All-sky assimilation for initial conditions and model improvements

Alan Geer

Thanks to: Katrin Lonitz, Stefano Migliorini, Marco Matricardi, Niels Bormann, Peter Weston

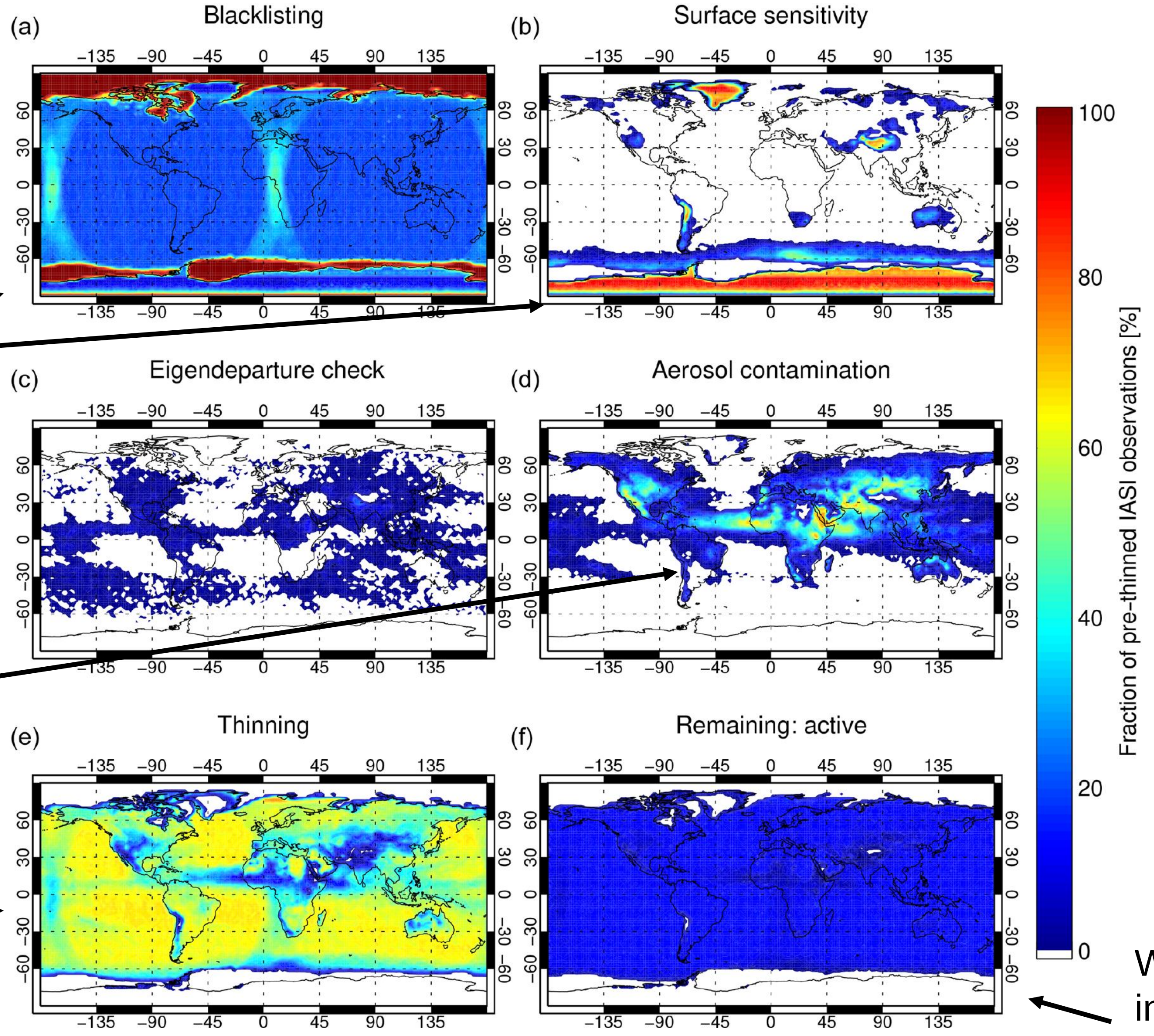
Satellite data rejections even after dealing with cloud and precipitation

As % of pre-thinned data

It's hard to represent the effect of land and sea-ice surfaces

For IR and vis, aerosol is still problematic

Need for spatial observation error correlations

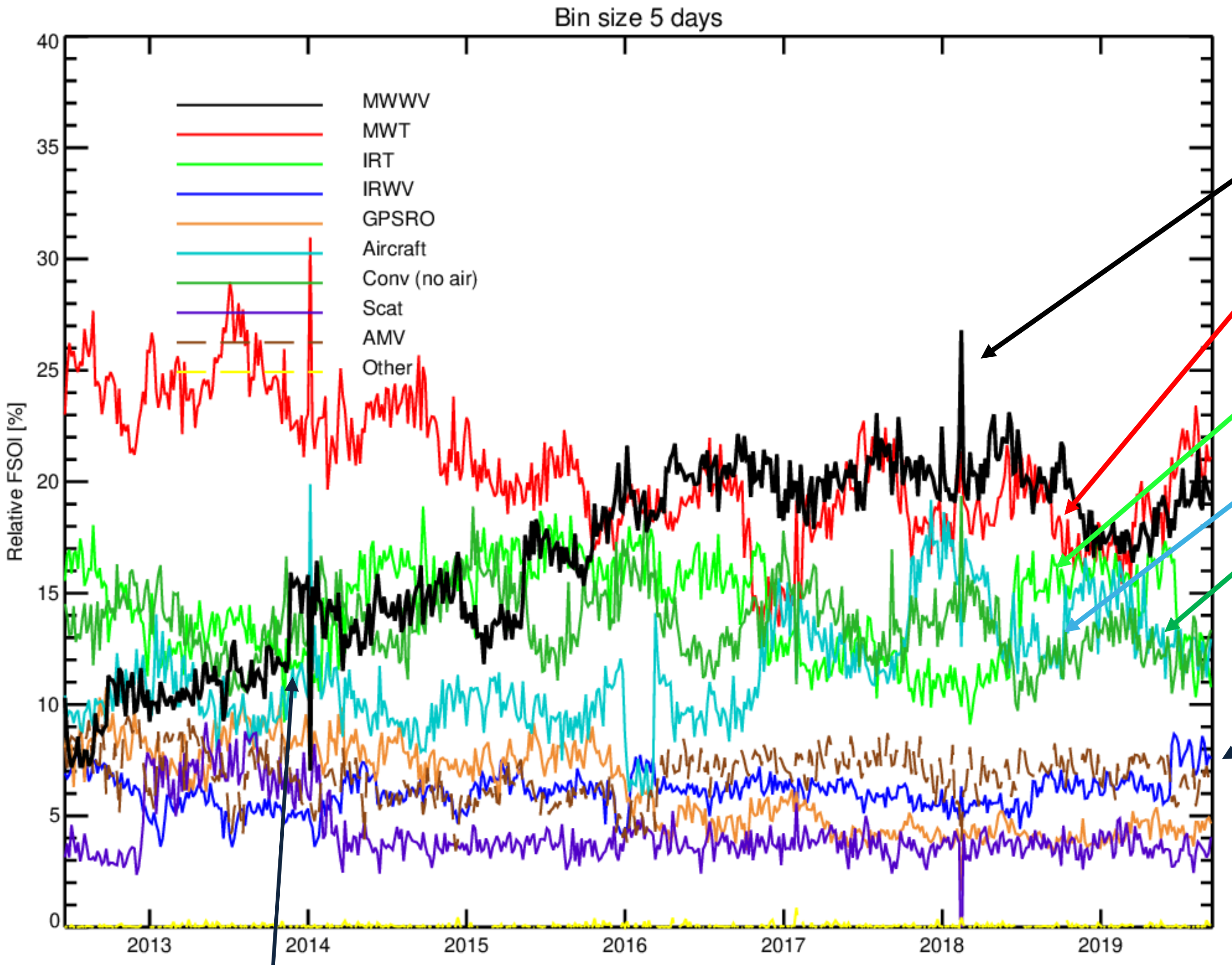


What Jo showed in intro: active all-sky IASI WV sounding

ECMWF

Impact of observing system components on ECMWF 24h forecast quality

Forecast sensitivity to observation impact (FSOI): adjoint based calculation



Top 5:

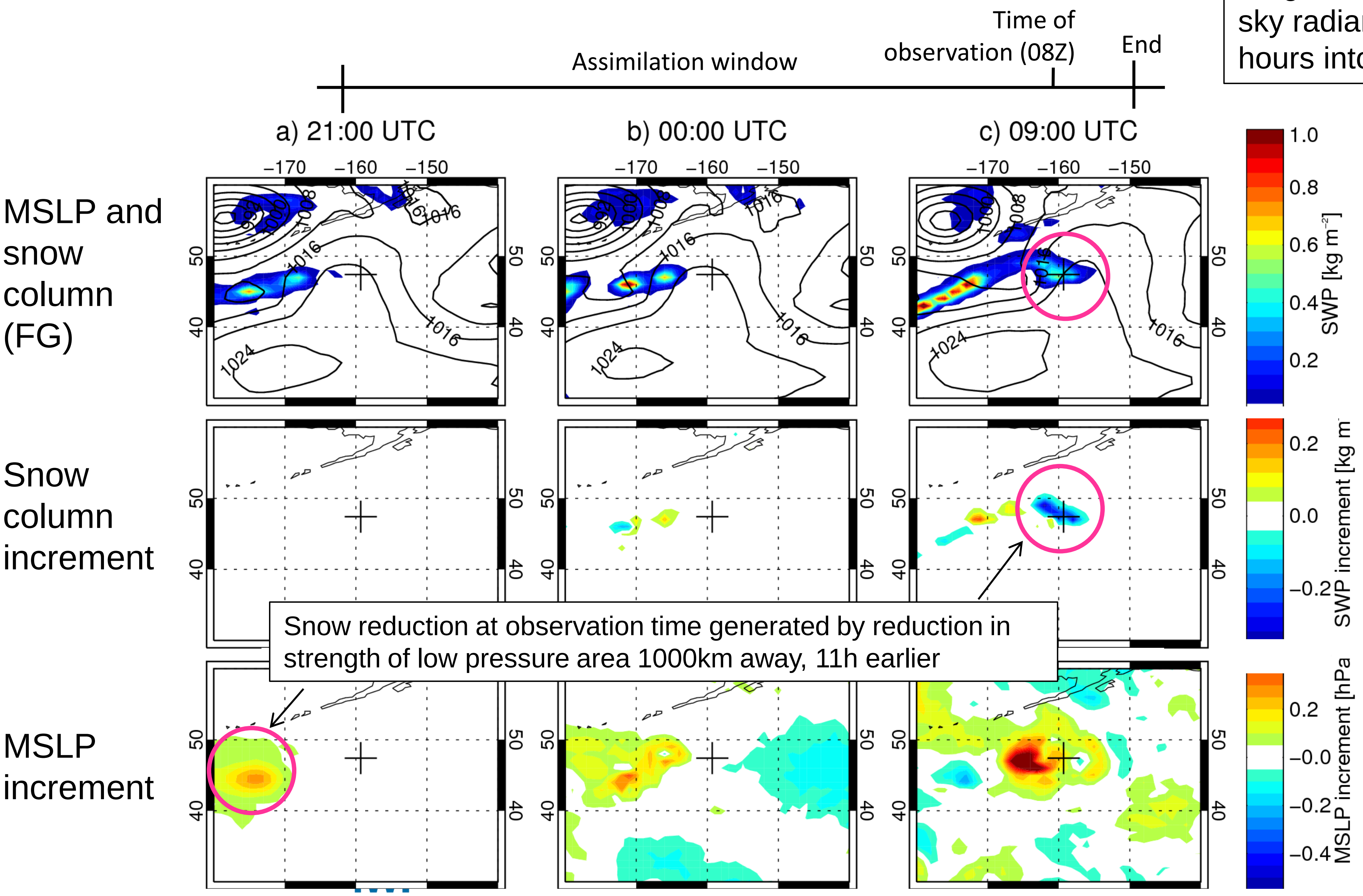
- All-sky microwave imager and humidity radiances
- Clear-sky microwave temperature radiances
- Clear-sky infrared temperature radiances
- Aircraft
- Other conventional data

Satellite infrared radiances sensitive to WV, assimilated in clear-sky and overcast situations only

First SSMIS water vapour sounding channels assimilated in all-sky conditions

Better forecast initial conditions: 4D-Var tracing

Single observation test case: all-sky radiance observation valid 11 hours into the 4D-Var window



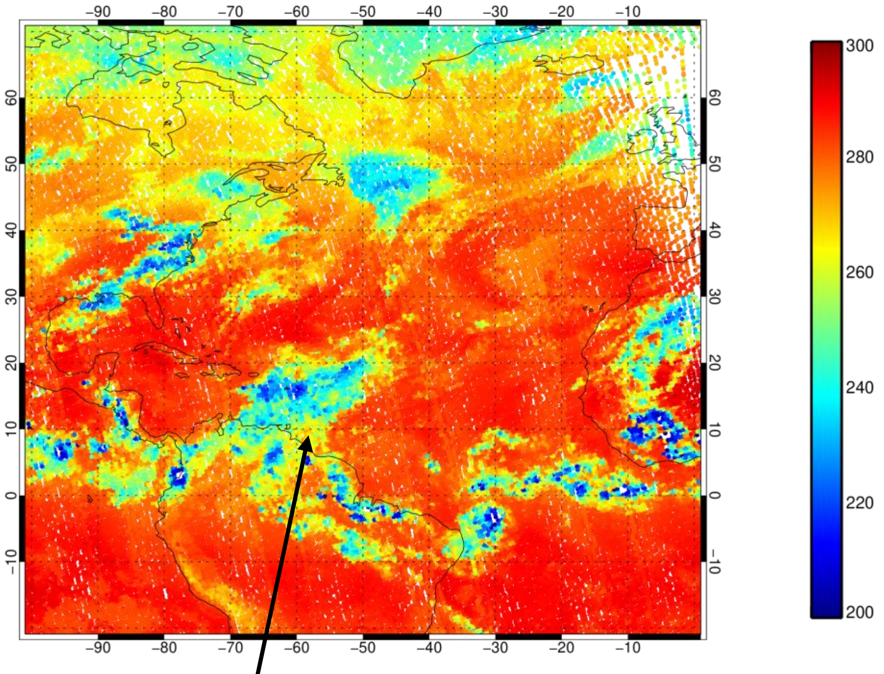
Current all-sky developments

- All-sky microwave
  - Apply it to temperature sounding channels
- All-sky at other frequencies
  - All-sky IR ←
  - Visible
  - Active (cloud and precipitation radar and lidar)
- Error modelling
  - Representation error – inflation in cloudy situations ←
  - Interchannel correlated observation error ←
- All-surface
  - Assimilating microwave observations that are strongly sensitive to land surfaces
- Model bias and development
  - Forecast models and observation operators ←

This talk:
Part 1: oveview
Part 2: all-sky IR and correlated errors
Part 3: model errors

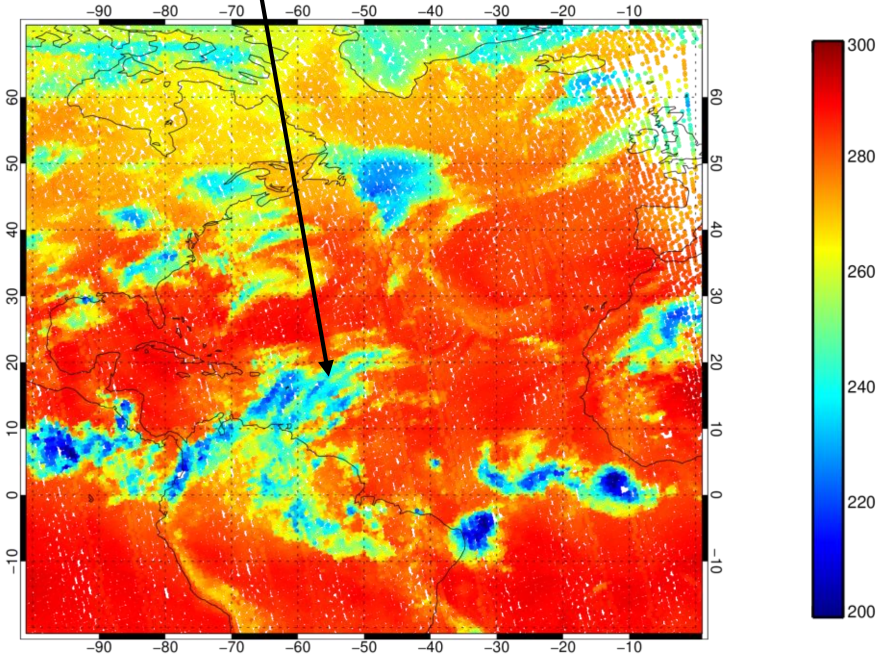
All-sky IASI (hyperspectral IR) channel 906

Obs



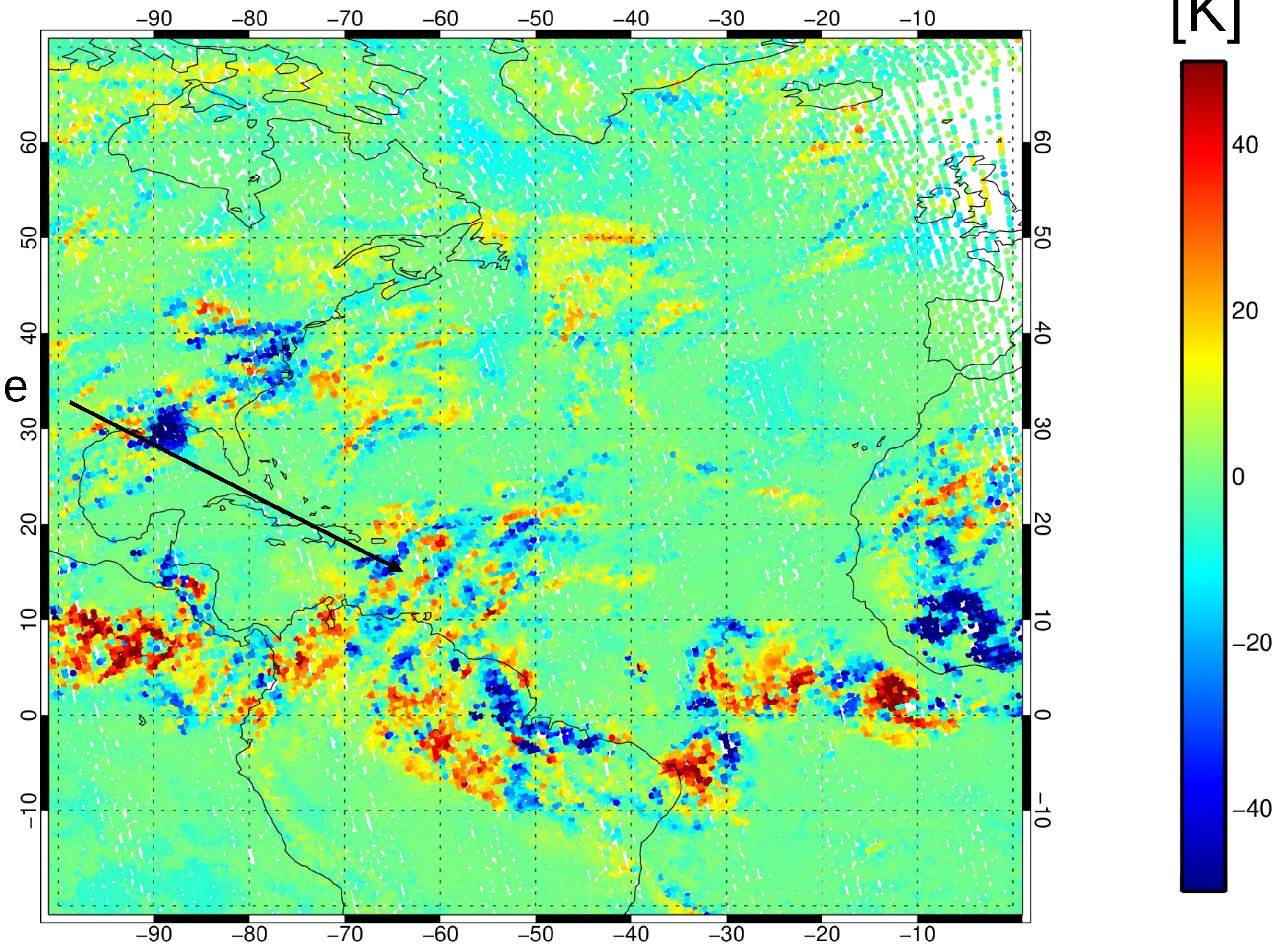
Errors of representation far beyond the gridpoint scale

Model
(12h
forecast)



Obs - model (O-B)

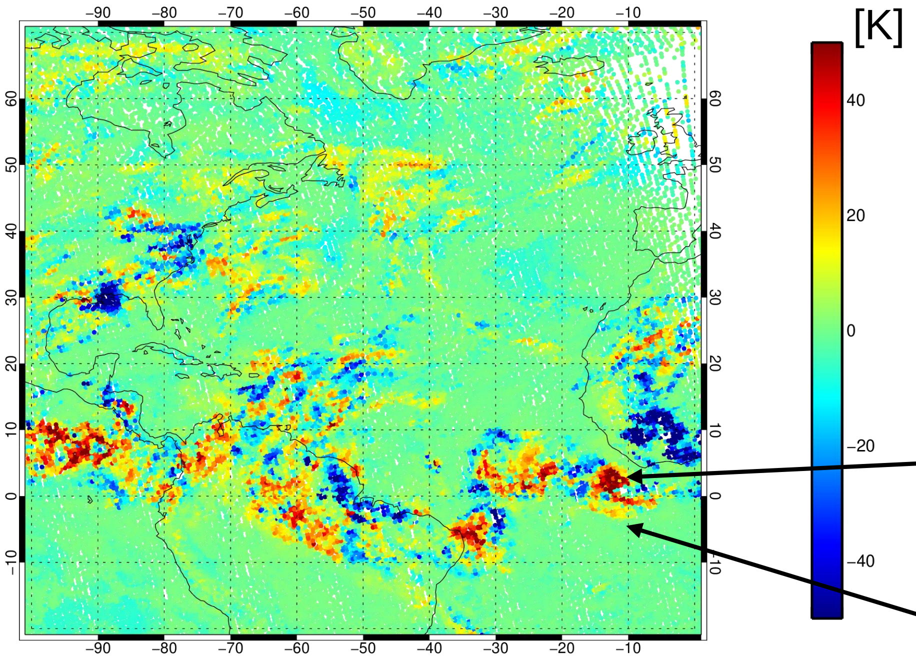
[K]



Properties of all-sky background departures

Obs - model (O-B)

IASI Ch. 906 (lower troposphere)

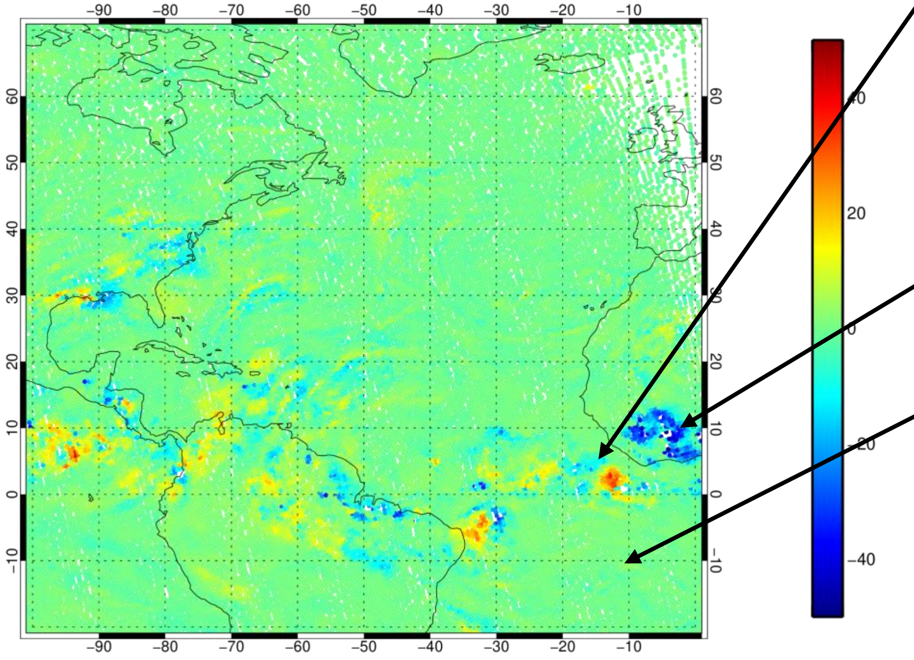


Spatially correlated

Interchannel correlated

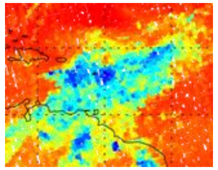
Much bigger in the presence of cloud than in clear skies

IASI Ch. 3002 (upper troposphere humidity /cloud)

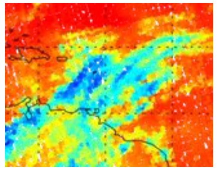


The “representation error spectrum”

Obs



Model



Many of the cloud errors are representation or model error – so do not try to exactly fit the analysis to the observations

Cloud misplacements are background error – do try to fit analysis to observations

Global forecasting

Regional forecasting

Nowcasting

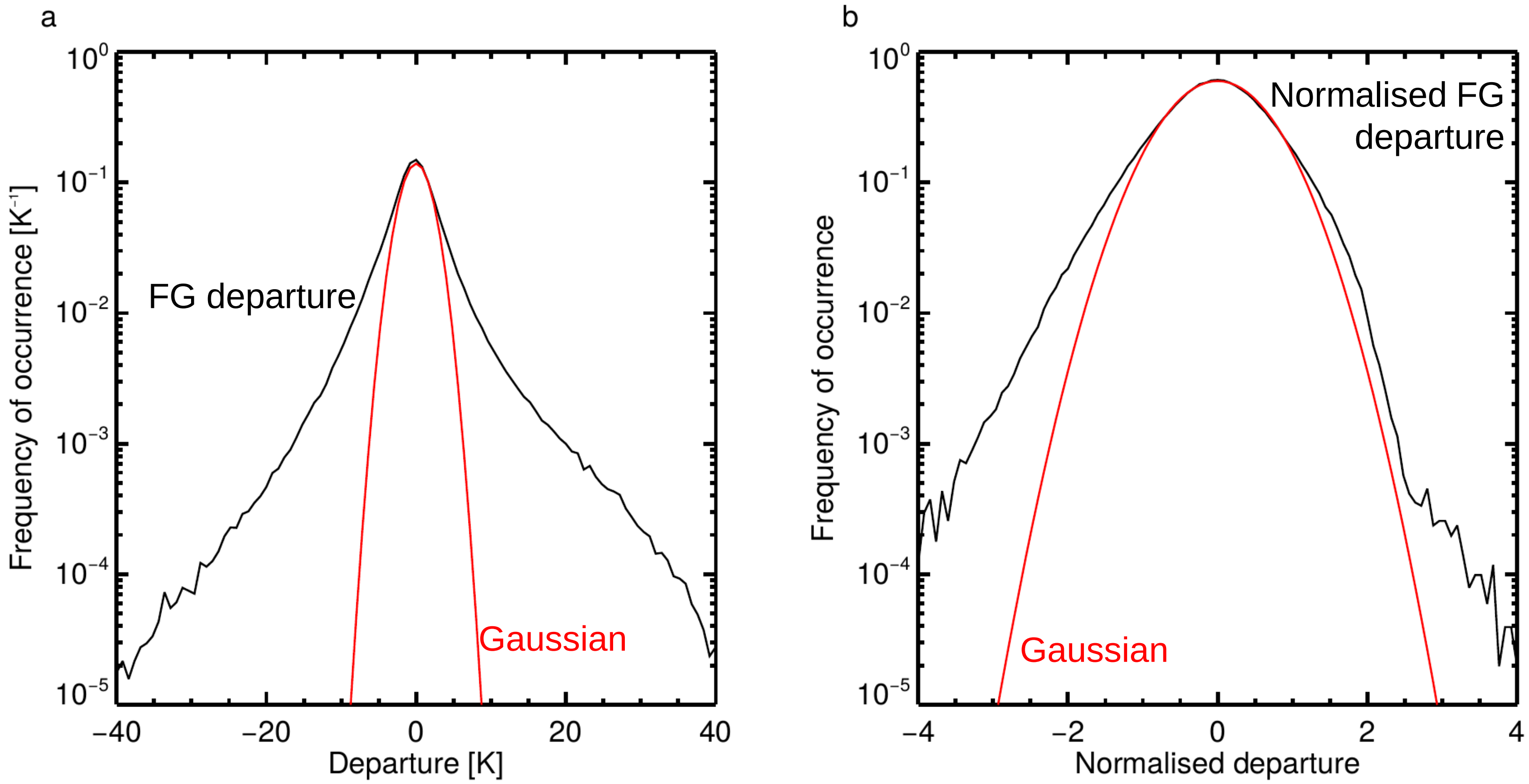
Cloud retrievals

Fit many observations
Try to make the forecast better

Fit one observation

Situation-dependent (as yet non-correlated) observation error

All-sky microwave radiances look a lot more Gaussian with an error model



Normalised by a symmetric observation error model binned by mean of observed and simulated cloud amount

Geer and Bauer (2010,2011)

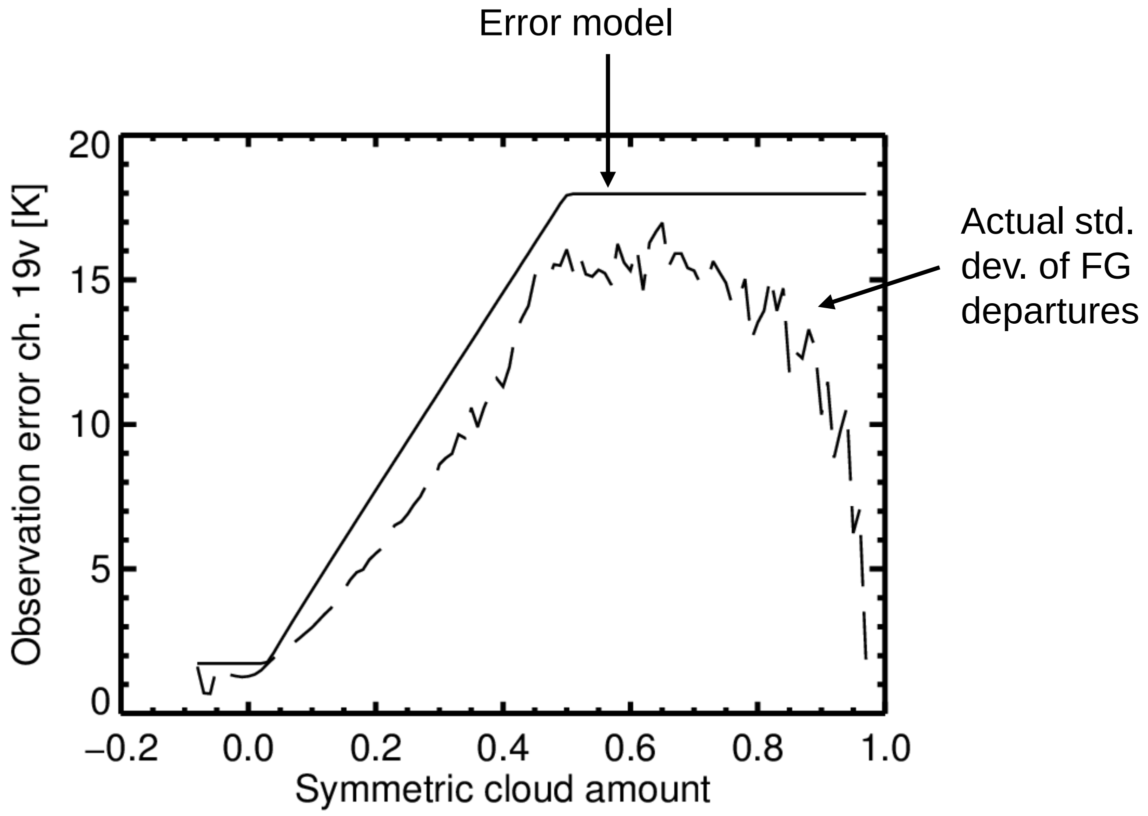
Various cloud proxy variables, e.g for all-sky IR Okamoto et al. (2014)

Current all-sky microwave error model – no interchannel error correlations

$$\mathbf{R}_i = \begin{matrix} \sigma^2_{19V} & 0 & 0 & \dots & 0 \\ 0 & \sigma^2_{19H} & 0 & \dots & 0 \\ 0 & 0 & \sigma^2_{22V} & \dots & 0 \\ \dots & \dots & \dots & \dots & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{183\pm7} \end{matrix}$$

Observation error covariance matrix tailored to one SSMIS observation (i)

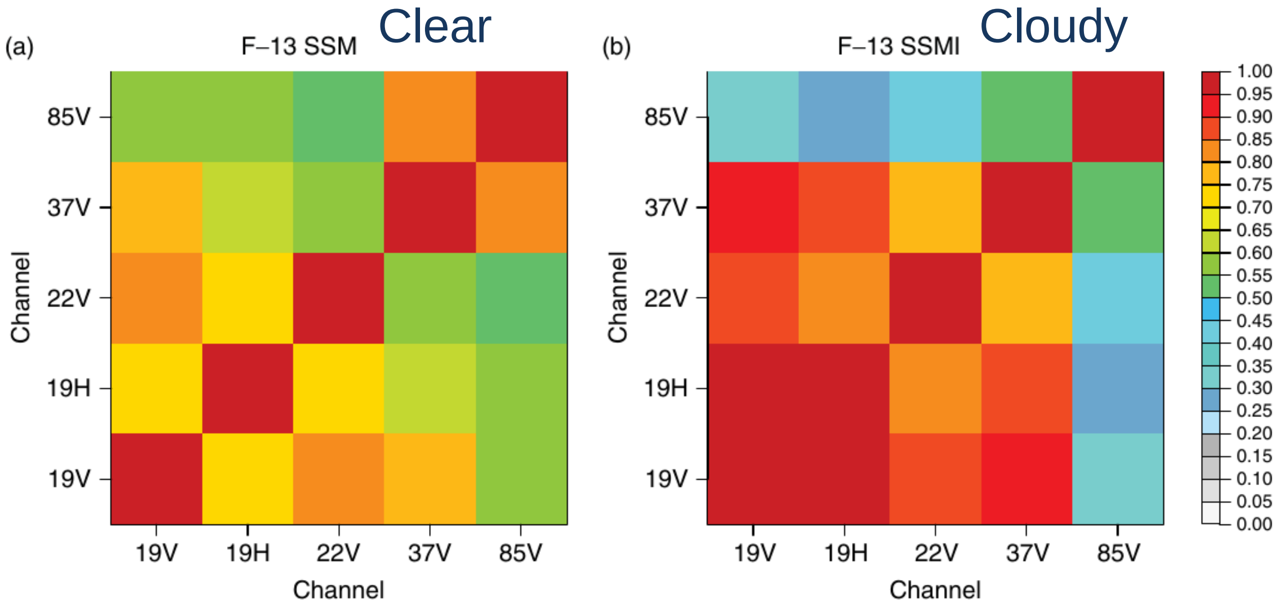
19v, 19h, 22v… = channel names



(C37 = average amount of “cloud” from observation and first guess)

Interchannel observation error correlations

Correlations are much larger in the presence of cloud



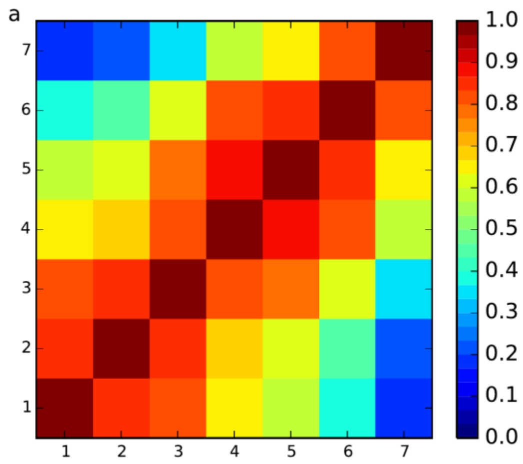
Desroziers diagnosed observation error covariances
(Bormann et al, 2010)

All-sky IASI WV assimilation and inter-channel correlated errors

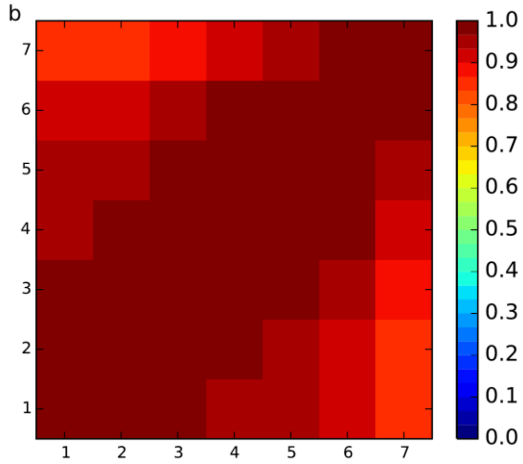
All-sky IR error model aim: correlated, situation dependent

Geer (2019, AMT)

All-sky IR testing: 7 mid-upper-tropospheric humidity channels of IASI



Correlation matrix for clear-sky situations (Bormann et al., 2016)



Global constant correlation matrix based on global all-sky IR departures

(Global constant error covariance taken directly from departures skipping Desroziers and error retuning)

A big approximation – ignore background error in the observation error modelling

$$E(\mathrm{dd}^T) = \mathrm{HBH}^T + \mathrm{R}$$

All-sky applications: assume representation error is observation error and is dominant

$$E(\mathrm{dd}^T) \approx \widetilde{\mathrm{R}}$$

Try to subtract background error properly:

- Desroziers (2005) statistics
- Ensemble HBHT estimates

One way to think about obs error covariance matrices

Departure – one channel (*i*)

$d_i = y_i - H_i(\mathrm{x})$

λ_j eigenvalue and e_j eigenvector *j*

Uncorrelated error

Correlated error represented by an eigendecomposition

Cost function

$$J^O(\mathrm{x}) = \frac{1}{2}\mathrm{d}^\mathrm{T}\widetilde{\mathbf{R}}\mathrm{d} = \frac{1}{2}\sum_{i=1}^{n}\left(\frac{d_i}{\sigma_i^o}\right)^2$$

$$J^O(\mathrm{x}) = \frac{1}{2}\mathrm{d}^\mathrm{T}\mathbf{E\Lambda E^T}\mathrm{d} = \frac{1}{2}\sum_{j=1}^{n}\left(\frac{\mathrm{e}_j^\mathrm{T}\mathrm{d}}{\lambda_j^{0.5}}\right)^2$$

"Eigendeparture *j*"

its observation error is its eigenvalue^0.5

Cost function gradient

$$J^{O\prime}(\mathrm{x}) = -\mathbf{H}^\mathrm{T}\widetilde{\mathbf{R}}^{-1}\mathrm{d} = \frac{1}{2}\sum_{i=1}^{n}\mathrm{h}_i\frac{d_i}{(\sigma_i^o)^2}$$

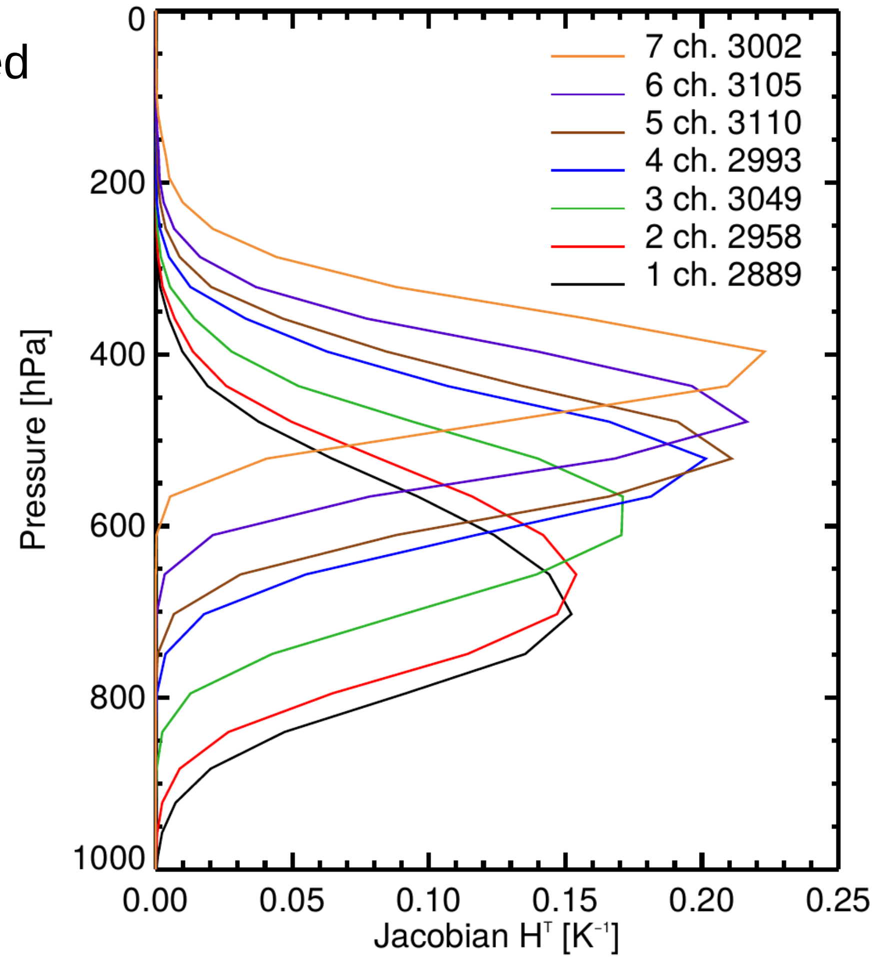
Jacobian – one obs

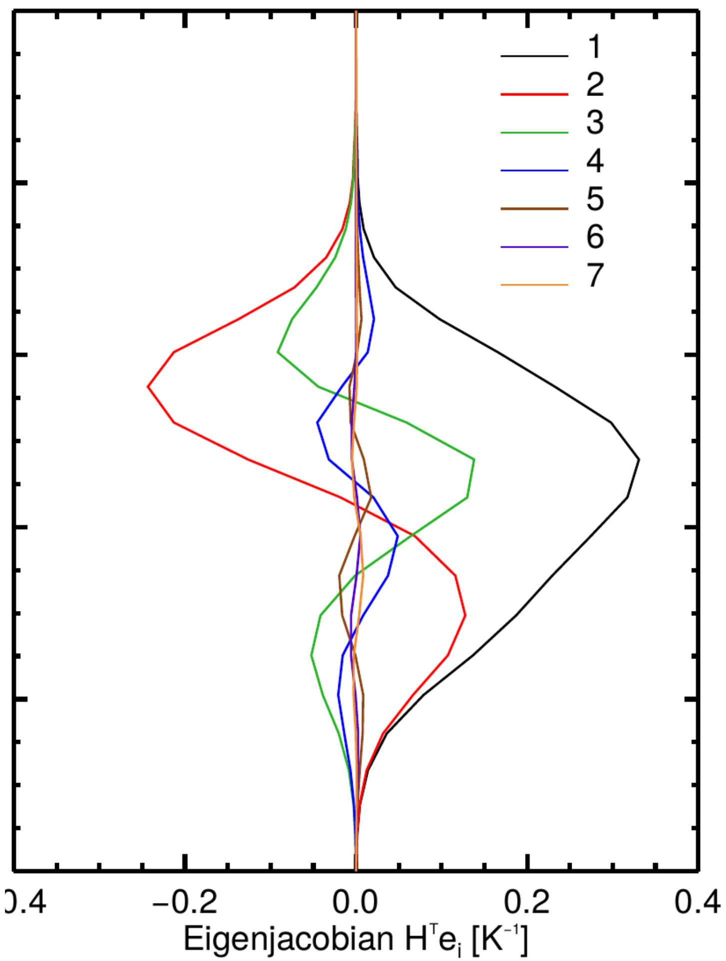
$$J^{O\prime}(\mathrm{x}) = -\mathbf{H}^\mathrm{T}\mathbf{E\Lambda^{-1}E^T}\mathrm{d} = \frac{1}{2}\sum_{i=1}^{n}\mathbf{H}^\mathrm{T}\mathrm{e}_j\frac{\mathrm{e}_j^\mathrm{T}\mathrm{d}}{\lambda_j}$$

"Eigenjacobian"

IASI temperature sensitivities (7 all-sky WV channels)

Jacobians (uncorrelated obs. error)





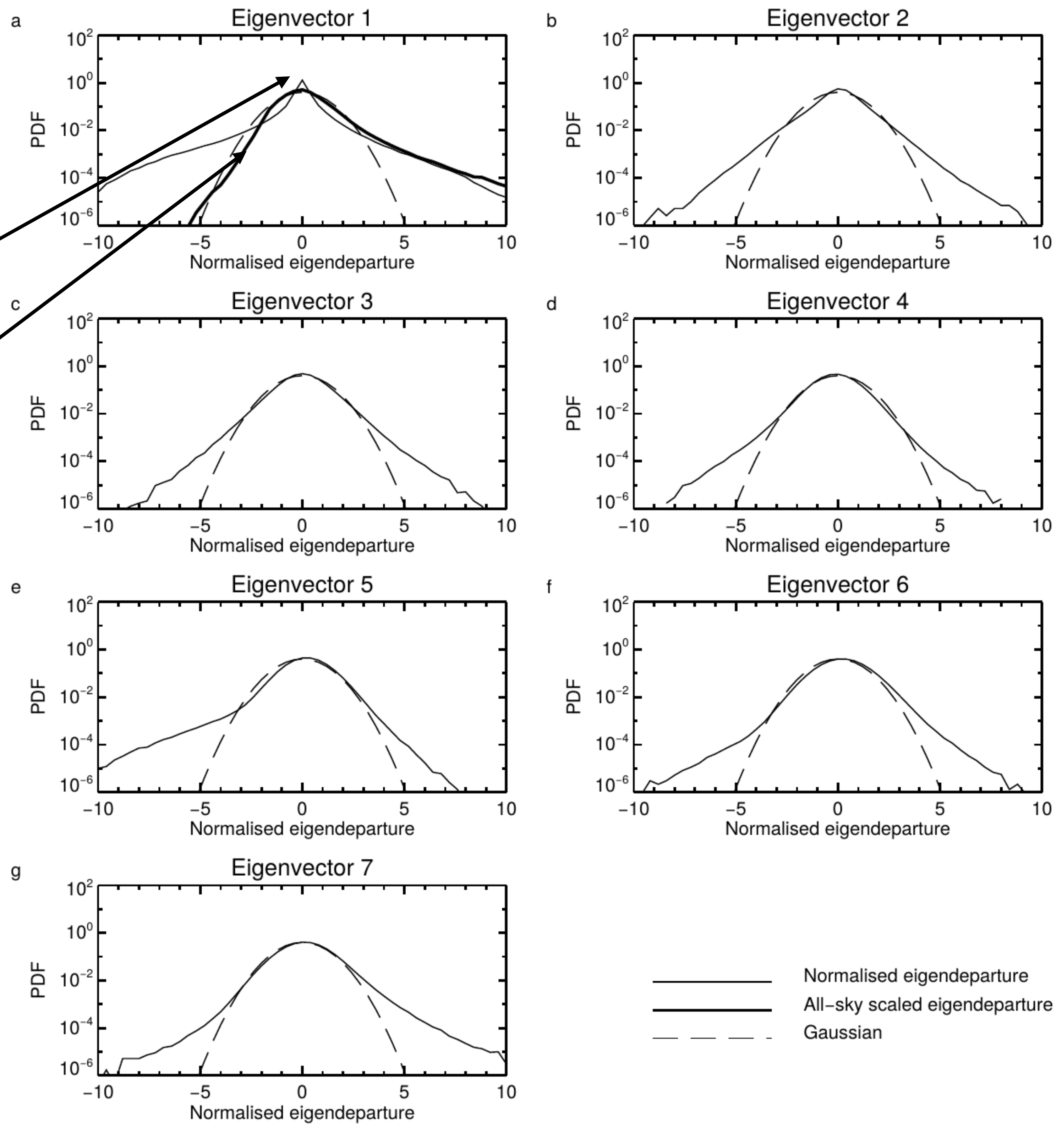
Eigenjacobians (correlated obs. error)

Apply an all-sky error scaling (symmetric, cloud dependent) to the leading eigenvalue/vector

With global constant leading eigenvalue

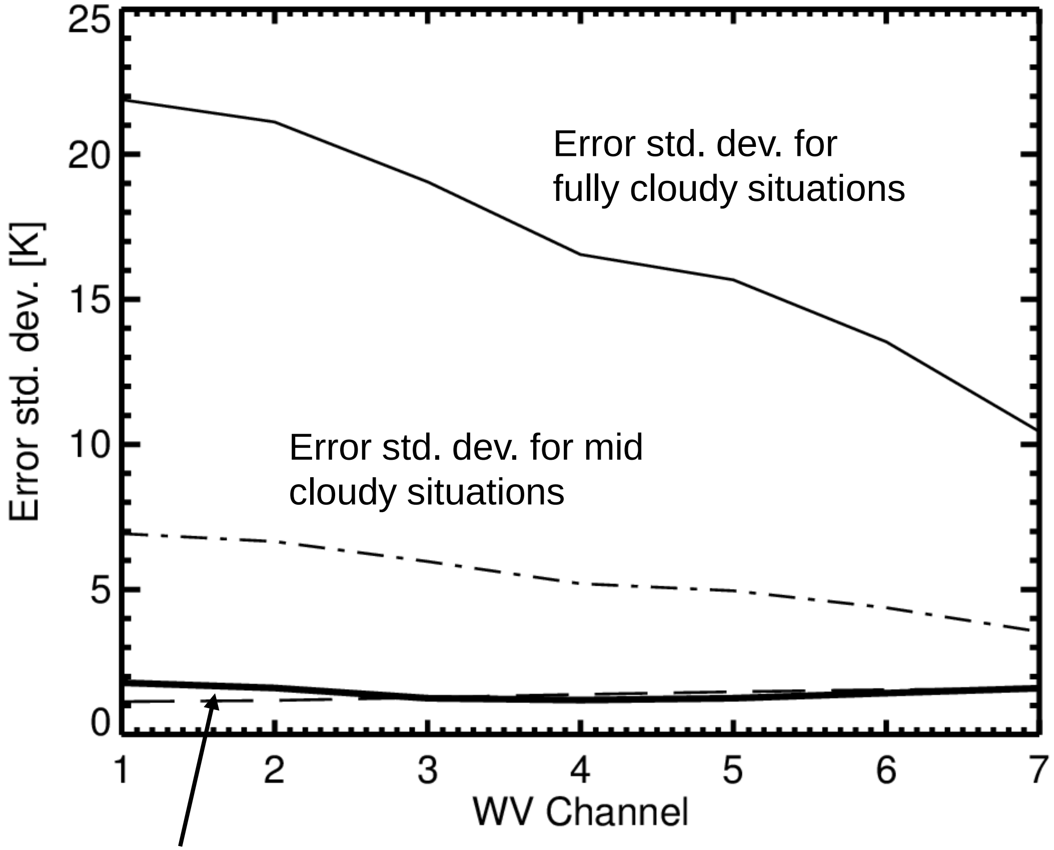
When scaled by all-sky error model

Near-Gaussianity of normalised background departures achieved within +/-3 range across all 7 eigenvectors

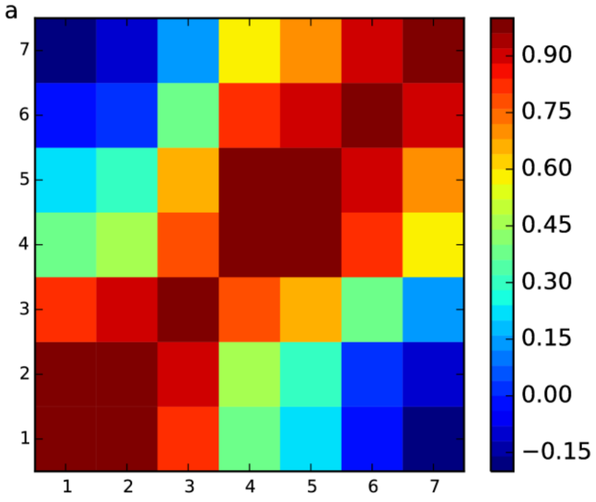


ECMWF

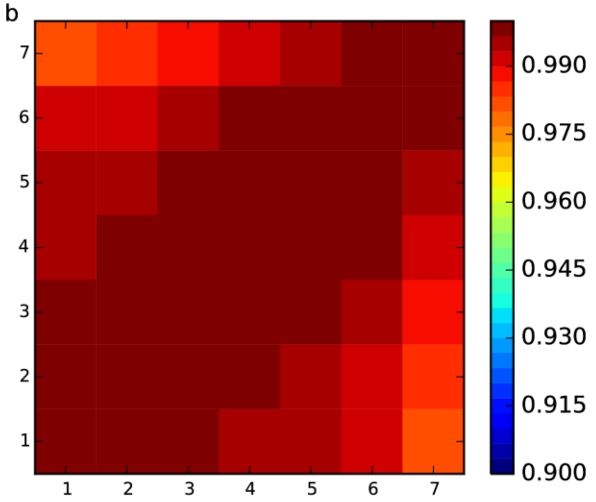
All-sky IR error model: one error covariance matrix with **eigenvalue scaling** as function of symmetric cloud amount -> adaptive covariance matrix



Similar error std. dev. in clear-sky situations from new model and existing clear-sky error model

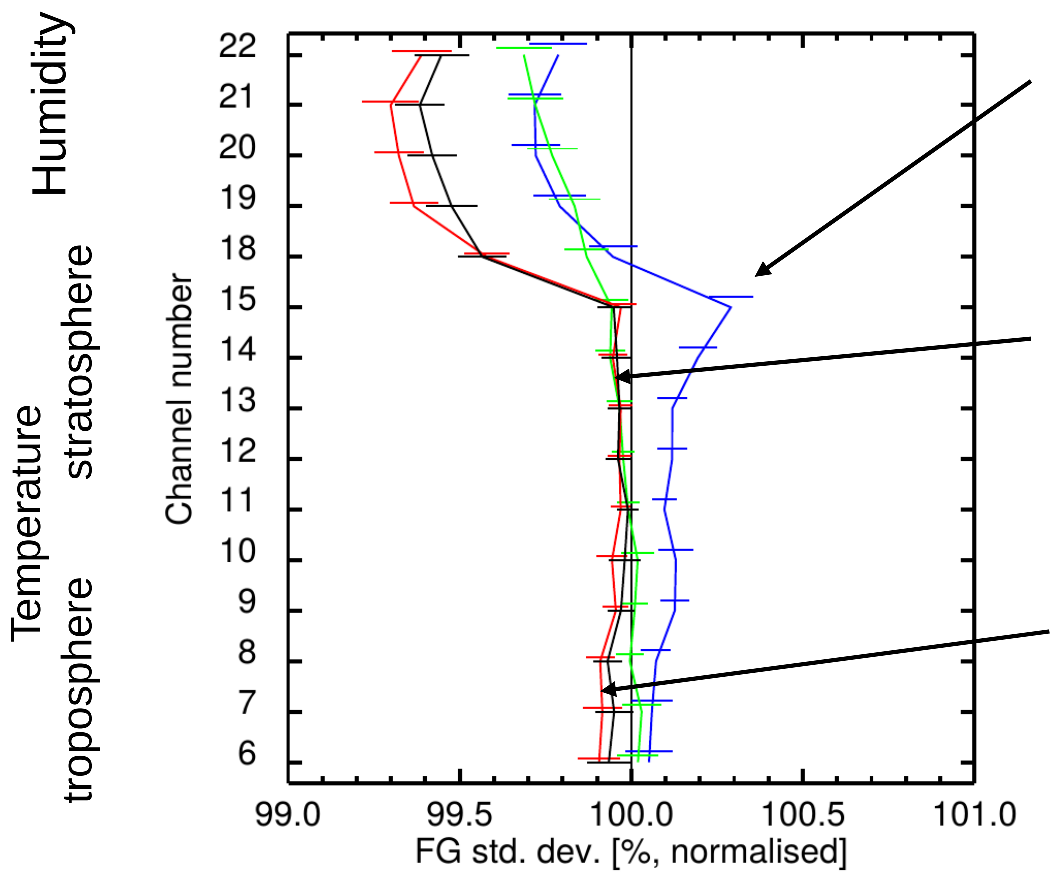


Correlation matrix for clear-sky situations



Correlation matrix for fully cloudy situations

Analysis fit and T+12 forecast verification: fit to ATMS when assimilating 7 all-sky IR WV channels of IASI



Initial situation-dependent interchannel correlated all-sky error model degrades forecasts (particularly stratosphere)

A diagonal model does not degrade (neither does it improve much)

Eigenvalue floor situation-dependent all-sky error model improves forecasts

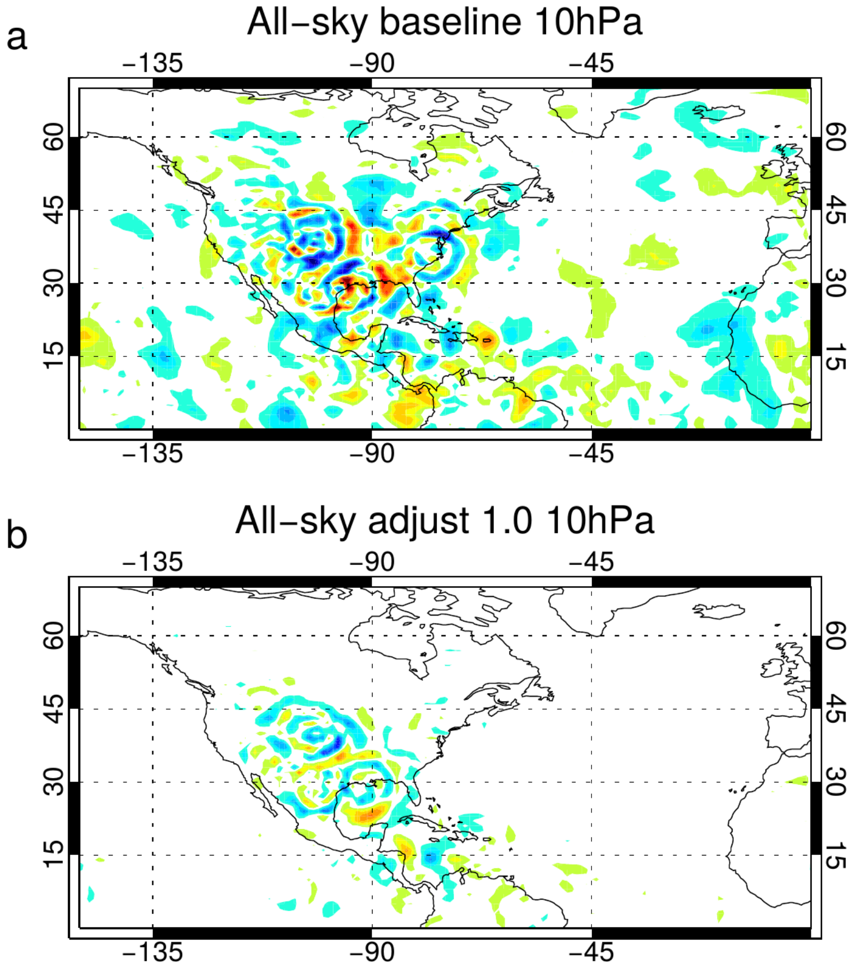
100% = Control: full system minus 7 IASI WV channels

Why eigenvalue floor is important

Stratospheric temperature increments generated by all-sky IR WV channels

Raw situation-dependent all-sky error model

Situation-dependent all-sky error model with 1.0 eigenvalue floor



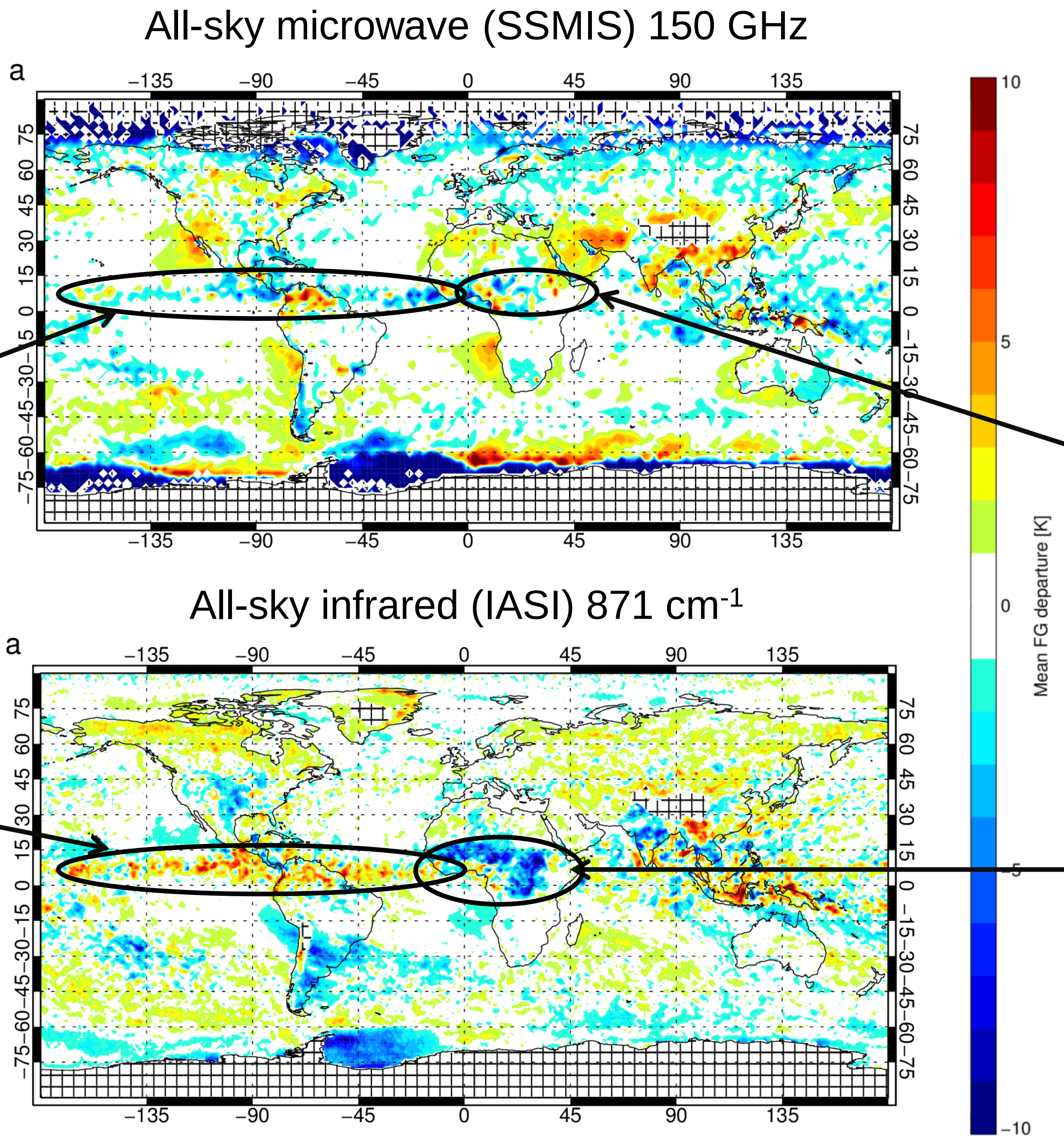
Using observation error covariance matrices is not just about conditioning:

- Eigendeparture biases are very different to Tb departure biases. Trailing eigenvalues amplify some weird and previously unseen bias patterns
- Trailing eigenjacobian (j=7) over very high clouds has 60% of its temperature sensitivity **in the stratosphere**
- Eigenjacobians of trailing eigenvectors map onto high-order vertical T oscillations: gravity waves?

All-sky assimilation and model errors

Microwave & IR (obs – sim) [K]

Mean, 1-20 June 2017

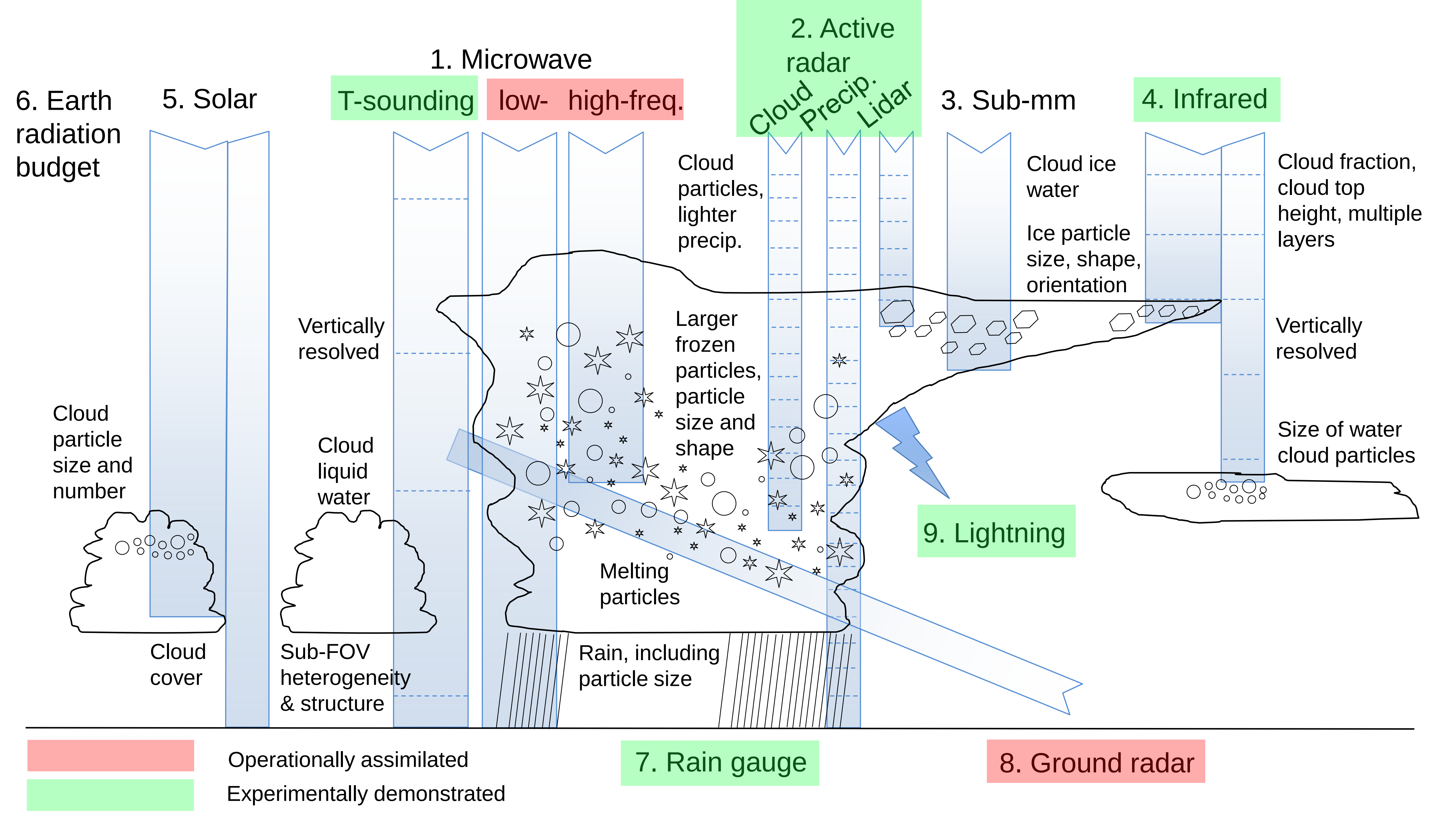


Insufficient “convection” in the maritime ITCZ?

Excessive “convection” in the maritime ITCZ?

Insufficient “convection” over land

- Consistent IR/MW signal
- No apparent MW bias because forward operator already incorporates kludge to reduce systematic error over land (Geer and Baordo 2014)



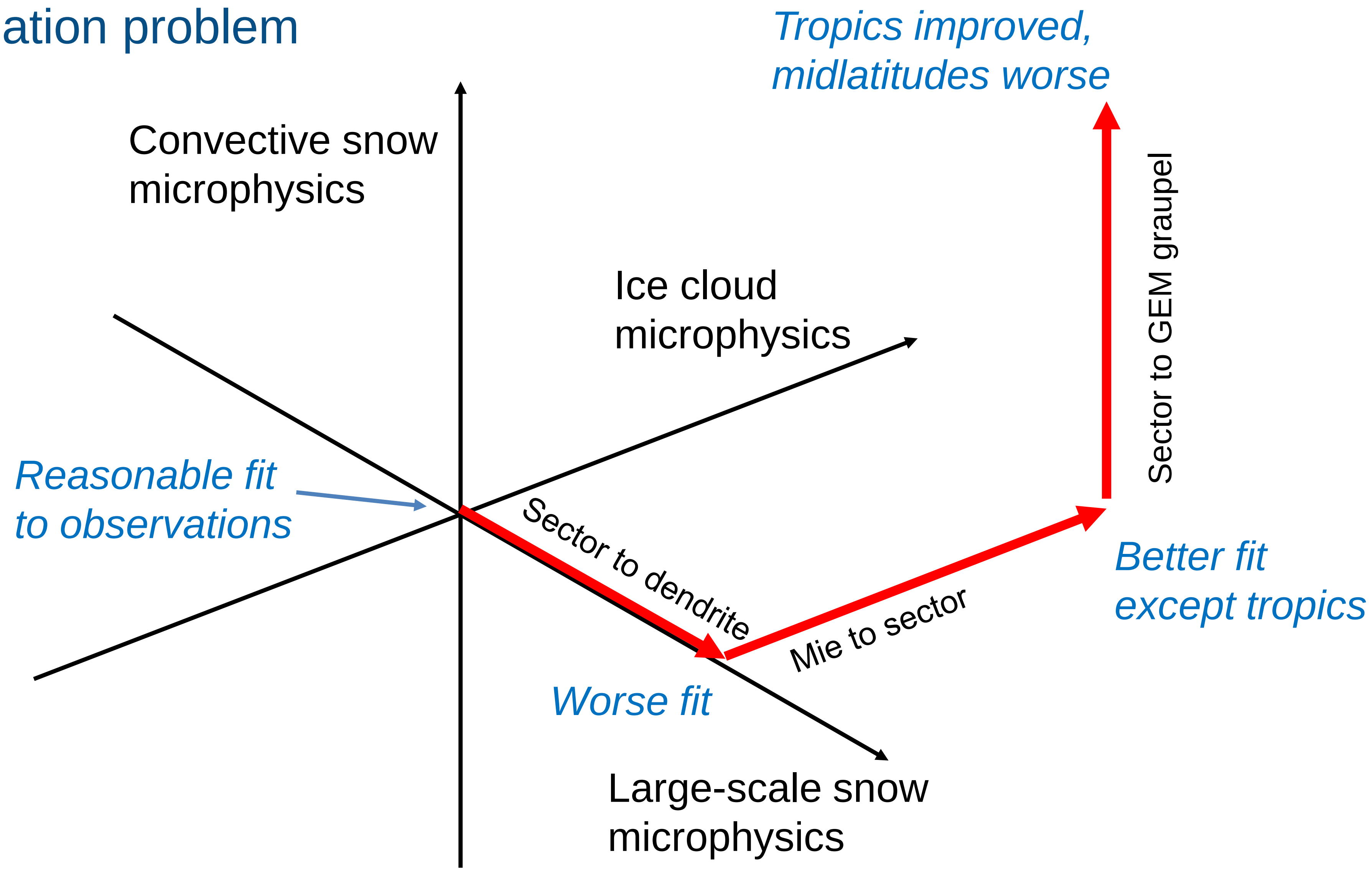
6. Earth radiation budget
5. Solar
1. Microwave
T-sounding
low- high-freq.
2. Active radar
Cloud
Precip.
Lidar
3. Sub-mm
4. Infrared
Cloud particles, lighter precip.
Cloud ice water
Ice particle size, shape, orientation
Cloud fraction, cloud top height, multiple layers
Vertically resolved
Larger frozen particles, particle size and shape
Vertically resolved
Cloud particle size and number
Cloud liquid water
Size of water cloud particles
9. Lightning
Melting particles
Cloud cover
Sub-FOV heterogeneity & structure
Rain, including particle size
Operationally assimilated
Experimentally demonstrated
7. Rain gauge
8. Ground radar

Some assumptions across forecast model and observation operators at ECMWF

Geer et al. (2017, ECMWF Tech. Memo. 815)

	Forecast model			Observation operators		
Assumption	**Large-scale condensation**	**Convection**	**Radiation**	**Microwave**	**Infrared**	**Radar/lidar**
Precipitation overlap	Max-random (with cloud)	Max	Exponential-exponential	Implied max	Implied max	Max-random
Snow particle	Sphere	N/A	Hexagonal column	Liu (2008) sector snowflake	N/A	Aggregate
Snow PSD	Cox (1988)	N/A	"Based on aircraft obs"	Field et al. (2007) tropical	N/A	Field et al. (2007)

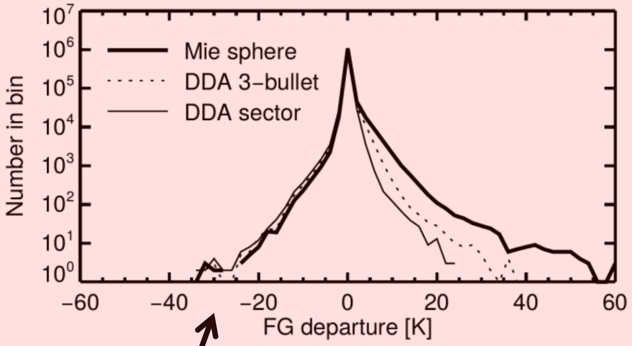
Multidimensional optimisation problem



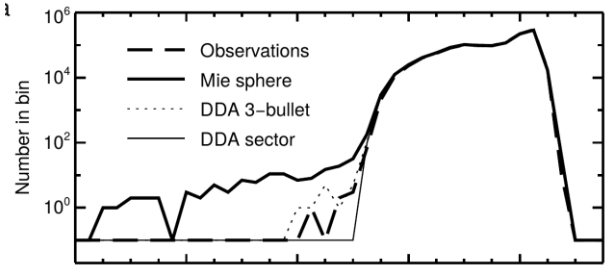
Metrics of fit for all-sky radiances

Metrics computed across all channels
Geer and Baordo (2014)

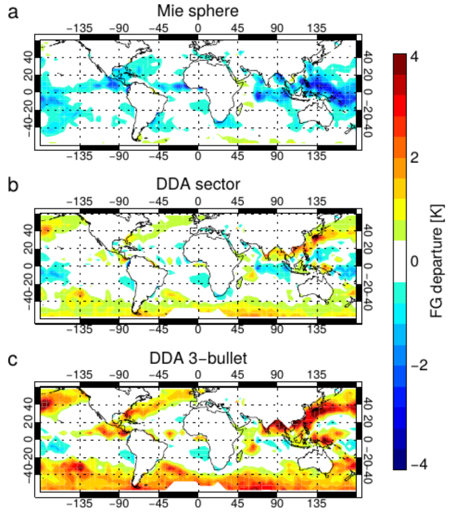
Skewness

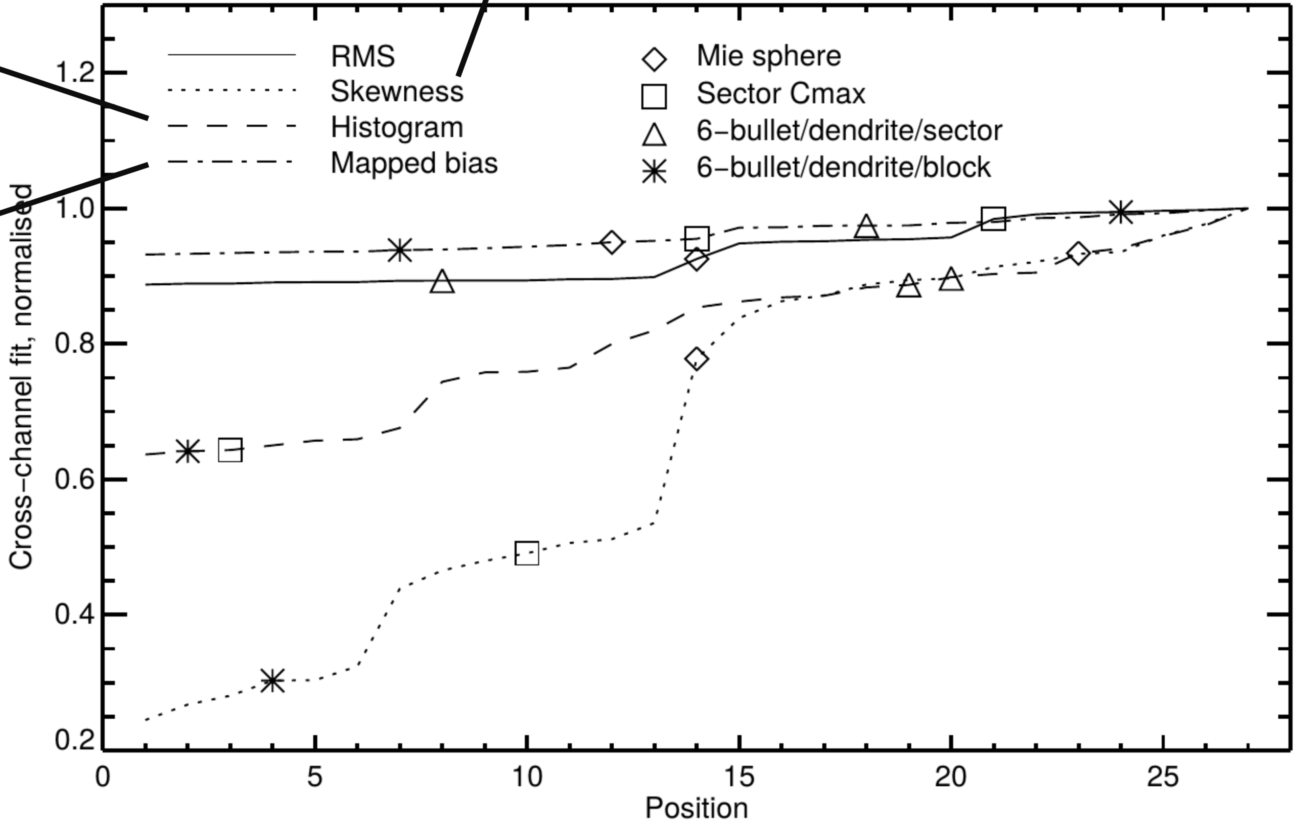


Histogram fit



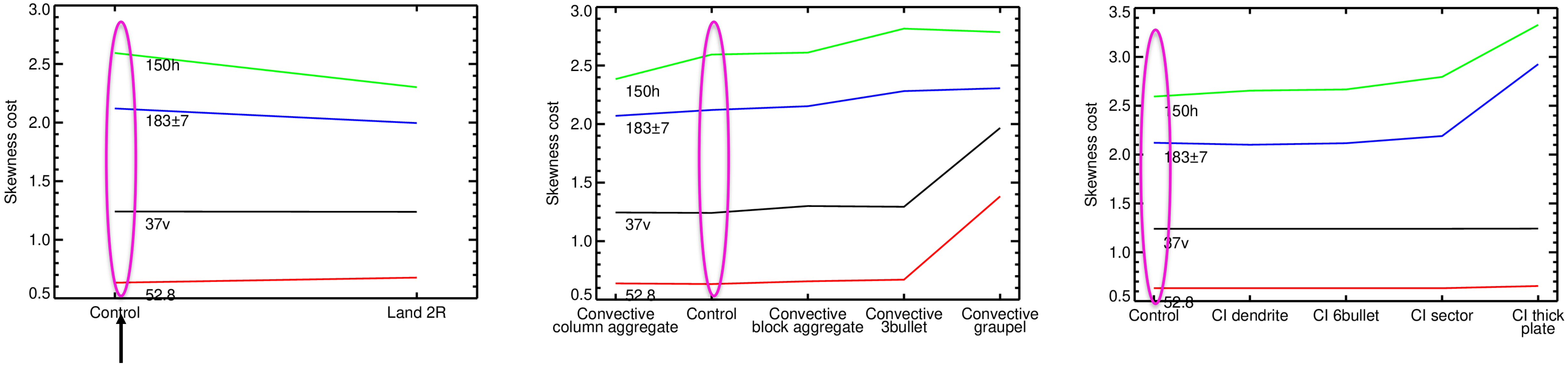
Mapped bias





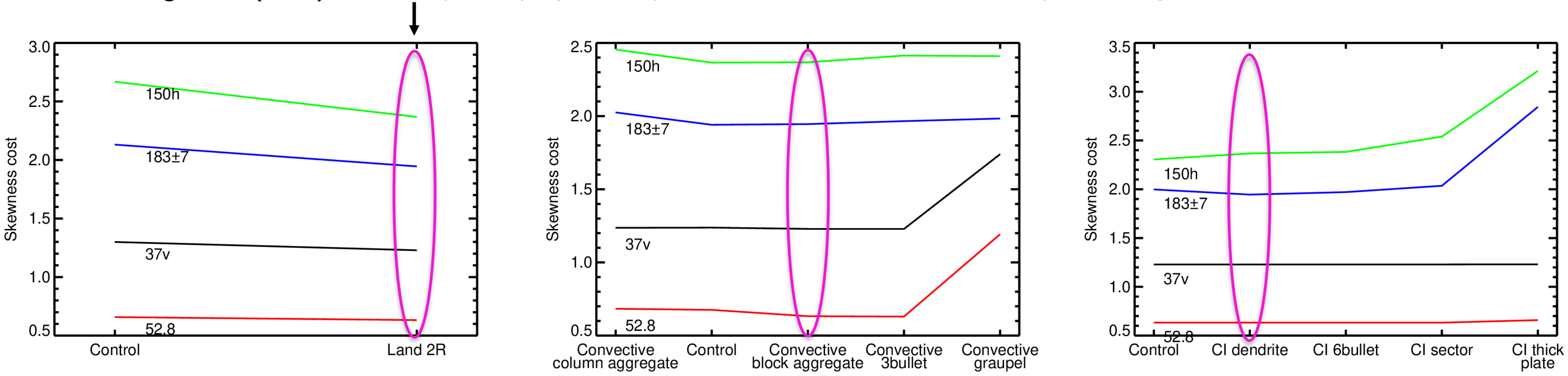
ECMWF

Cloud fraction | Convective snow particle shape | Cloud ice particle shape



First guess (now)

“Analysis” (objectively determined macro/microphysics upgrade)



Summary

- All-sky assimilation for
  - Improved initial conditions
  - Developing forecast models
- Key challenges in all-sky assimilation
  - Error of representation
  - Correlated observation errors
  - Cloud and precipitation-related biases
    - Need to improve forecast model and observation operator microphysical assumptions
  - Extension to more sensors
    - Temperature sounding microwave, Infrared, visible
    - Active sensors
- Key challenges generally
  - Land and sea-ice surfaces
  - Aerosol
  - Spatially / temporally correlated representation error