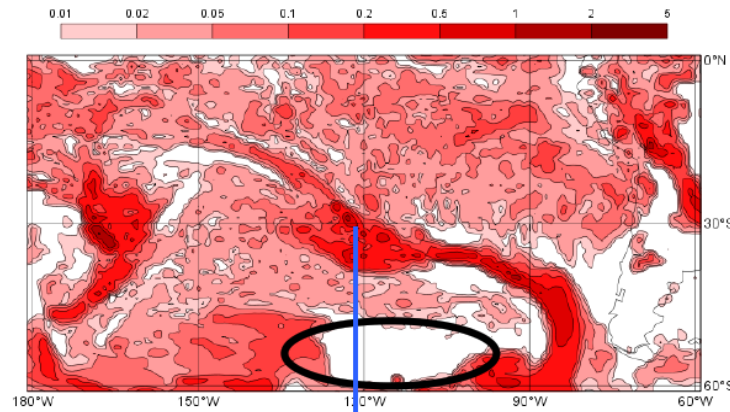
Calipso shows liquid water, not ice in this area

[www.calipso.larc.nasa.gov/products/lidar/browse\\_images/show\\_dat30&browse\\_date=2013-08-24](http://www.calipso.larc.nasa.gov/products/lidar/browse_images/show_dat30&browse_date=2013-08-24)

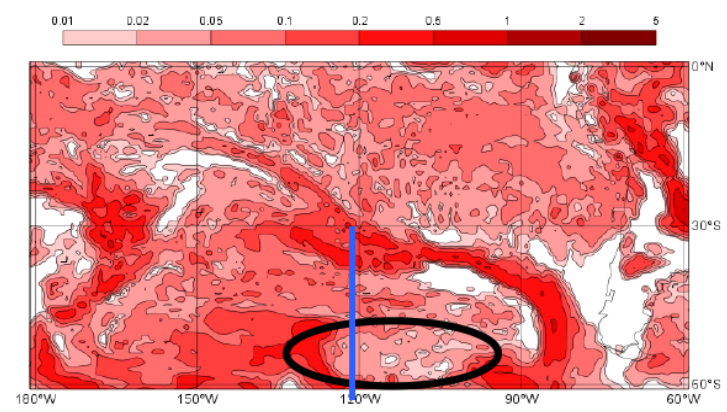
# Allow SLW detrainment from shallow convection scheme

Thanks to Richard Forbes and Katrin Lonitz

IFS T+12 total column liquid water path ( $\text{kg m}^{-2}$ )

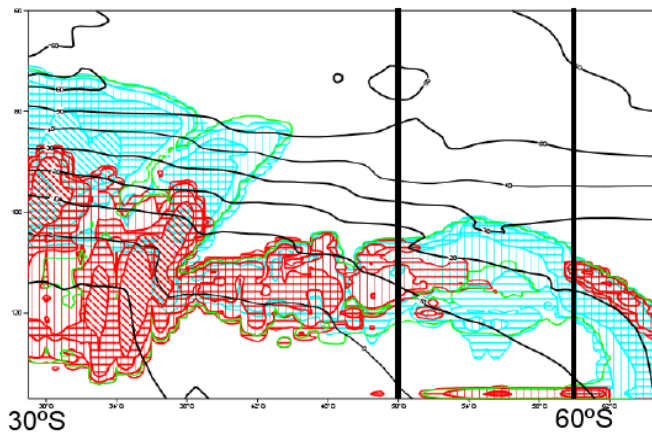


Cycle 40r1

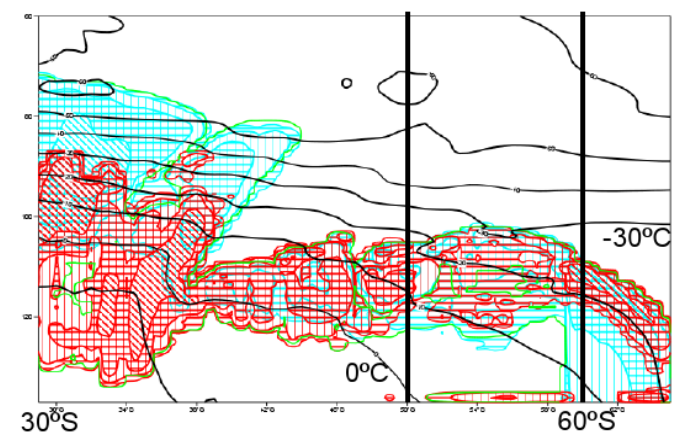


Cycle 40r1+40r3physics+SLW convection

Vertical cross  
section through  
CAO



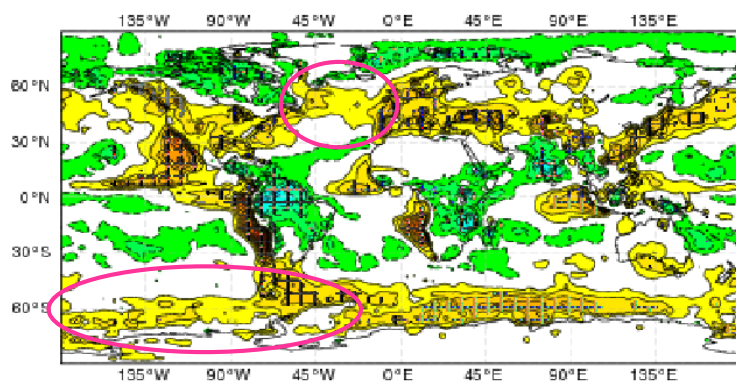
IFS T+12 cross section along 122W showing ice (blue) and liquid (red) water contents (log scale) and temperature (black contours)



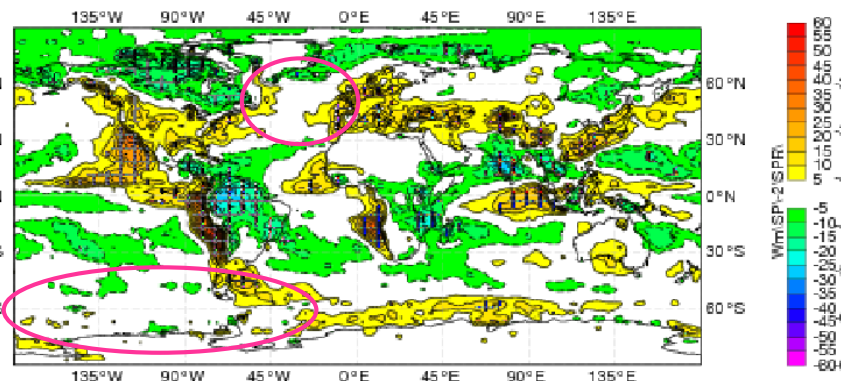
# Cold air outbreak bias also affected SW radiative forcing

Thanks to Richard Forbes and Katrin Lonitz

CERES Net TOA SW discrepancy before improvement



CERES Net TOA SW discrepancy after improvement



# All-sky assimilation benefits:

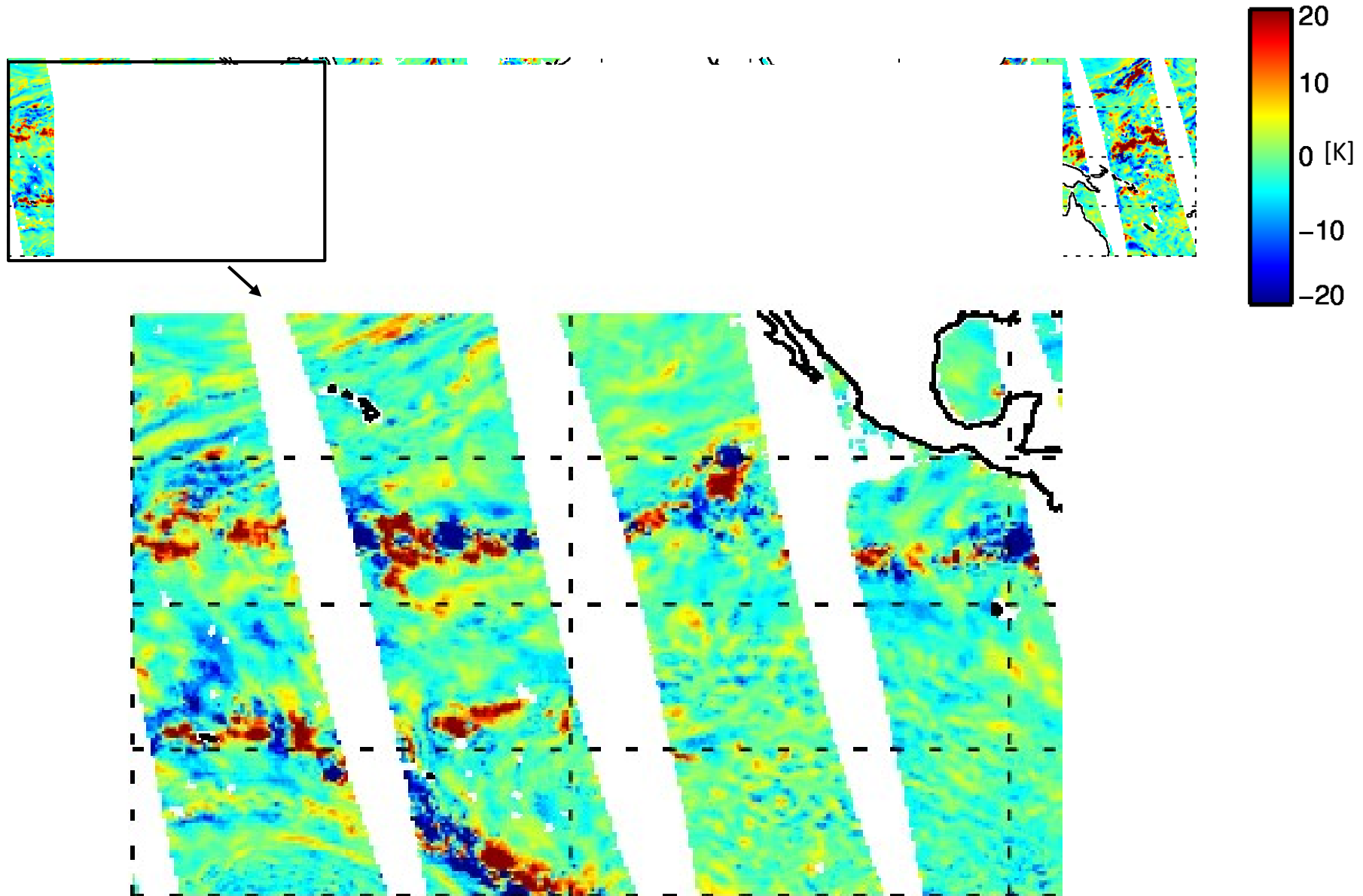
- Better initial conditions in the moist and dynamical parts of the analysis:
  - Better synoptic forecasts out to day 6
  - All-sky microwave “WV” observations now rival the impact of the full infrared clear-sky observing system (geo-sounders, AIRS, IASI, CRIS)
  - Improved cloud and precipitation forecasts? See later.
- Better diagnostic constraint of cloud and precipitation in the forecast model
  - Diagnosis of systematic model errors, e.g:
    - Cold air outbreaks – supercooled liquid water
    - Maritime stratocumulus – insufficient diurnal cycle

Uncertainties: “mislocation”, i.e. the lack of either representivity **or** predictability of cloud and precipitation at smaller scales

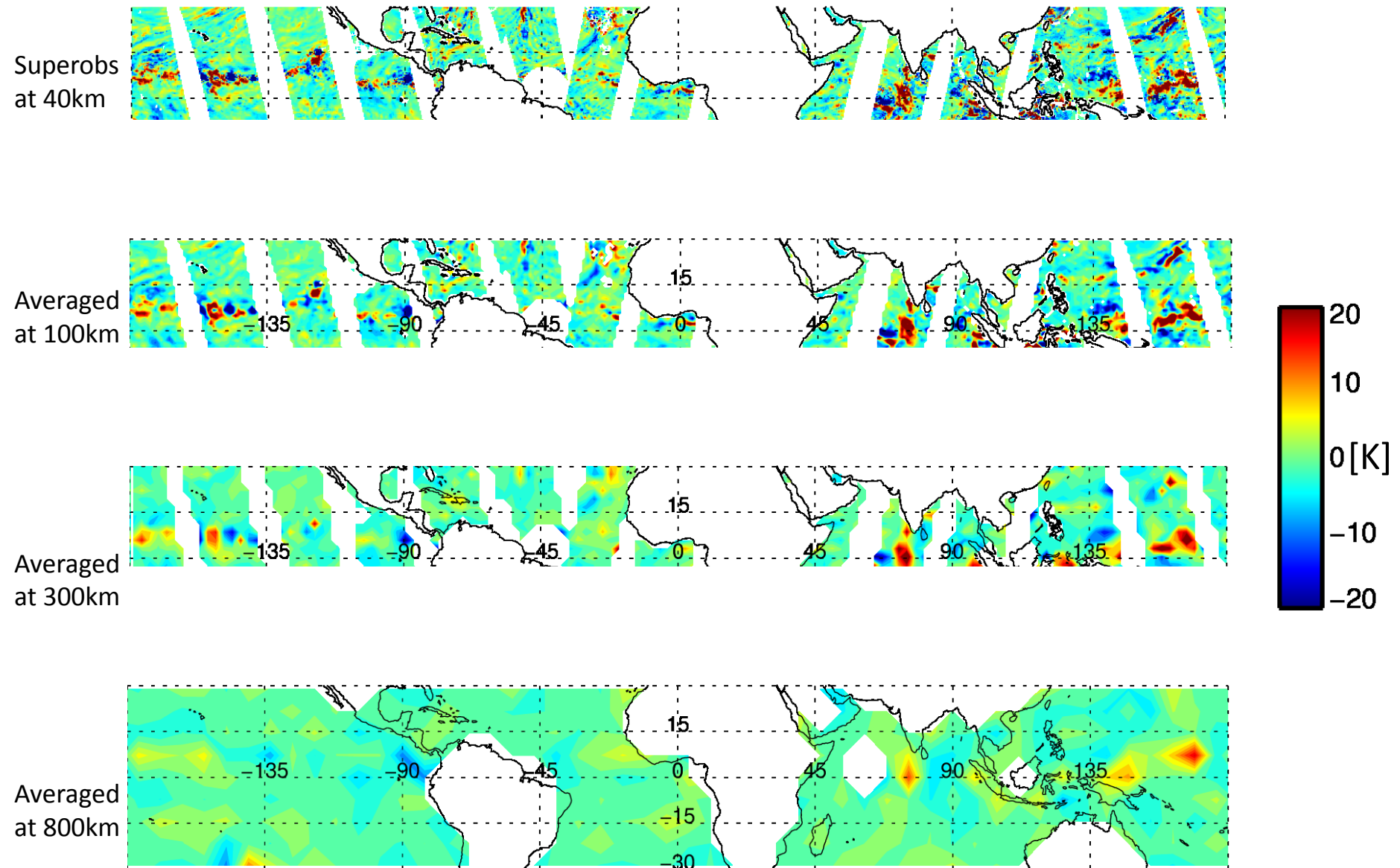


# Spatial scales in FG departures at 19h

SSM/I/Superfhrs in 40km by 40km boxes compared to 20km res (T620co) model

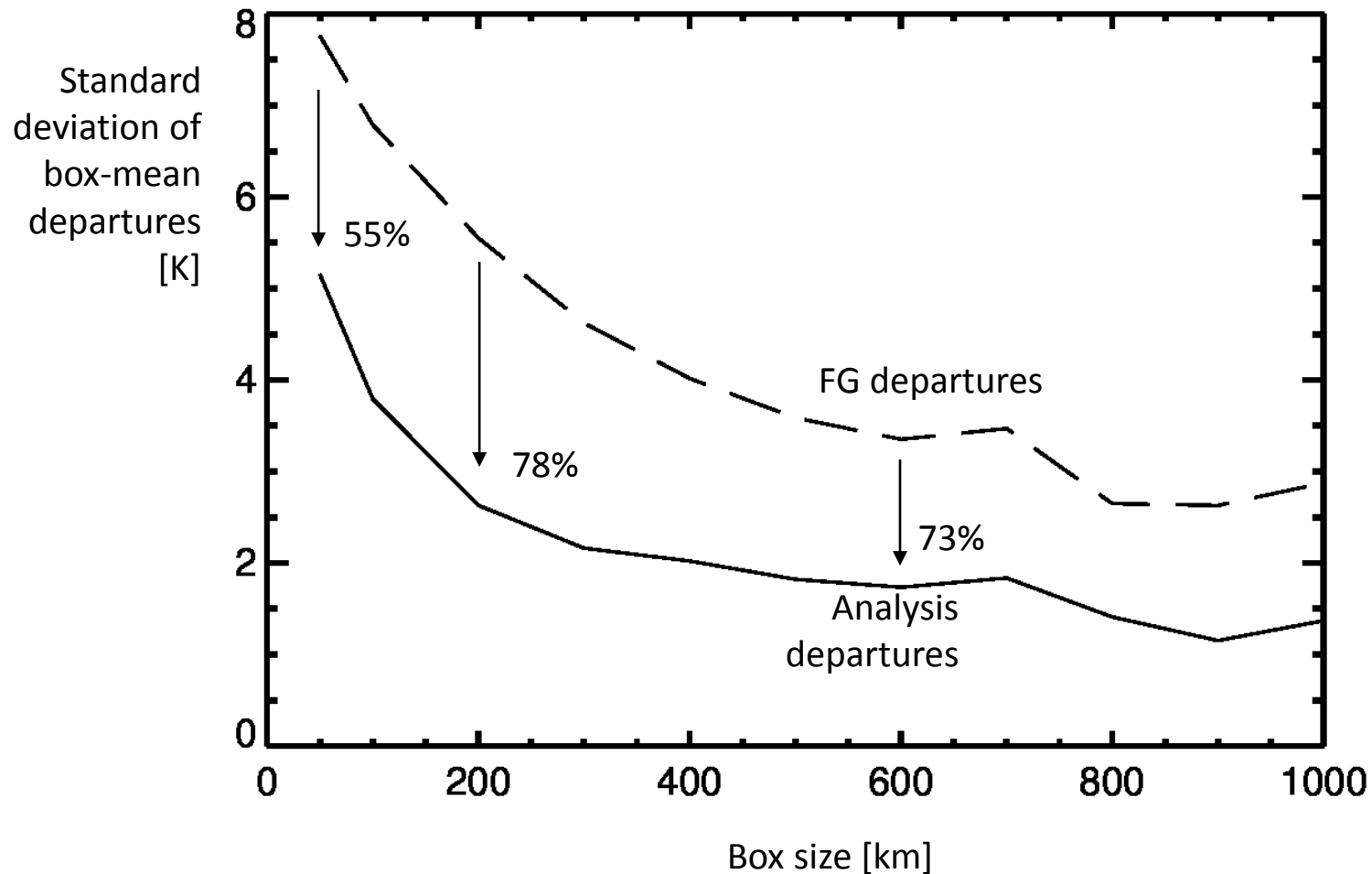


# Annly box-averaging to FG departures



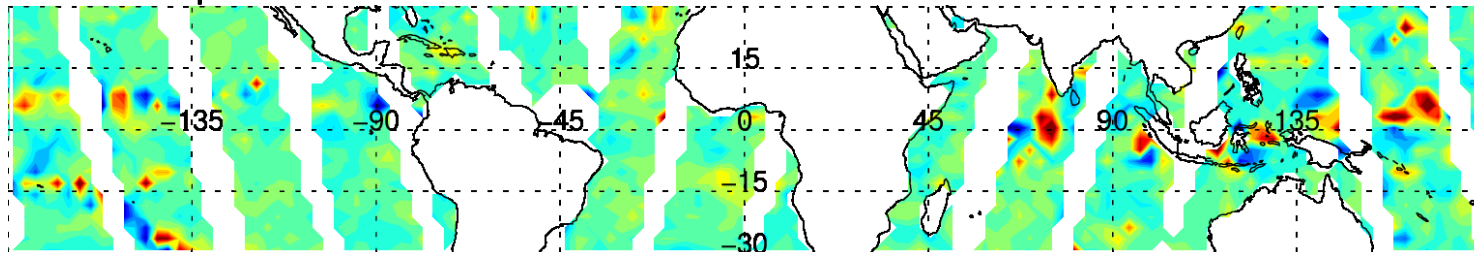
# FG and analysis departure standard deviation: scales

SSMI/S F-17 19h, 10-11 Dec 2014, 30S-30N

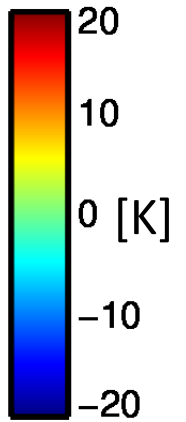
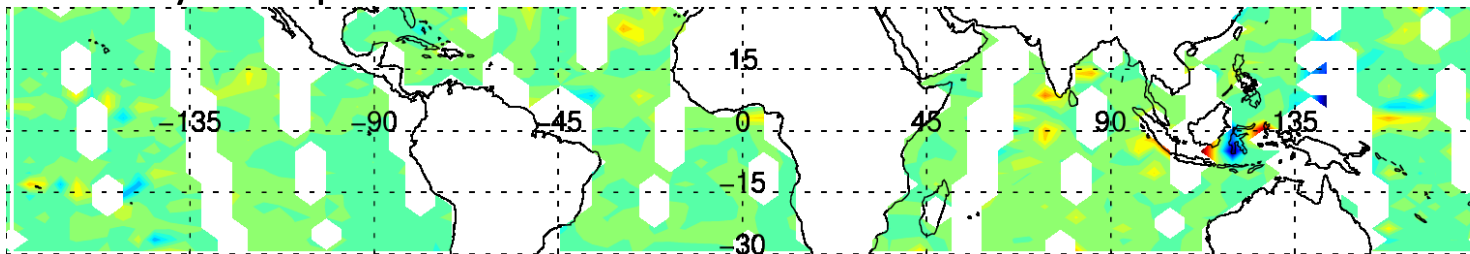


# Averaged in 300km boxes

FG departure

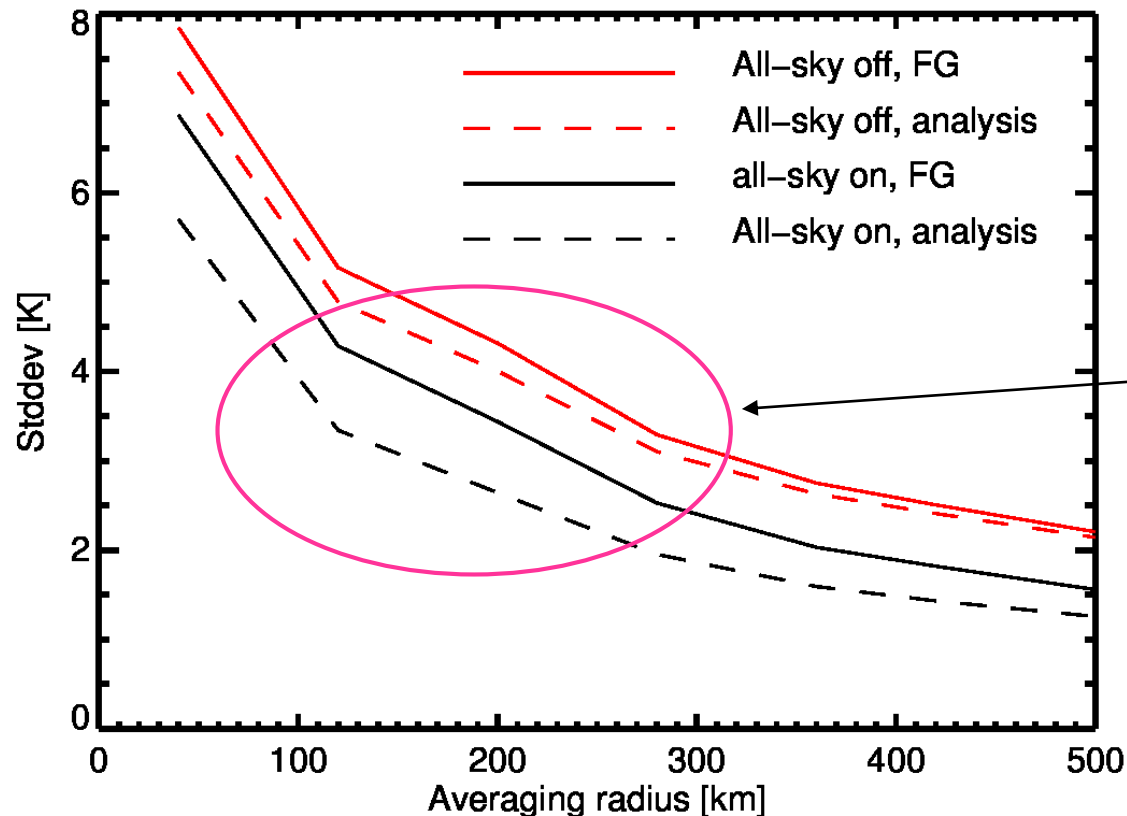


Analysis departure



# Impact on precipitation: 19GHz fits to independent data

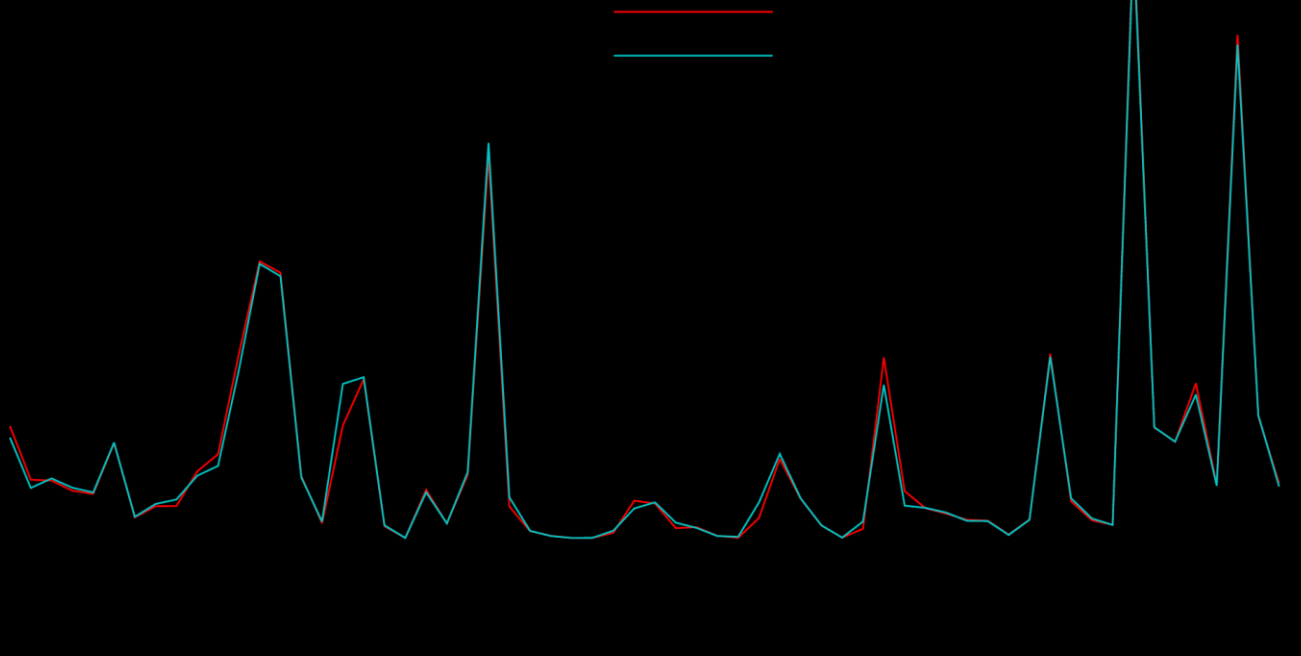
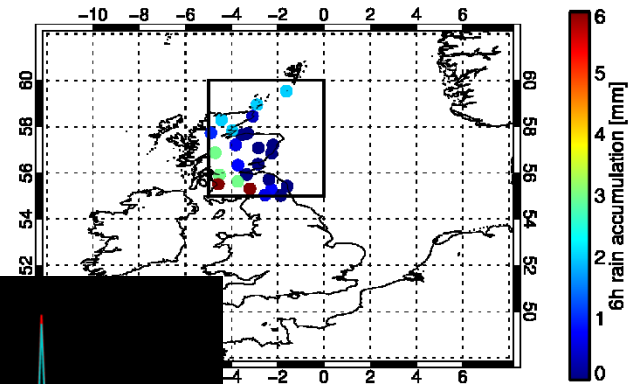
SSMIS F-16, not assimilated and at least 1h orbit displacement from active all-sky sensors



All-sky assimilation reduces “precipitation” analysis and short-range forecast errors, particularly on 100 – 300 km scales

# Rain reality check

6h precipitation accumulations in a 5x5° box over Scotland  
T+6 to T+12 forecast compared to rain gauges



- Globally there is no significant difference in fit to rain-gauges between all-sky on and all-sky off
- Even with 6h accumulation and 5 degree averaging, many locations verify badly

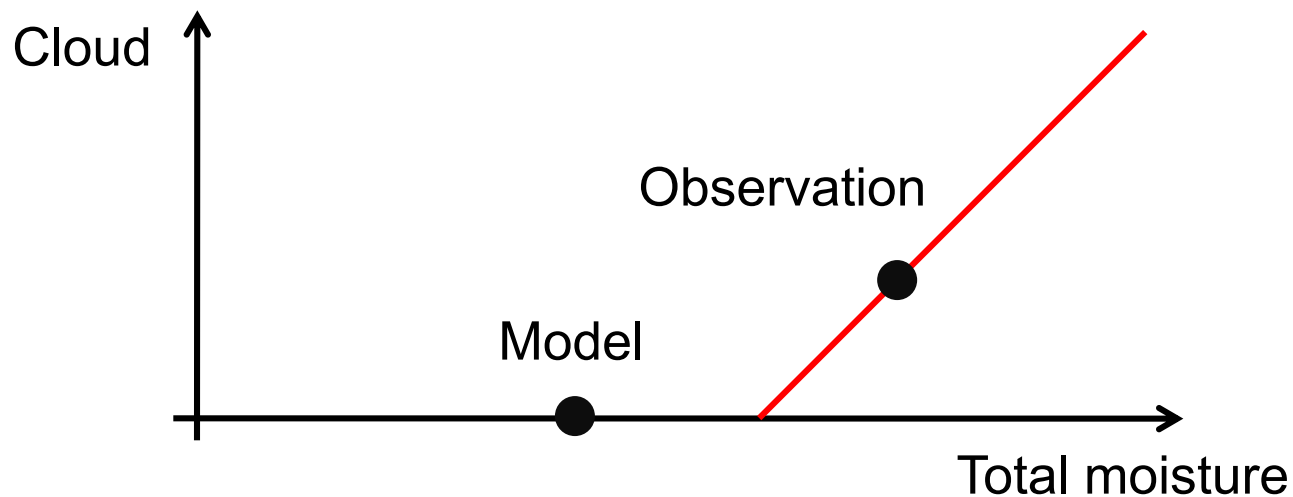
# Why the discrepancy?

- The issue – impact of all-sky:
  - Independent 19 GHz microwave observations show clear precipitation improvements in analysis and forecast, especially on broader scales
  - Rain gauges apparently do not
- Well-known continuing challenges for predicting and observing precipitation:
  - All-sky microwave observations see the vertical integral of atmospheric hydrometeors. This does not necessarily relate to the surface rain rate.
  - It is up to the forecast model to convert atmospheric hydrometeors into realistic surface rainfall (state-dependent systematic errors probably dominate)
  - Representivity and accuracy of the rain gauges
  - Predominantly oceanic microwave observations vs. land gauges.

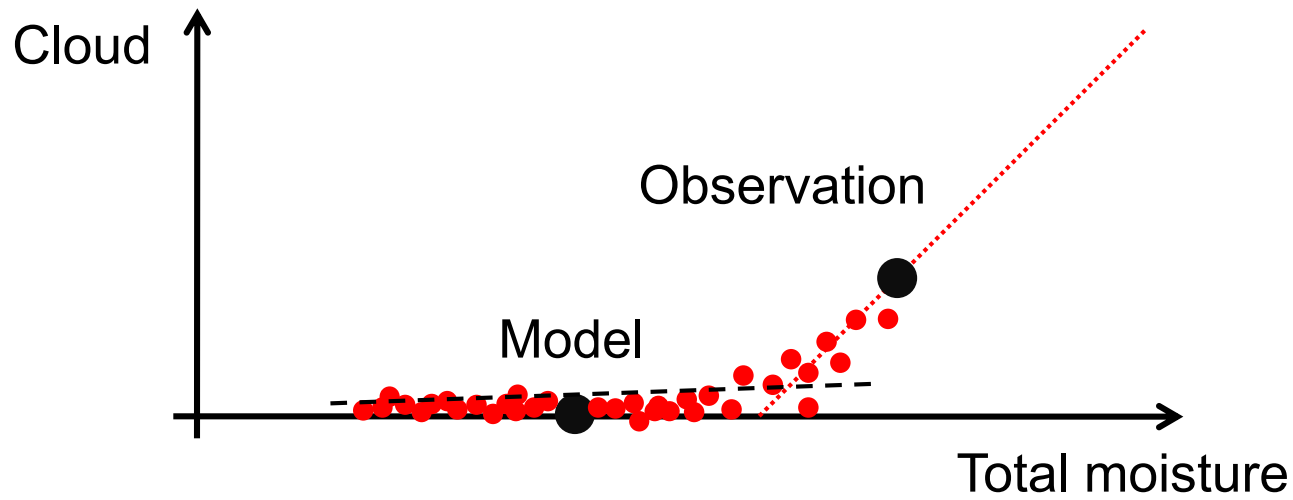
## Uncertainties: nonlinearity



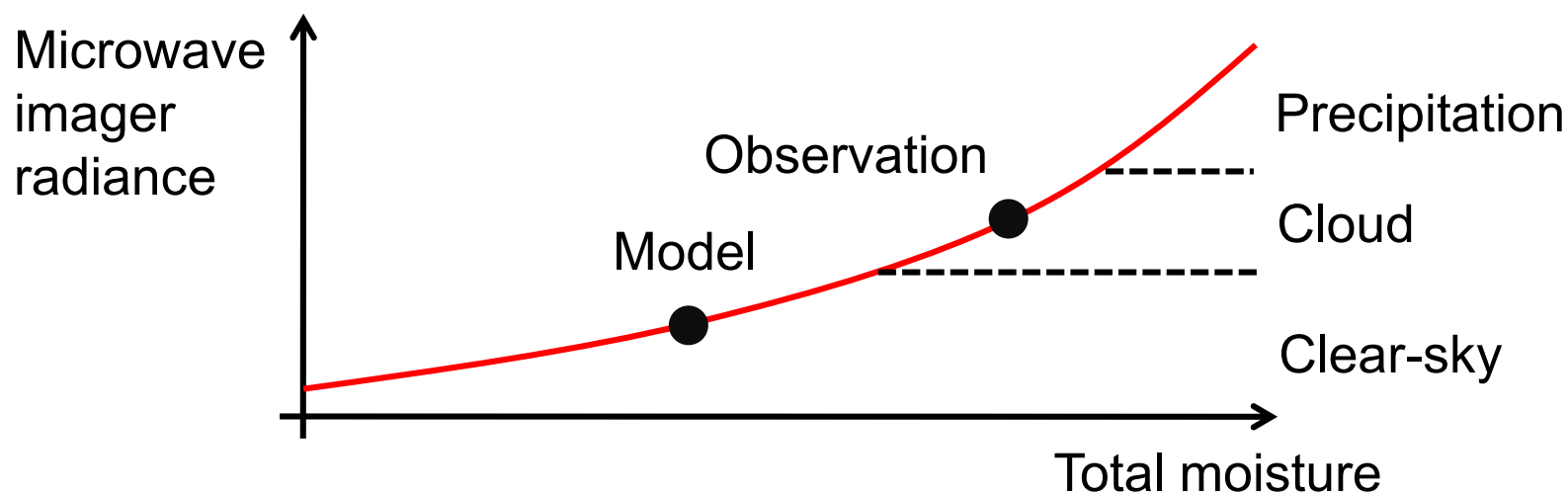
# The zero-gradient problem



# The zero-gradient problem in an ensemble context

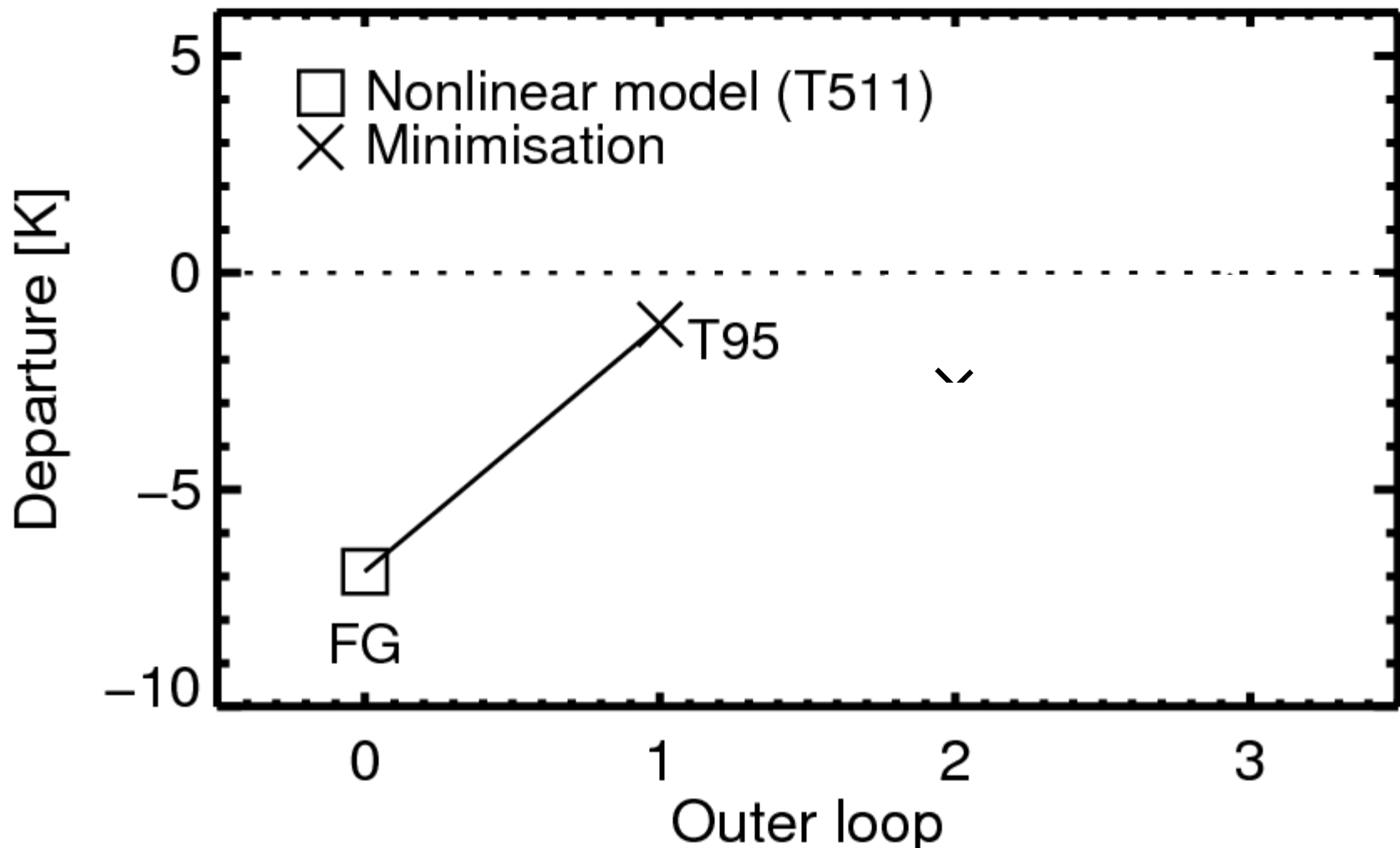


## “Water vapour” radiance sensitivities help to avoid the zero gradient problem



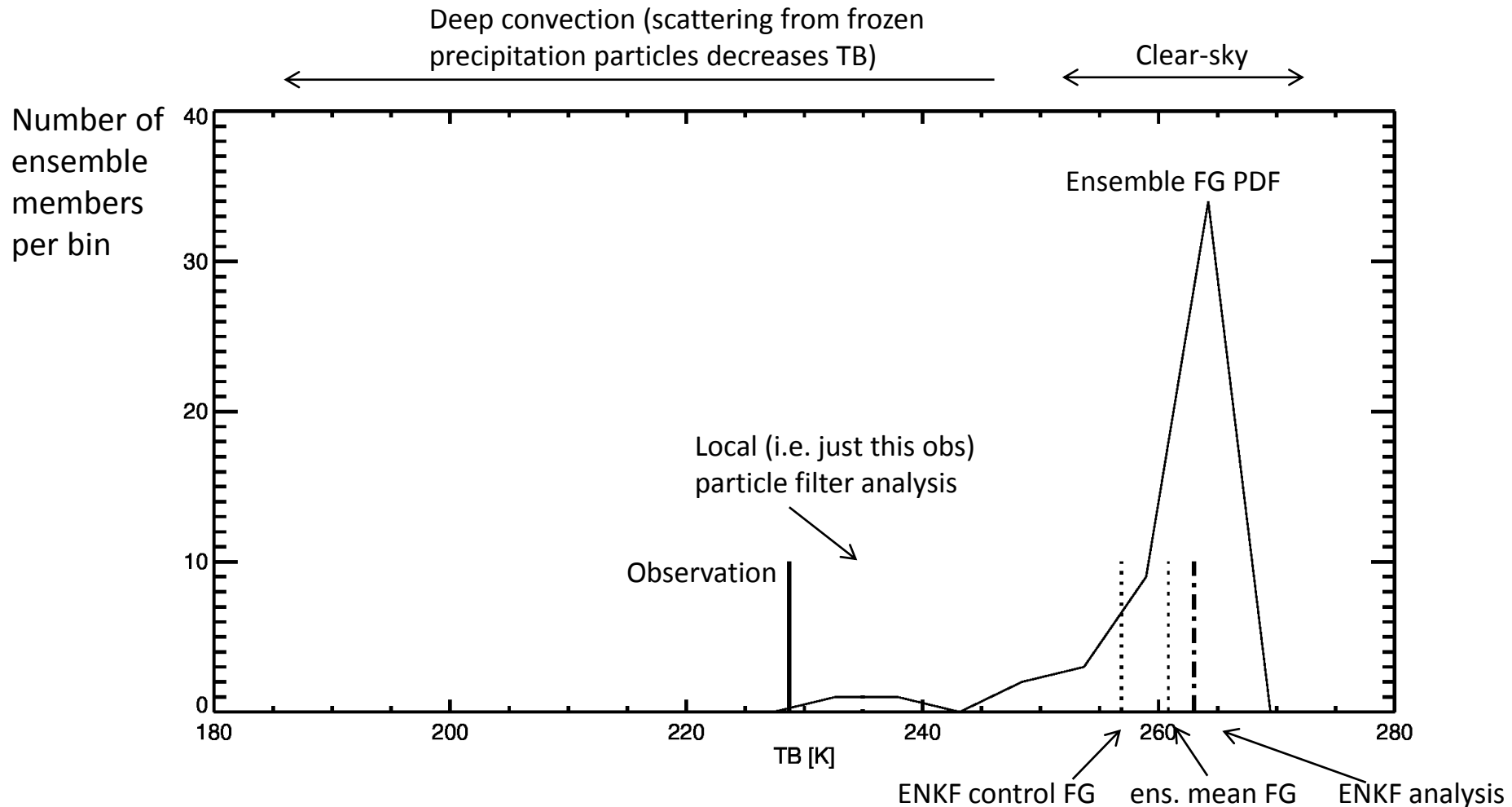
# Incremental 4D-Var can handle nonlinearities

Single observation example from Bauer et al. (QJ, 2010)



# Ensemble view

SSMIS 183±6.6 GHz brightness temp (TB) sensitive to deep convection and mid-tropospheric WV  
50 member ensemble



# Single-obs versus full observing system

- Single observation assimilation is “easy”:
  - All-sky incremental 4D-Var has consistently demonstrated its ability to fit single observations of cloud and precipitation in nonlinear regimes (Bauer et al. 2010, TM 741)
  - 1D-Var and 1D particle filters can also fit cloud and precipitation very successfully (we have not tested all-sky single obs EnKF)
- The real aim is to best fit **all** observations, and to produce a successful forecast
  - The analysis does not attempt (and cannot) fit all the small-scale precipitation variability
  - The analysis is taking place at broader scales than that of a single cloud or precipitation observation

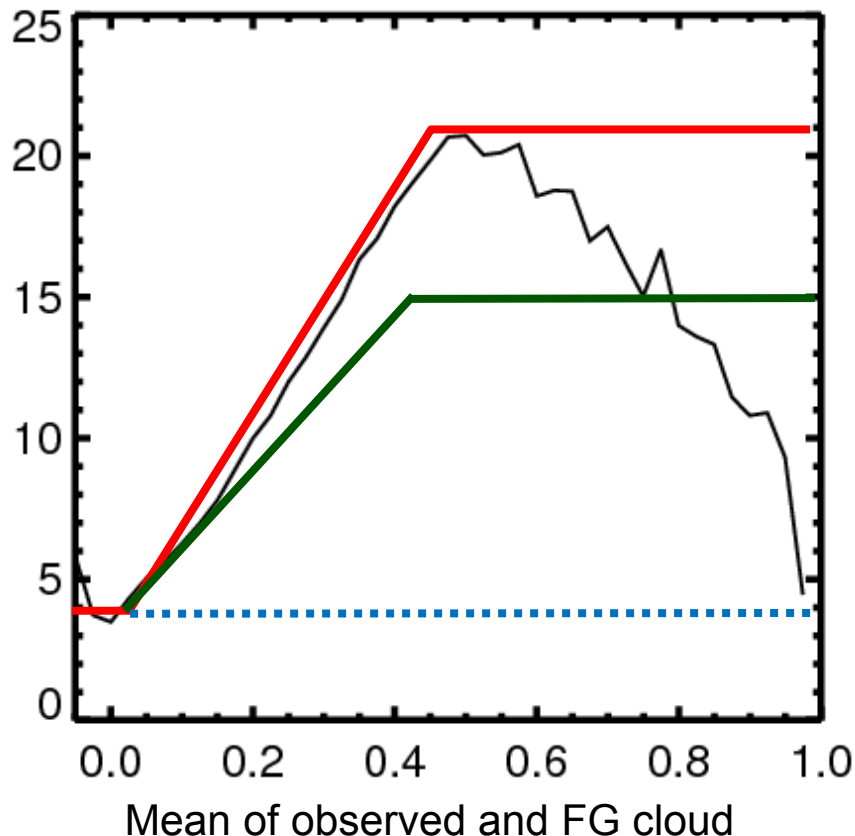
Quantifying uncertainties: what is observation error  
and what background error?

# Symmetric observation error model

## Background error ( $HBH^T$ ) versus observation error ( $R$ )

Geer and Bauer (2011, QJ)

Standard deviation  
of FG departures  
 $= \sqrt{HBH^T + R}$   
[K]



Observation error  
model with  $\alpha=1$

$HBH^T \ll R$

$\alpha=0.5$

$HBH^T \approx R$

$\alpha=0.0$

$HBH^T \gg R$



# Using EnKF to diagnose model & obs error

As a function of “precipitation amount”, errors in SSMIS channel 19h (sensitive to rain)



All-sky error model ( $\alpha=1$ )  
is slightly cautious  
compared to the real total  
error (the std. dev. of FG  
departures)

Still, the observation error  
appears to be larger than  
the background error (the  
spread) in precipitation

Ensemble spread accounts  
for a substantial part of  
total error

(roughly) Clear sky

Rainy

# All-sky EnKF at ECMWF

Massimo Bonavita and Mats Hamrud (EnKF talk tomorrow)

- Hamrud et al., Bonavita et al. (MWR, 2015) initial version did not include all-sky radiance assimilation
  - All-sky observation error modelling needed some thought.
- New series of initial experiments developing all-sky capability (50 members, Tco319, just EnKF, not hybrid):
  - New observation error model boosts errors as a function of nonlinearity estimate
  - “VarQC” downweights outlying observations (vital for all-sky)
  - Careful choice of vertical localisation makes for much better results
  - Impact of all-sky in the EnKF looks similar to that in the full 4D-Var system
- How can an EnKF (making a linear analysis) replicate much of the impact of all-sky found in incremental 4D-Var (nonlinear)?
  - See earlier slides showing much of the impact of 4D-Var all-sky assimilation is at broader spatial scales in more linear regimes.

# Conclusion

## ● Uncertainties:

- Difficulty of improving the surface precipitation forecast over land
- Small-scale unpredictability of cloud and precipitation (<100km)
  - All-sky error models typically represent this as observation error
  - However the aim is not to fit the observed cloud and precipitation exactly (unpredictable scales, nonlinear processes)

## ● Benefits of cloud and precipitation assimilation:

- On larger more linear spatial scales, we are simultaneously fitting many individual, unpredictable observations (plus lots of more-predictable traditional observations)
- All-sky microwave WV has become a major part of the observing system, improving ECMWF operational synoptic forecasts out to day 6
- It also helps diagnose and motivate forecast model improvements addressing systematic errors in cloud and precipitation

Backup slides

# The 4D-Var costfunction

1. We will vary model state  $x$   
to find the best analysis

2. Aiming to improve the fit between observations  
 $y$  and simulated observations  $H(M(x))$

$$J(x) = (y - H(M(x)))^T \mathbf{R}^{-1} (y - H(M(x))) + (x - x_b)^T \mathbf{B}^{-1} (x - x_b)$$

3. But it must not get too far away  
from the model background  $x_b$

4. The relative weight given to observations versus  
model background is controlled by their respective  
error matrices  $R$  and  $B$

# To find the costfunction minimum, follow the gradient:

- For observation  $i$  at start of minimisation (at background  $x_b$ ), gradient of the cost function  $J$  is:

$$\nabla J(x) \Big|_i^{x_b} = \mathbf{M}_1^T \mathbf{M}_2^T \dots \mathbf{M}_{14}^T \mathbf{M}_{15}^T \mathbf{H}_i^T \mathbf{R}^{-1} (y_i - H_i(M_{1-15}(x_b)))$$

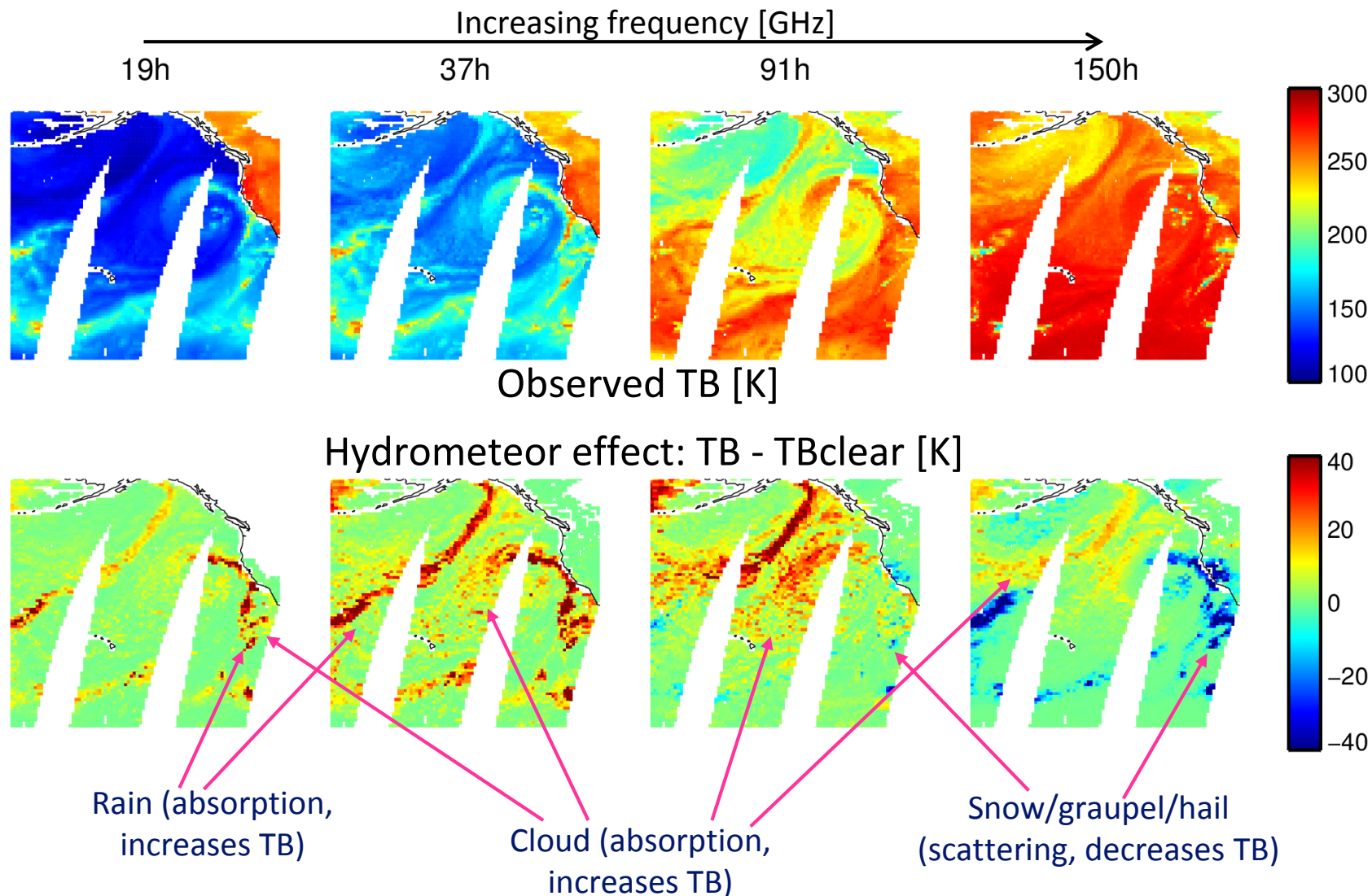
Gradient of cost function with respect to control variables  
 Adjoint of forecast model including moist physics  
 Adjoint observation operator  
 Observed value  
 Nonlinear observation operator  
 Nonlinear forward forecast model timesteps 1-15  
 Model background  
 Observation error  
 First guess departure

$\begin{pmatrix} u^* \\ v^* \\ T^* \\ q^* \end{pmatrix}$ 
 $\begin{pmatrix} u^* \\ v^* \\ T^* \\ q^* \end{pmatrix}$ 
 $\begin{pmatrix} u^* \\ v^* \\ T^* \\ q^* \\ clw^* \\ ciw^* \\ rain^* \\ snow^* \end{pmatrix}$ 
 $\begin{pmatrix} u \\ v \\ T \\ q \\ clw \\ ciw \\ rain \\ snow \end{pmatrix}$ 
 $\begin{pmatrix} u \\ v \\ T \\ q \\ clw \\ ciw \\ rain \\ snow \end{pmatrix}$

$z^*$  is shorthand for  $\partial J / \partial z$

# Window channels (“imaging”):

surface properties, water vapour, cloud and precipitation



# Sounding channels: temperature, water vapour, cloud and precipitation

