Seamless cloudspotting:

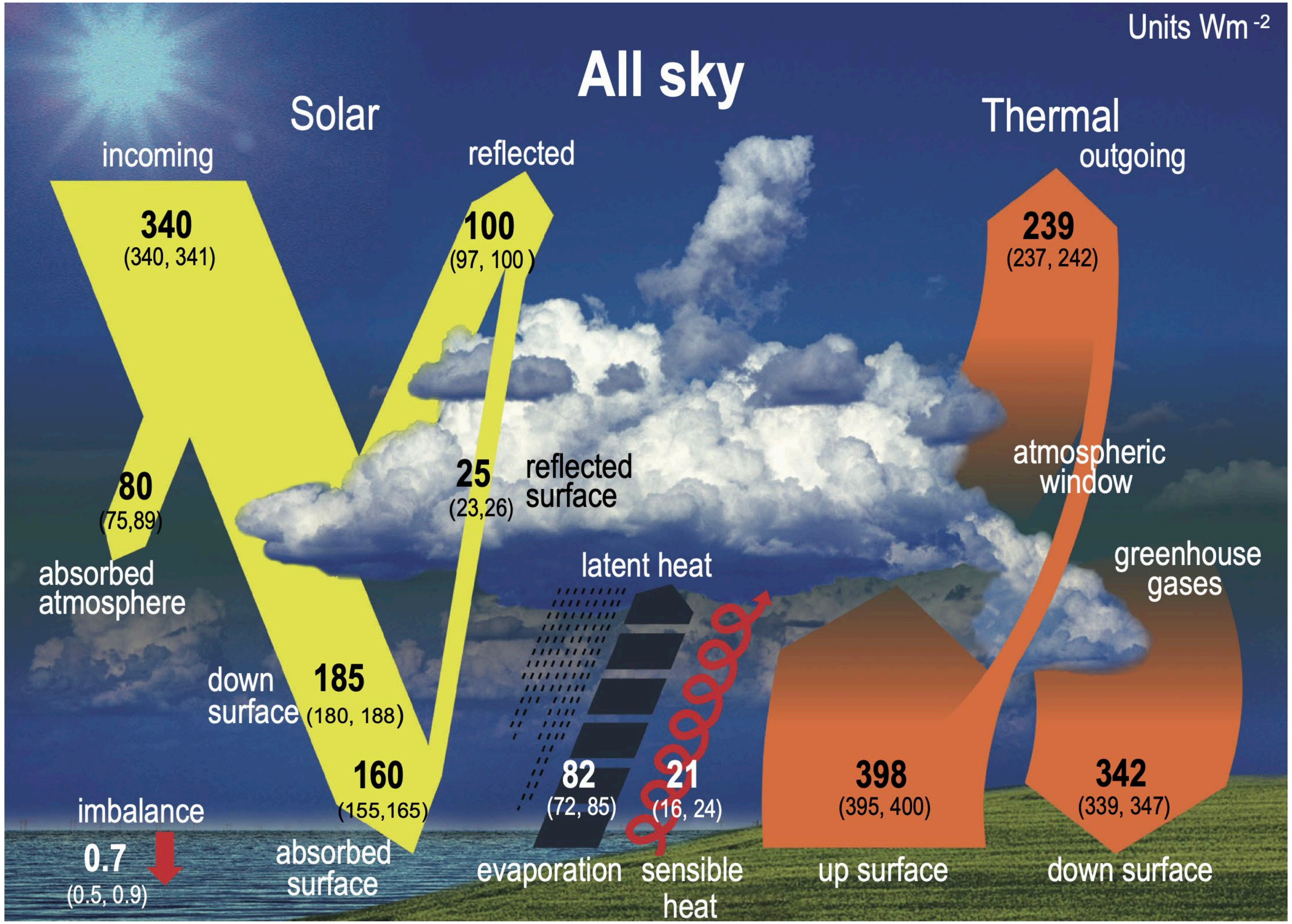
Constraining clouds and microphysical processes via data assimilation

Mark Fielding

Thanks: Marta Janisková, Richard Forbes and colleagues

Clouds are a crucial component of Earth's radiation budget

Shorter timescales

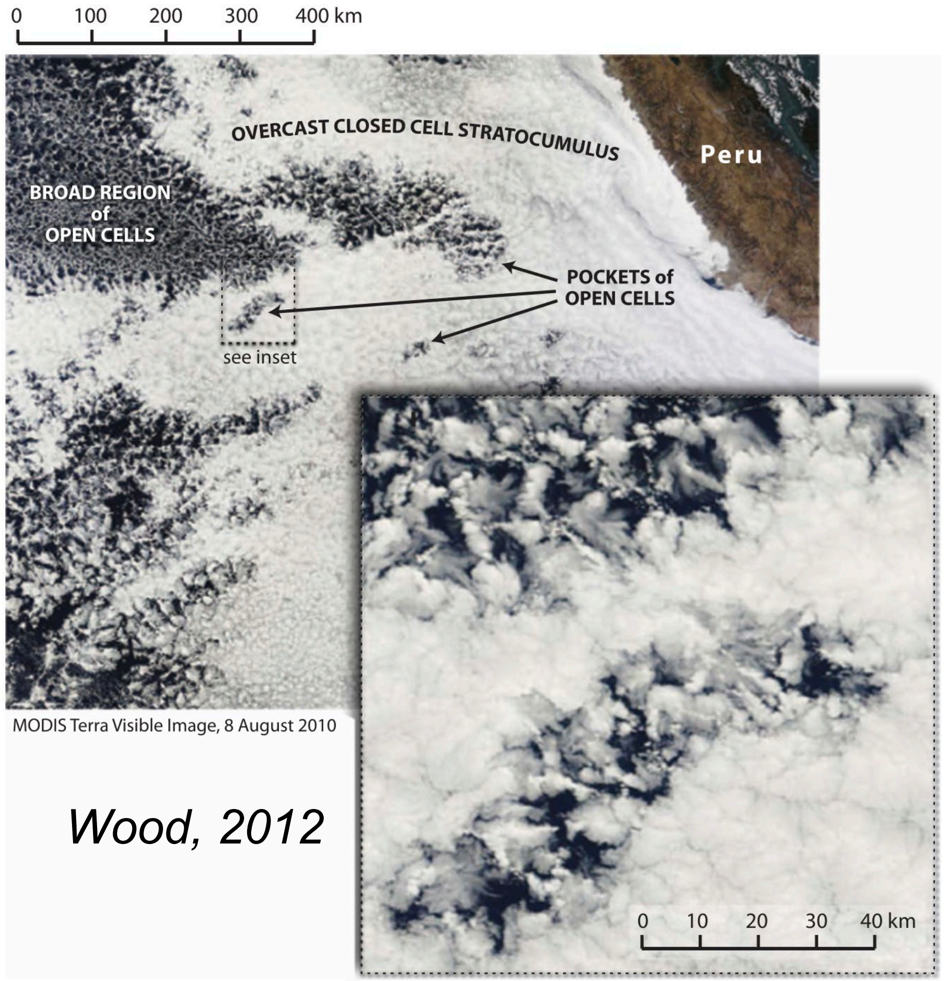


Longer timescales

IPCC AR6 CH7

Clouds are challenging to constrain due to their spatial variability

In the horizontal…



Wood, 2012

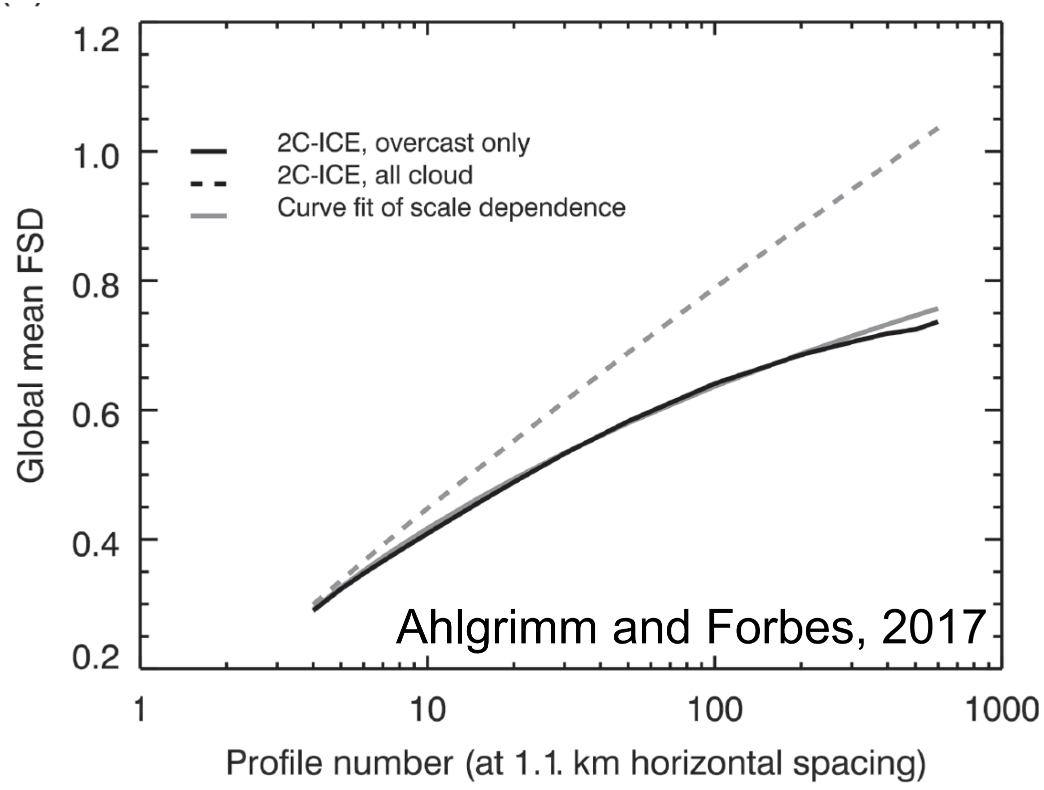
…and vertical

Sub-grid assumptions in cloud parameterizations (and simulations of cloud observations) should be scale-dependent

Sub-grid *condensate* variability

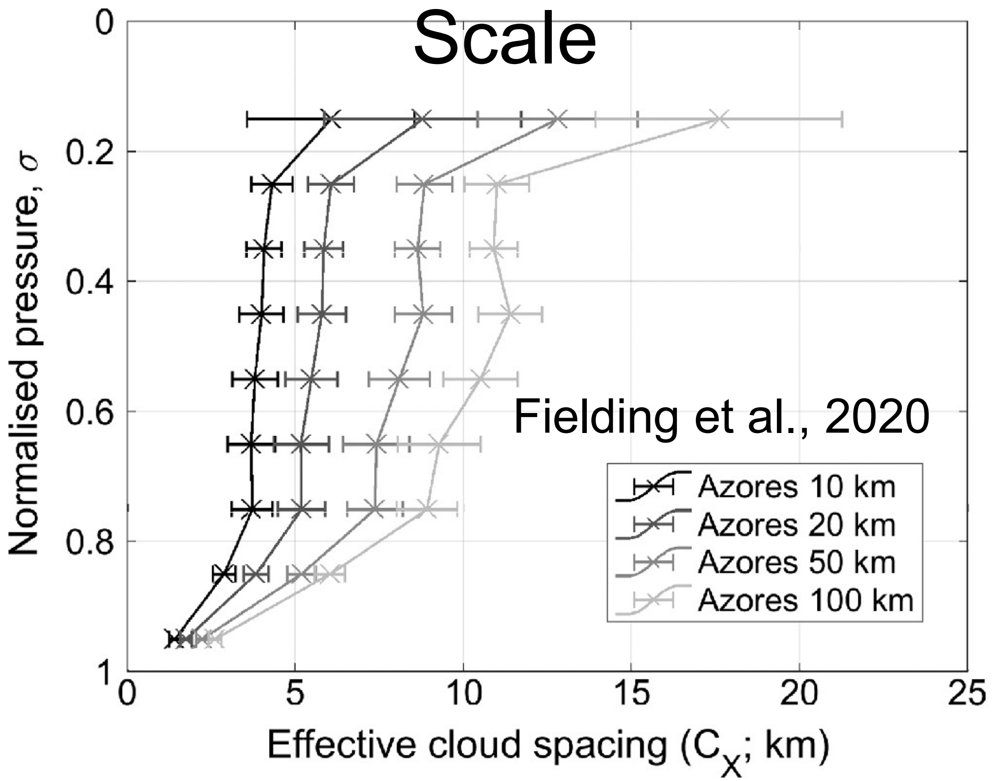
Sub-grid *structure* variability

Variability



Scale

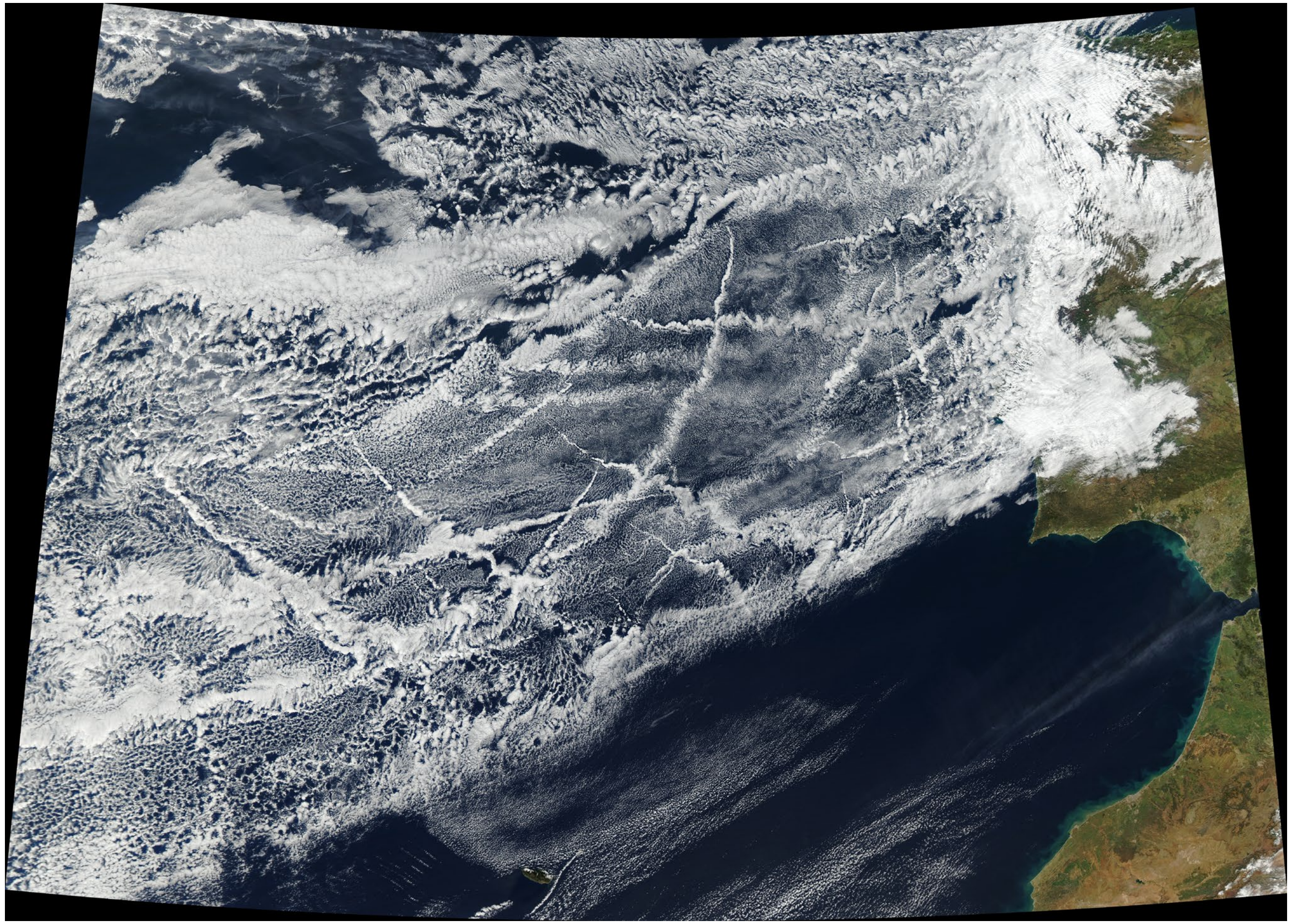
Height



Cloud sizes for given cloud fraction

Clouds are challenging to constrain due to the sensitivity of their microphysics

Courtesy: Barbara Fielding



Courtesy: NASA MODIS

Small perturbations can have large impact in cloud properties

How can we improve representation of clouds in NWP models?

Better fit to observations

Improved analysis

- Via data assimilation
  - greatest impact on clouds/precipitation in first 24-hours

Improved forecast model

- **Comparison studies between models and observations/retrievals**
  - Improved physical understanding
  - Characterisation of model parameters
- Increased complexity of model and/or parameterizations
- Tuning of uncertain model parameters to improve forecast skill

Improved initial conditions

Data assimilation of clouds at ECMWF in a nutshell

- Adjust control vector, **x**, to minimize 4D-Var cost function, *J*(**x**):

Penalty for departure from background

$$J(x) = \frac{1}{2}\left(x - x^{\mathrm{b}}\right)^{T} \widetilde{\mathbf{B}}^{-1}\left(x - x^{\mathrm{b}}\right) + \frac{1}{2} d^{T} \widetilde{\mathbf{R}}^{-1} d$$

Cost function

Penalty for departure from observations

$$d = y - b - H(x)$$

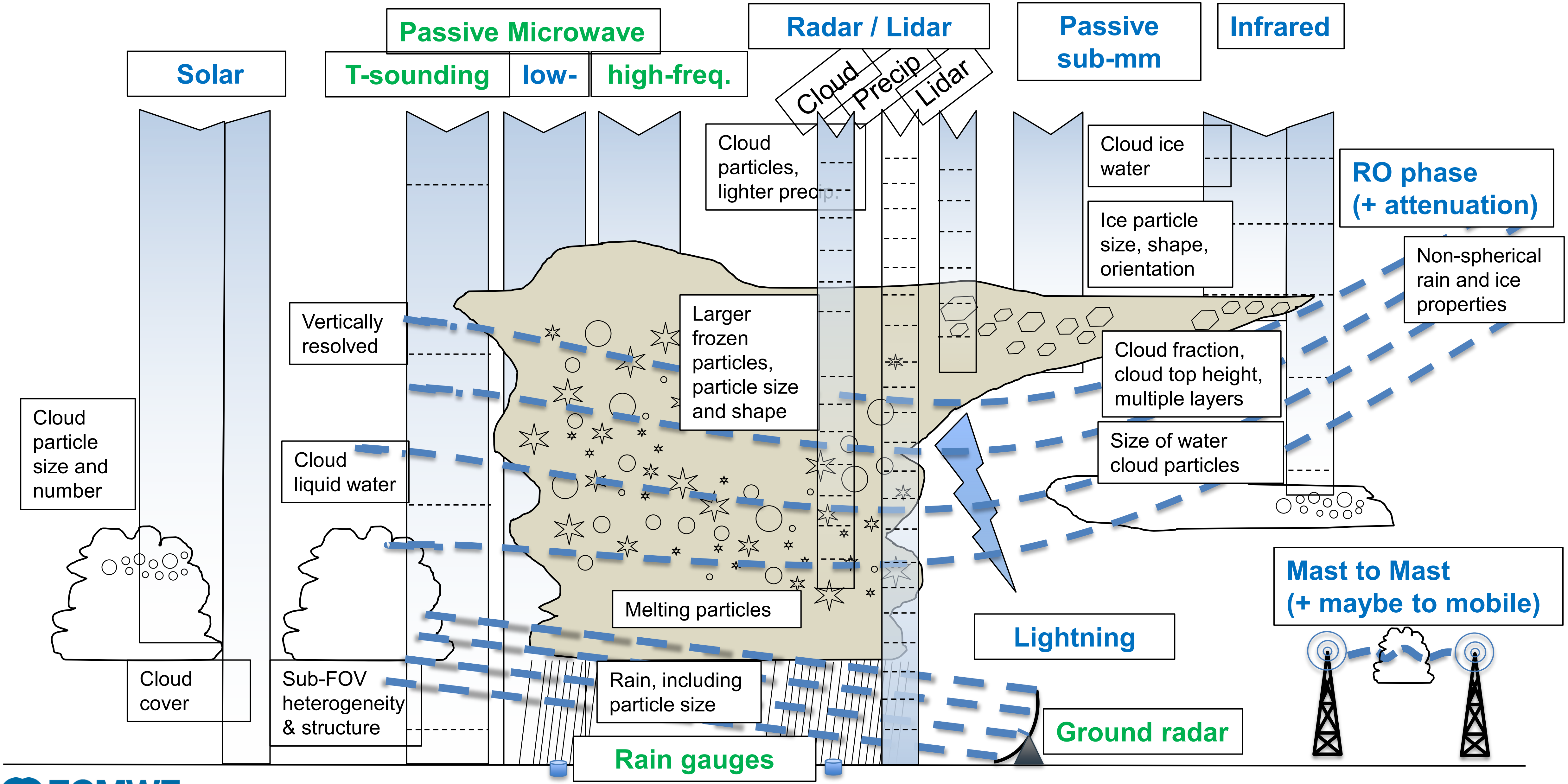
Observations

Model equivalent

Bias correction

- Clouds are inferred from temperature and humidity via diagnostic cloud scheme; currently no cloud variables in control vector.

Cloud and precipitation sensitive satellite observations: now and near future

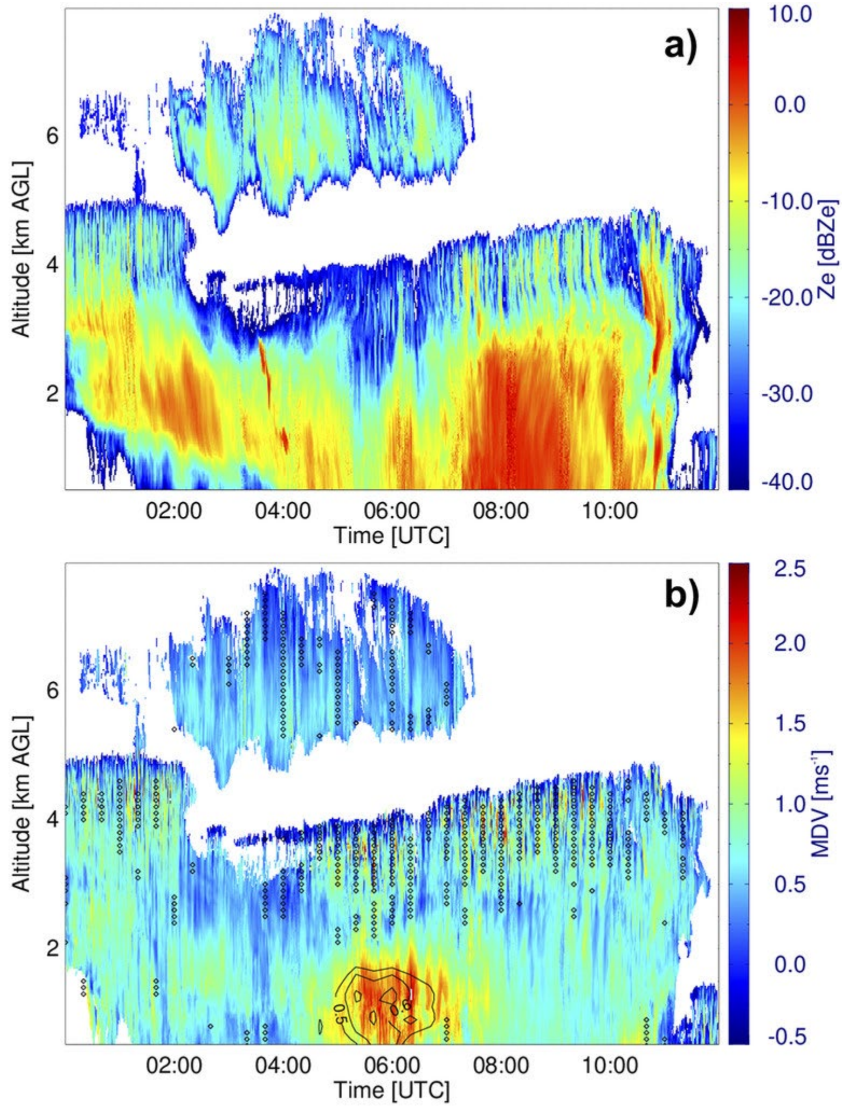


Slide adapted from Alan Geer

Cloud radars are the workhorses for cloud research

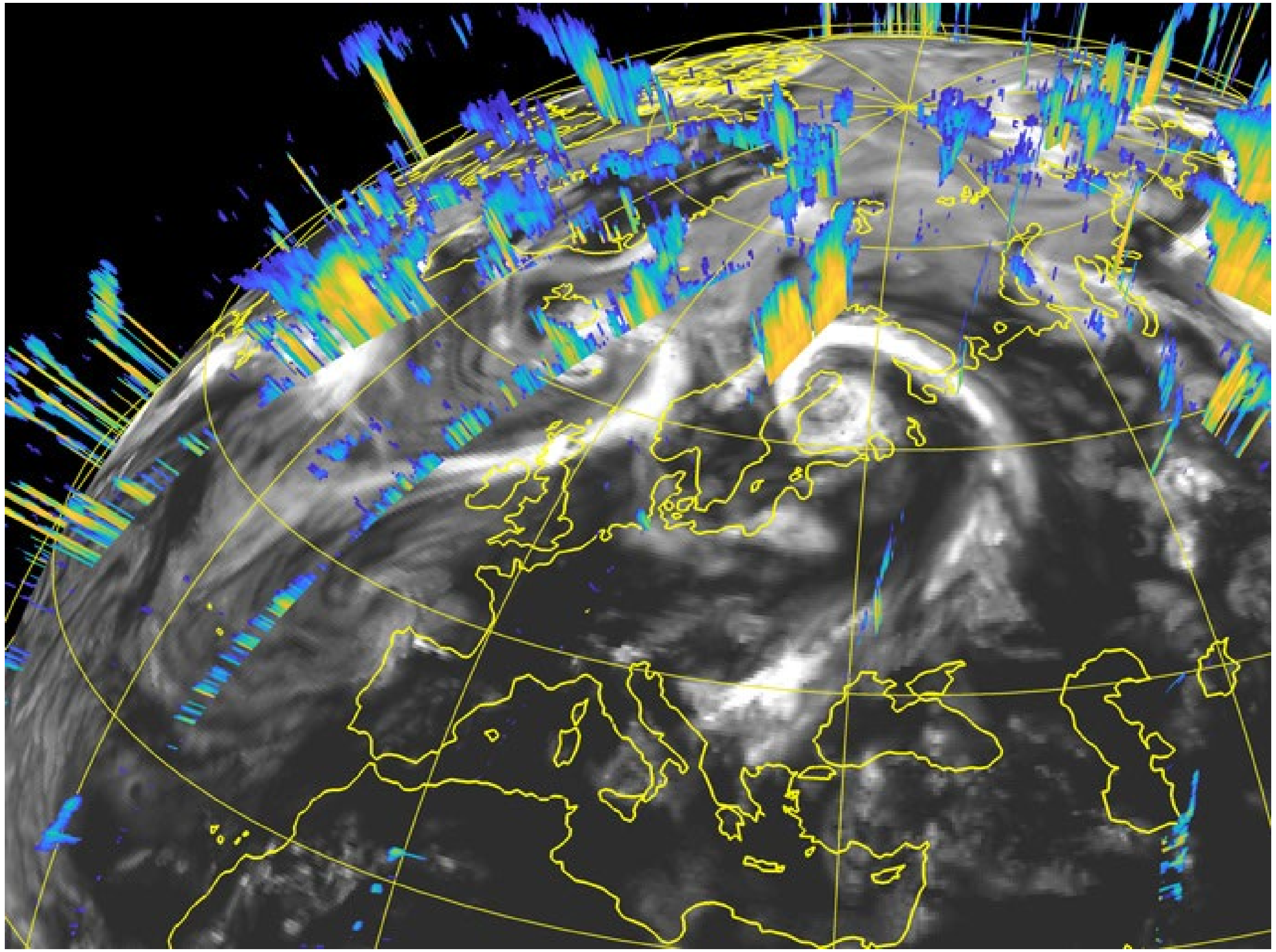
Ground-based radars have provided unrivalled cloud measurements for past three decades

Courtesty: University of Köln

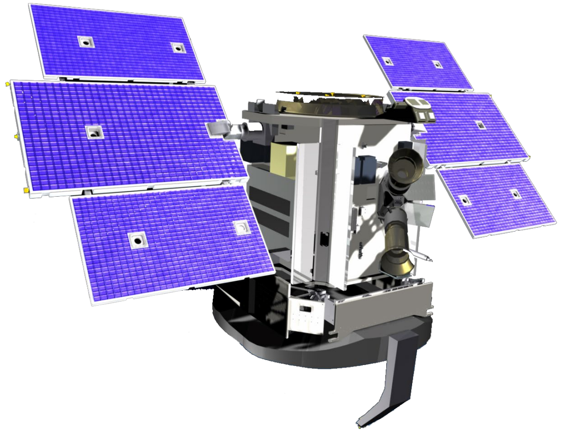


Kneifel and Moisseev, 2020

Space-borne cloud radars provide much greater spatial context

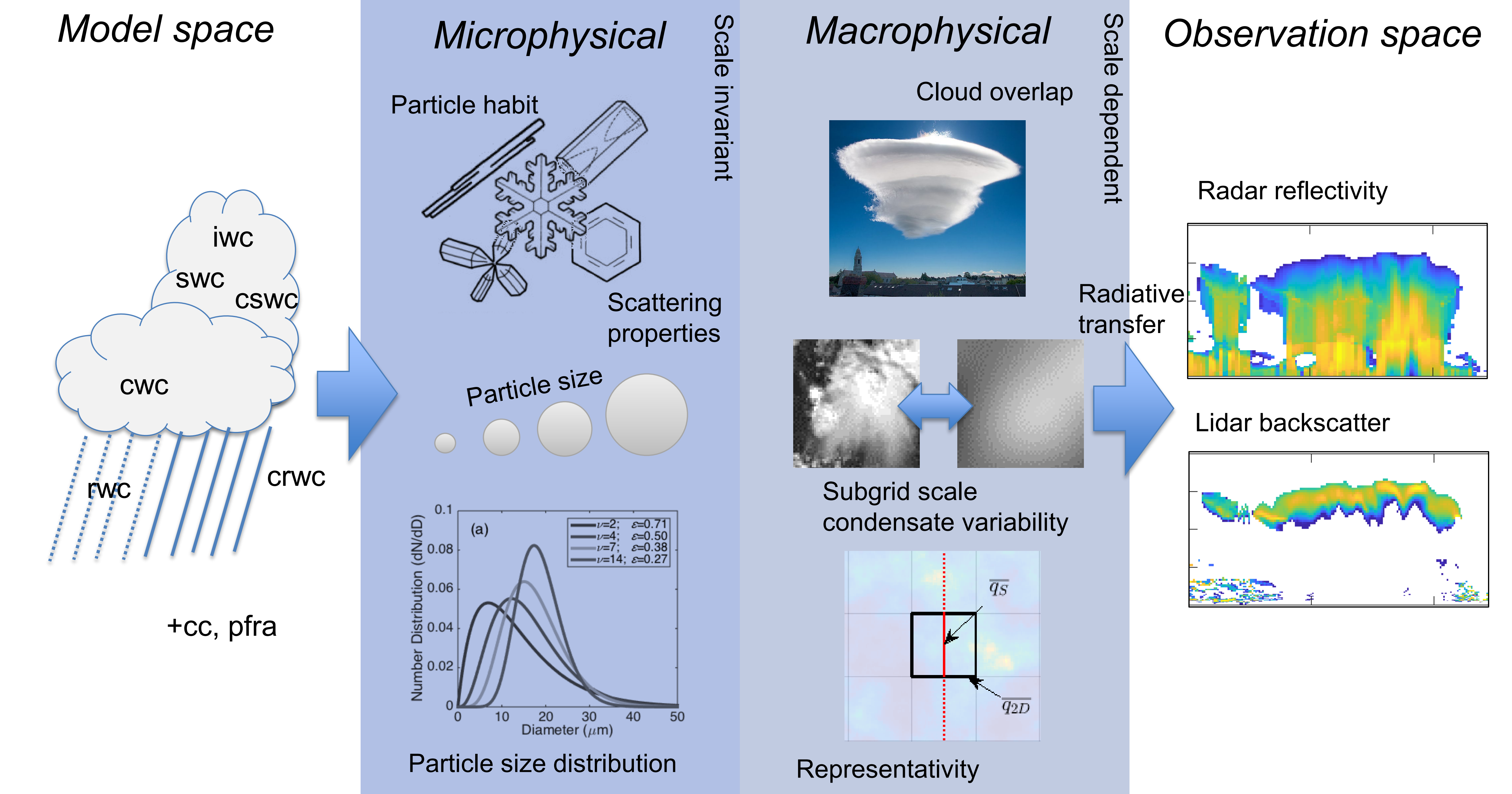


CloudSat
2006 -

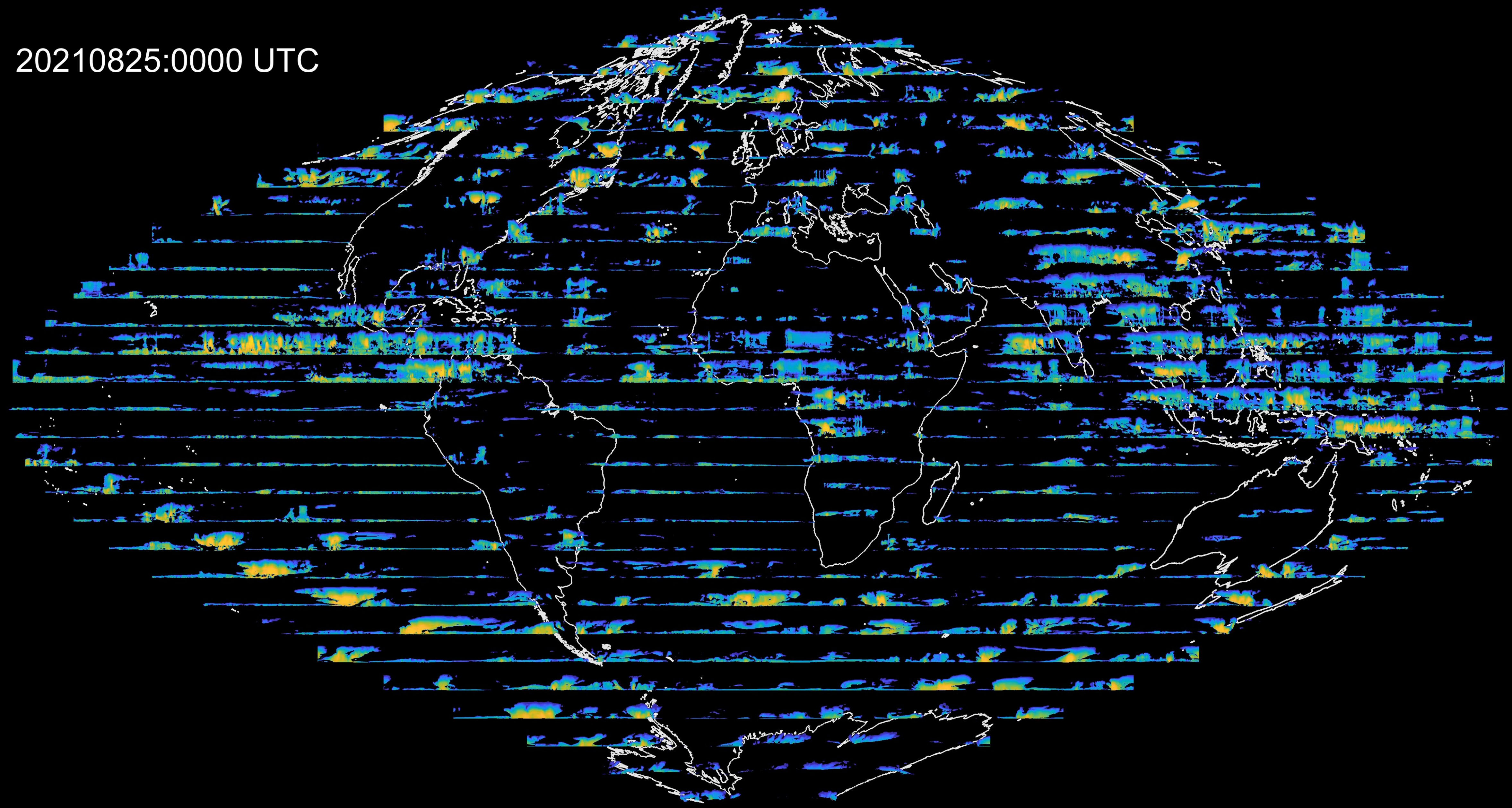


EarthCARE
c.2024 -

First space-borne cloud radar to provide NRT data



Aim for: accuracy, consistency, efficiency and uncertainty-aware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A hierarchy of approaches for using data assimilation to improve NWP forecasts

- Improved initialization through assimilation of observations

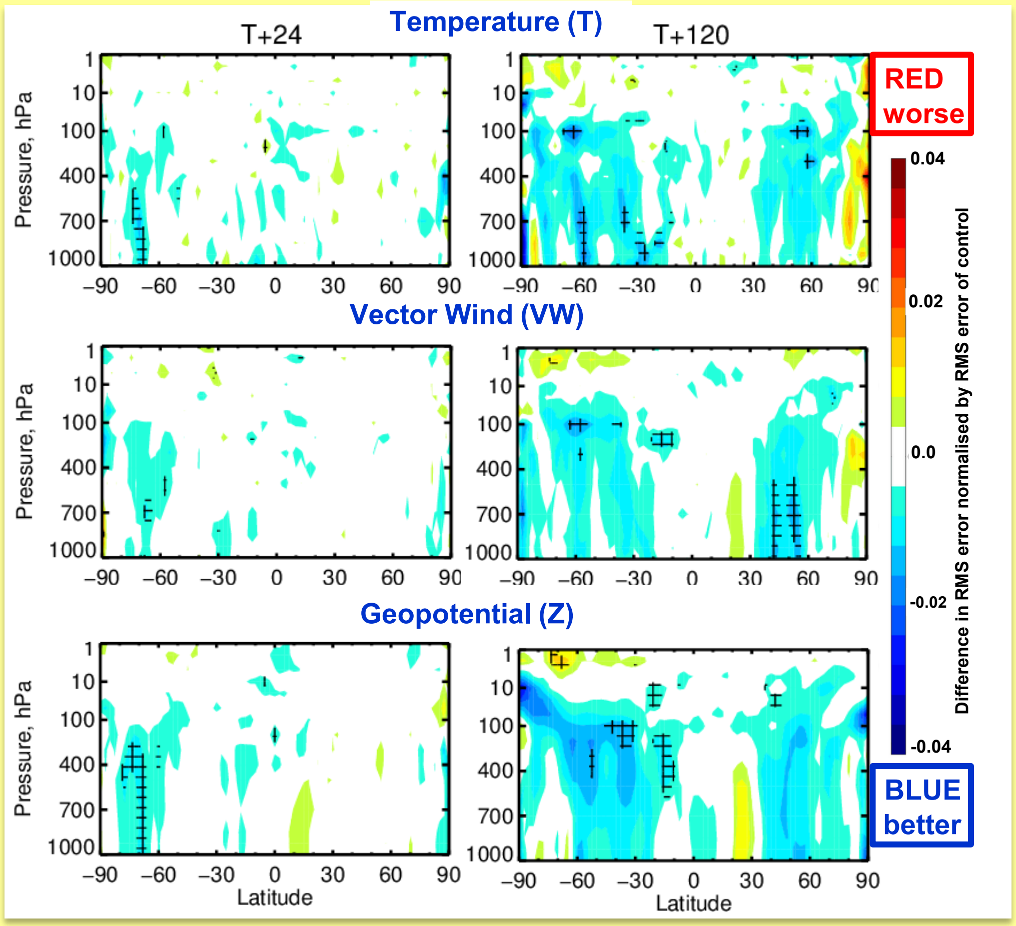
- Model evaluation and improvement via first guess departures

- Parameter estimation within observation operators

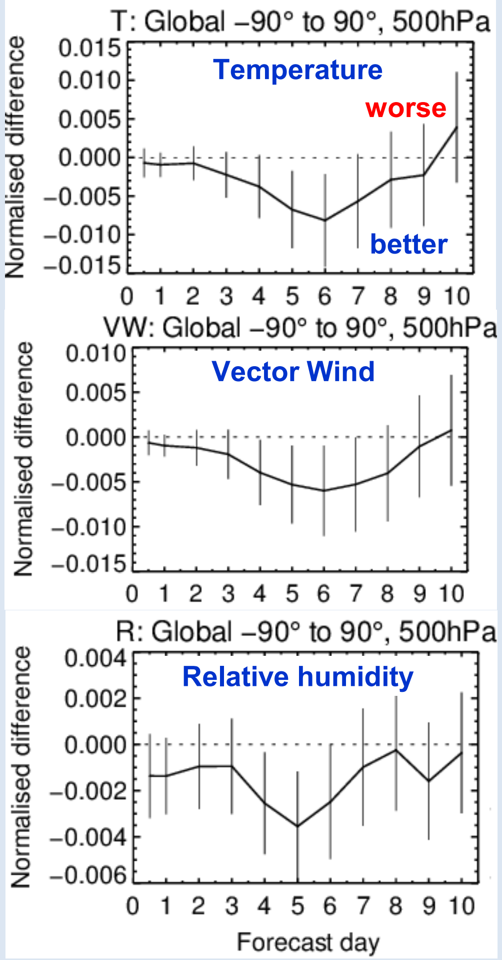
- Combined state and model parameter estimation

What impact can we expect from assimilating EarthCARE radar and lidar?

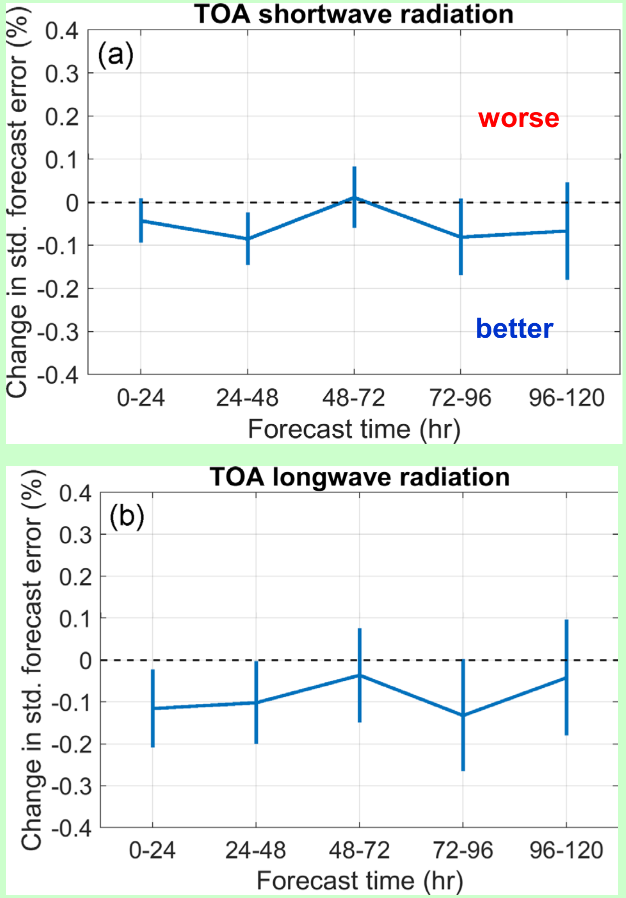
- 4D-Var experiments using CloudSat & CALIPSO show improvements to medium range foreca



11-month combined period: 1 August 2007 – 31 August 2008



Forecast error reduction grows with forecast lead time



Improvements to forecast of TOA radiation based on verification against independent CERES observations

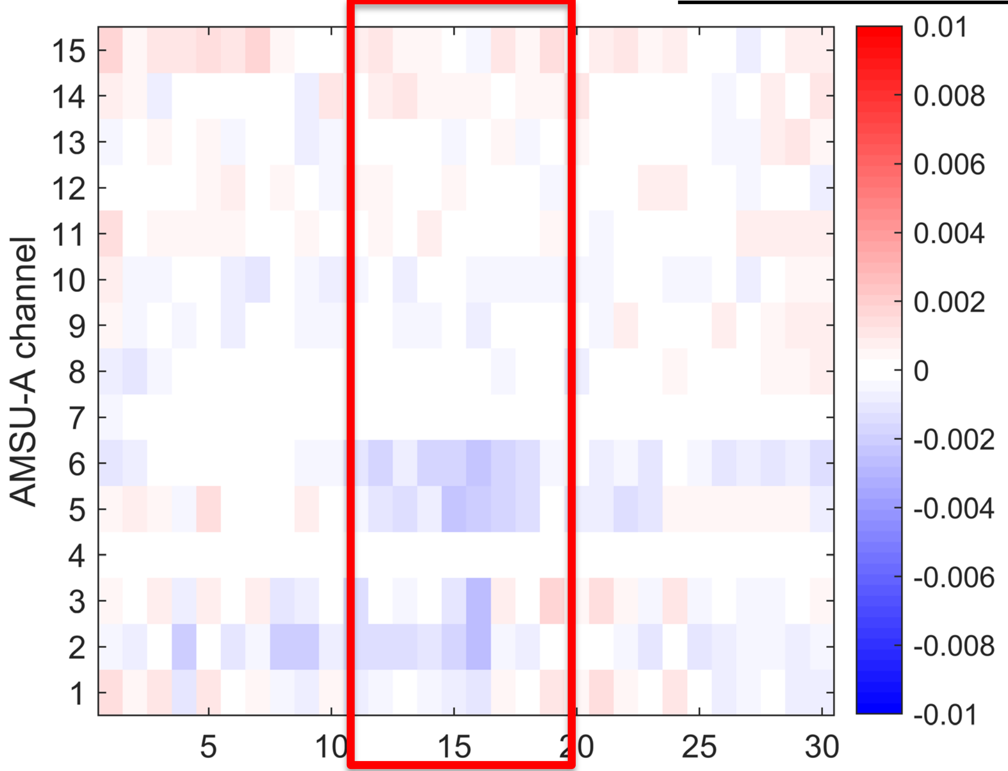
…and also improves fit to *microwave* radiances!

- AMSU-A sensor aboard Aqua provides opportunity to assess impact of radar and lidar on co-located microwave radiances
- Microwave radiances simulated by RTTOV within IFS all-sky framework

Channel	Frequency (GHz)	Peak sensitivity (hP
1	23.8	Surface
2	31.4	Surface
3	50.3	Surface
4	52.8	920–810
5	53.596 ± 0.115	650–530
6	54.4	390–320
7	54.94	260–200
8	55.5	170–135
9	$57.29 = f_0$	85–70
10	$f_0 \pm 0.217$	50–40
11	$f_0 \pm 0.3222 \pm 0.048$	25–20
12	$f_0 \pm 0.3222 \pm 0.022$	10
13	$f_0 \pm 0.3222 \pm 0.010$	5
14	$f_0 \pm 0.3222 \pm 0.0045$	3
15	89.0	Surface

Duncan et al., 2022

<u>Change in analysis fit to AMSU-A channels</u>



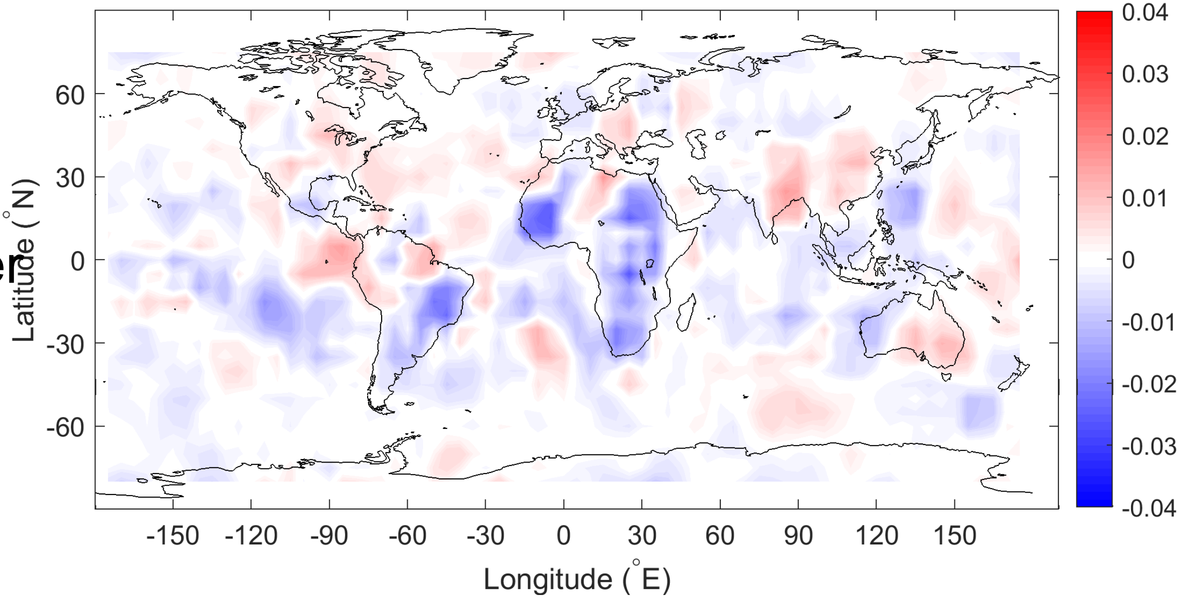
Worse fit

Better fit

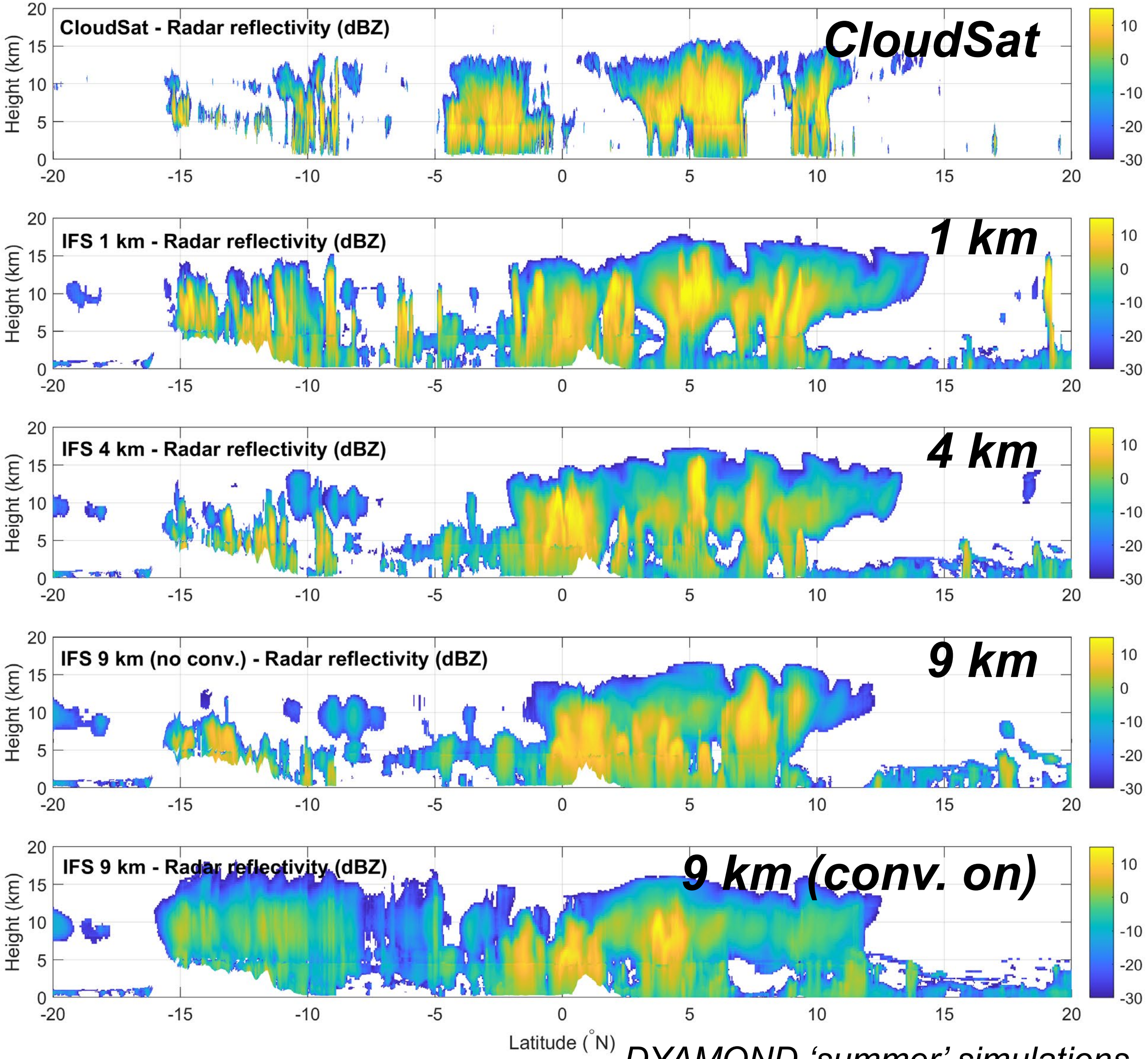
~2000 km

AMSU-A swath

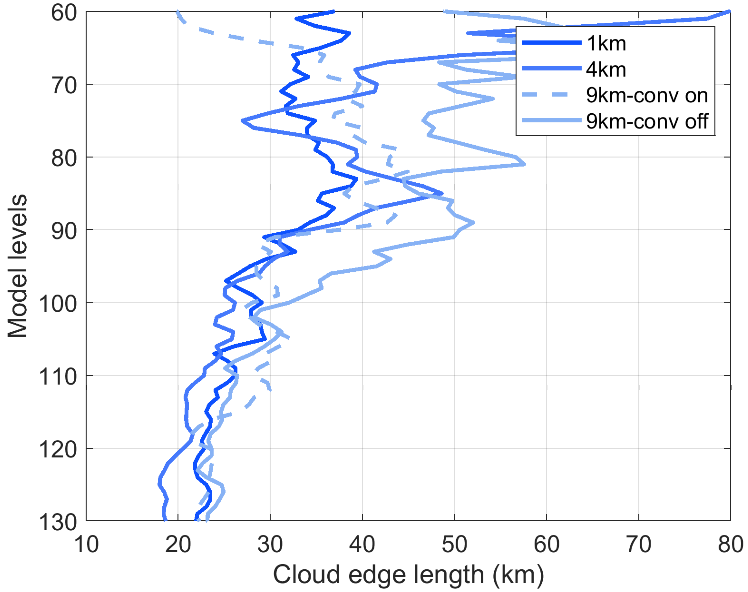
<u>Change in analysis fit to AMSU-A channel 2</u>

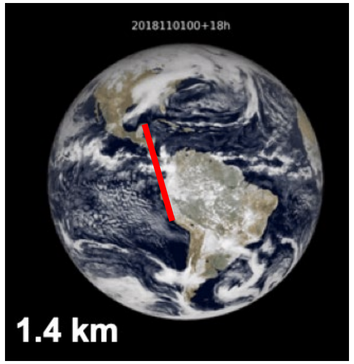


Inline observation operators provide direct comparison with observations



DYAMOND 'summer' simulations

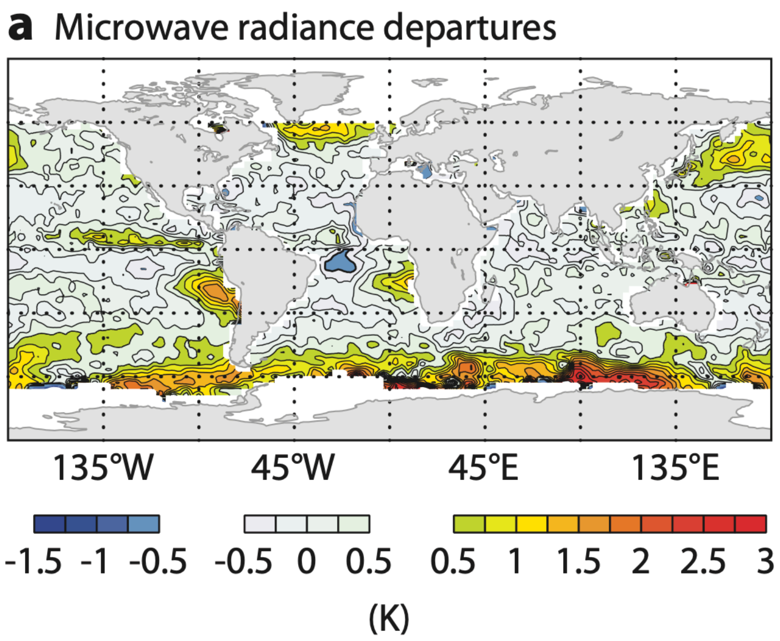


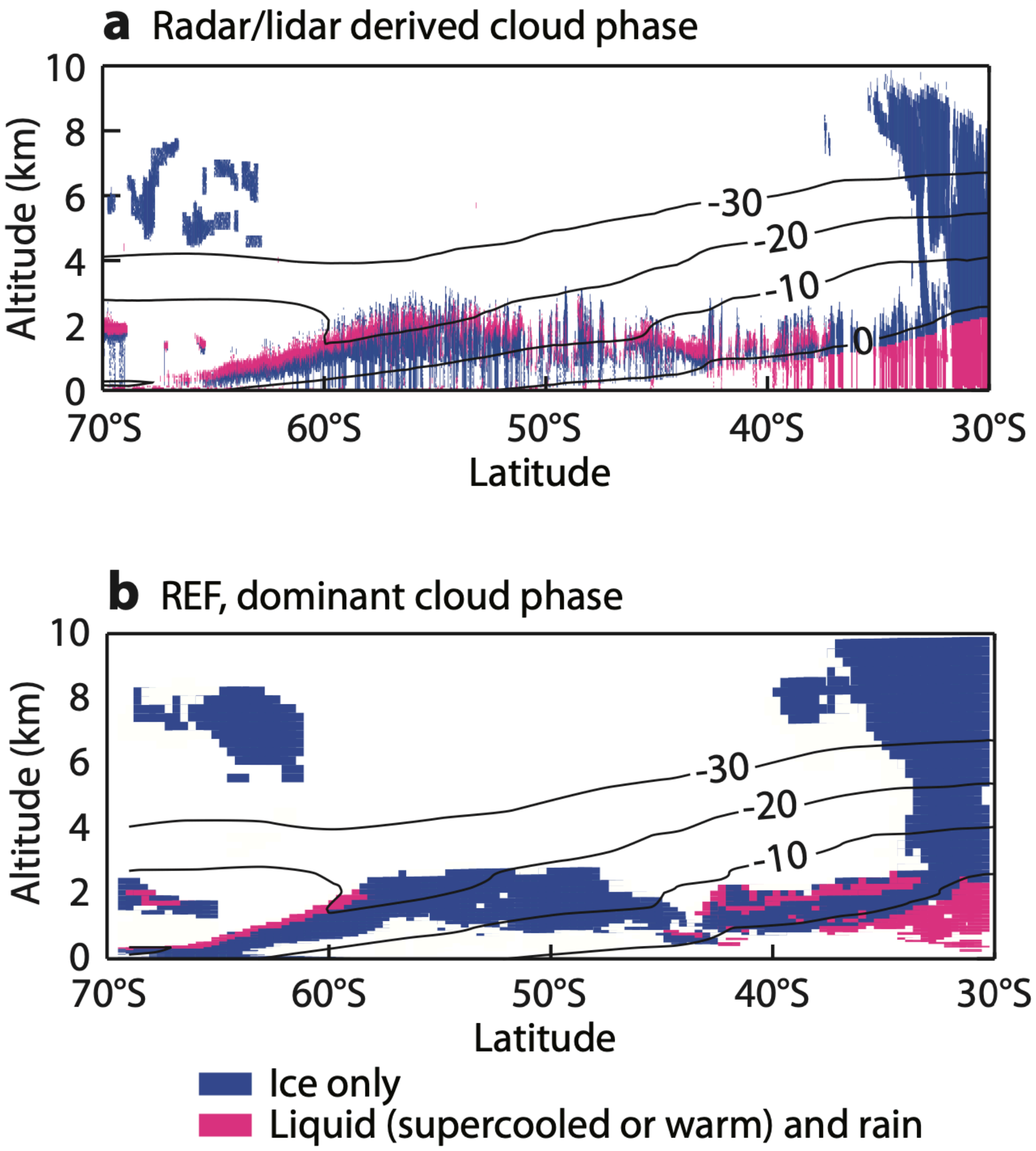


Courtesy: P. Lopez

- Radar reflectivity provides detailed information on cloud structure.
- Useful for evaluating model analysis/reanalysis or forecast skill when combined with other instruments.

Combining active and passive sensors for model evaluation



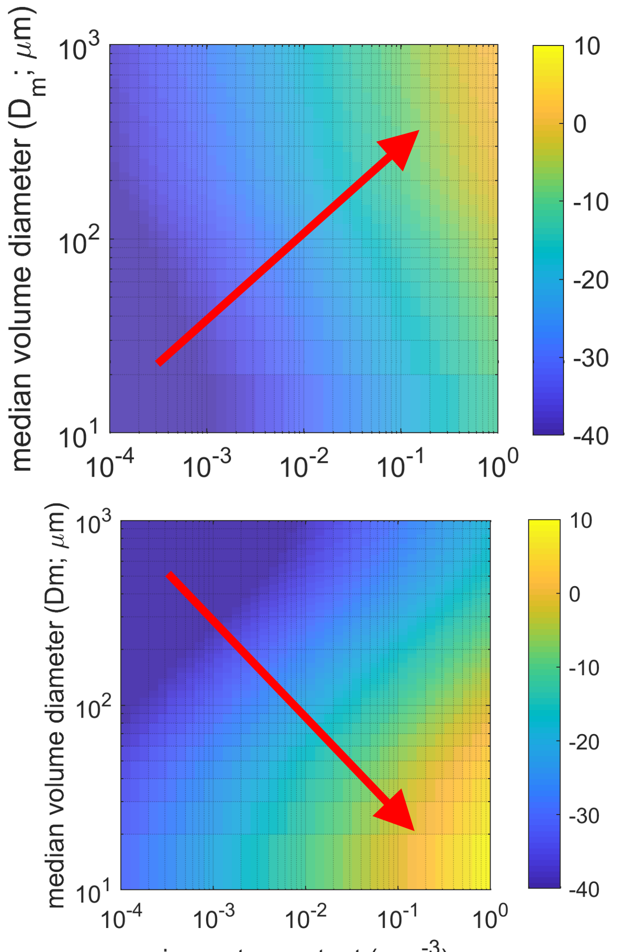


- ***Modification of convective supercooled liquid water detrainment***

Forbes et al., 2015

Microphysical parameter estimation via radar/lidar/passive synergy

- Significant proportion of uncertainty in observation operator is due to microphysical uncert
- Radar and lidar are sensitive to different moments of cloud/ice particle size distributions

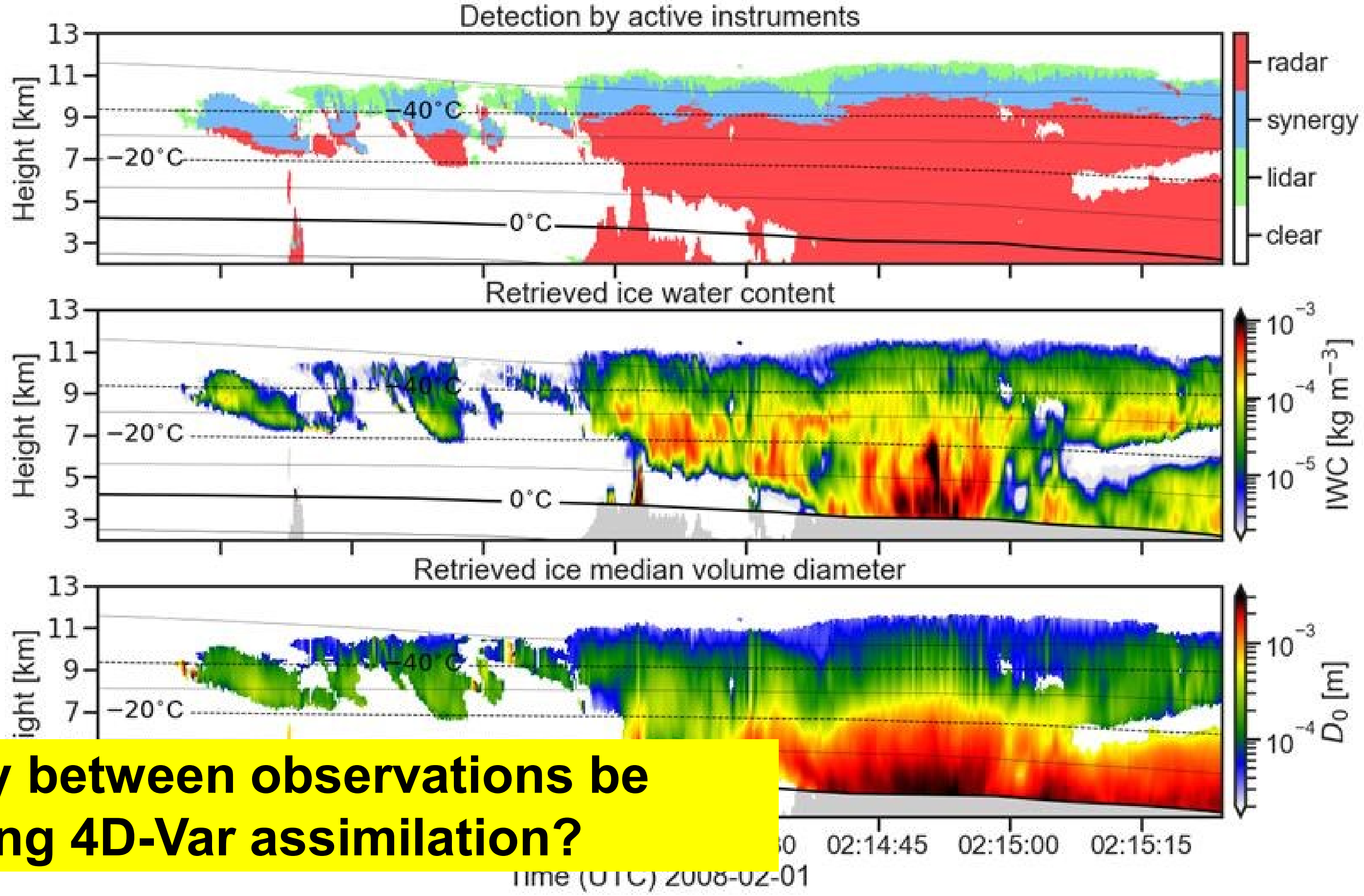


For a given iwc: radar reflectivity increases with particle size

dBZ

For a given iwc: Lidar backscatter decreases with particle size

dBβ



- **Could synergy between observations be exploited during 4D-Var assimilation?**

CAPTIVATE retrievals and plotting courtesy of Shannon Mason

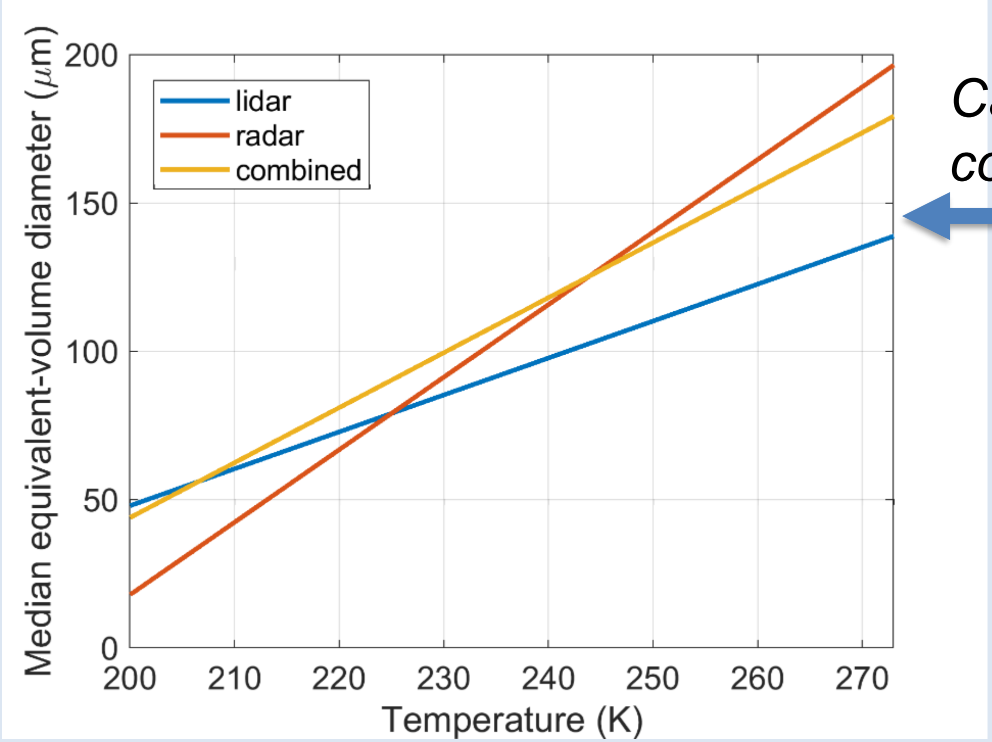
Proof of principle: off-line parameter estimation of observation operator microphysical assumptions

Radar and lidar

- Minimize cost function, J, assuming model analysis ice water content, w_a is truth:

$$J([D_{\min}, D_k]) = \left(y - h(w_a, D_m)\right)^2$$

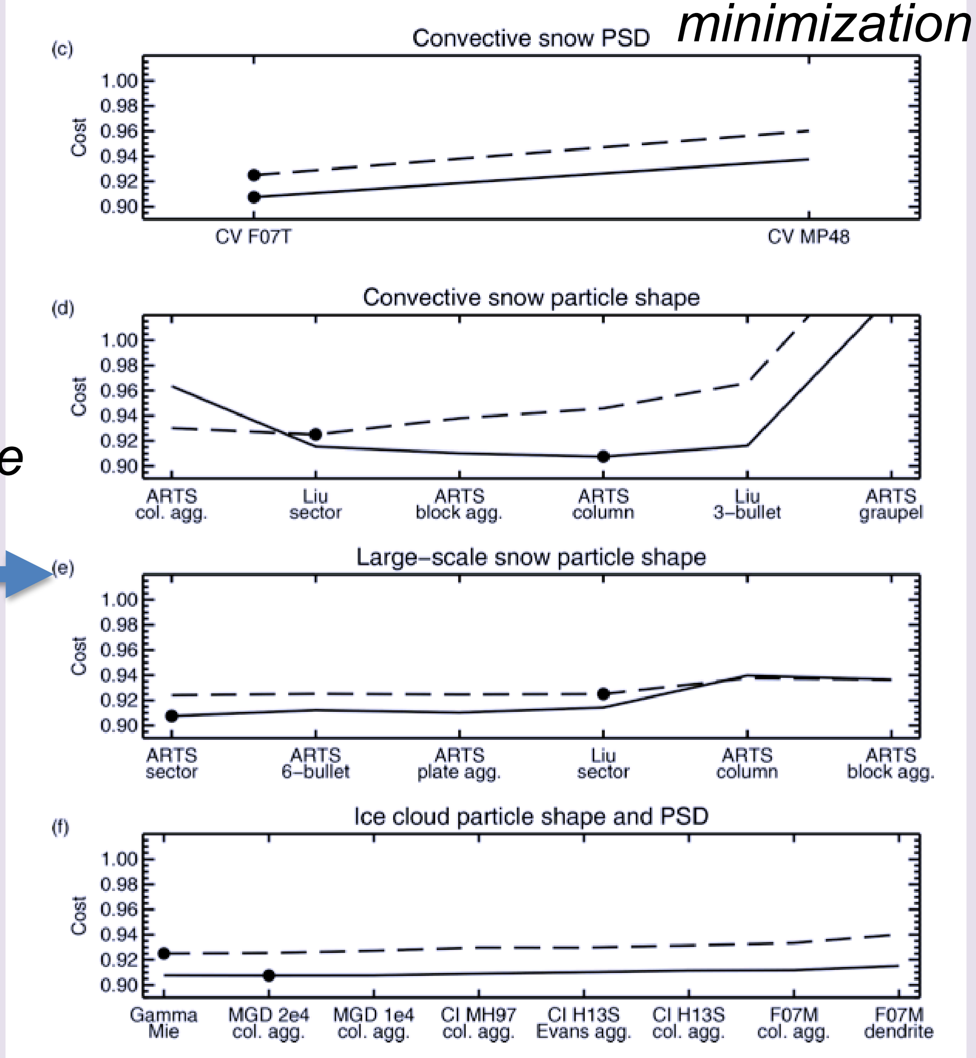
where $$D_m = \max(D_{\min} + (T-200)D_k, D_{\min})$$



Can these be combined?

Microwave radiances

➢ *Multi-parameter minimization*



Geer 2021, AMT

Constraining drizzle microphysics within the IFS Single Column Model

- Warm-rain processes are a key driver for the global distribution of clouds; stratocumulus to cumulus transition zones remain poorly represented in most global models.
- ARM observational field site in the Azores provides a unique set of measurements, ideally situated to capture a range of cloud regimes.
- Use radar simulator placed within IFS SCM for parameter estimation of uncertain autoconversion and accretion processes.

Azores field site. Courtesy: ARM

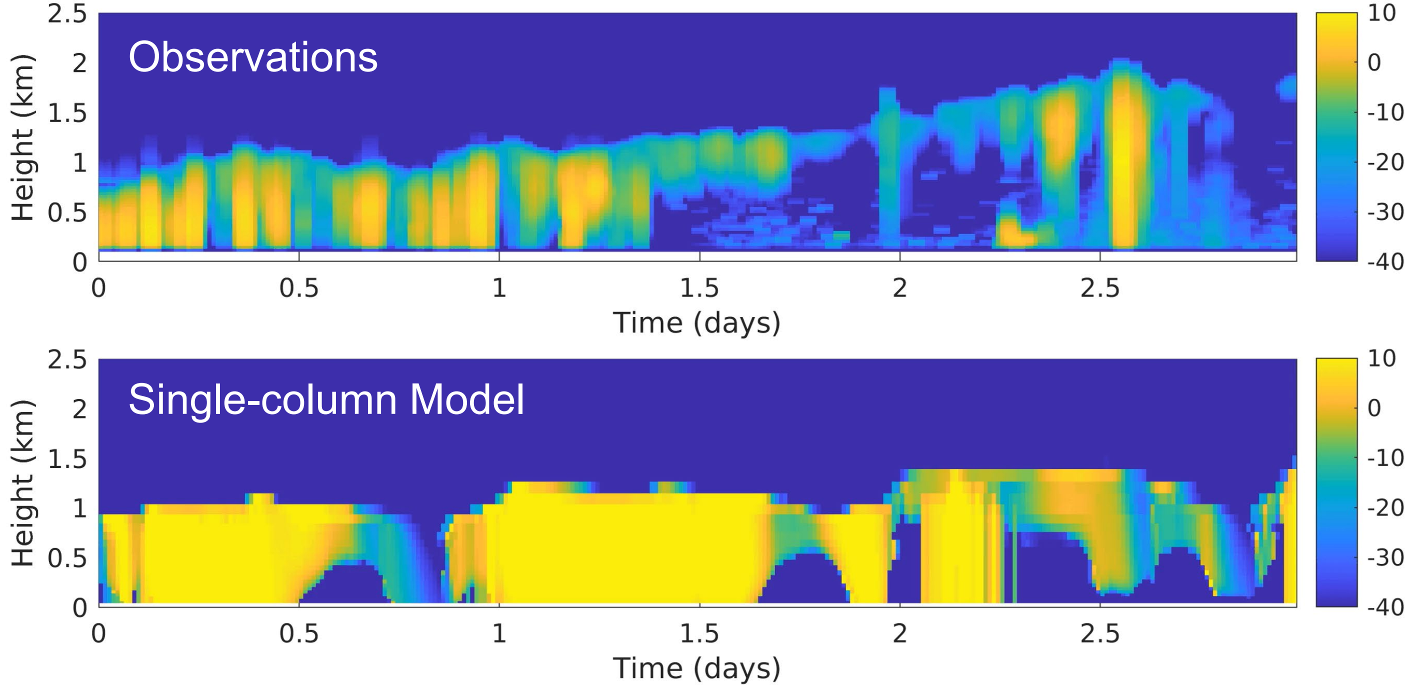
Fitting SCM to observations by adjusting warm-rain microphysical parameters

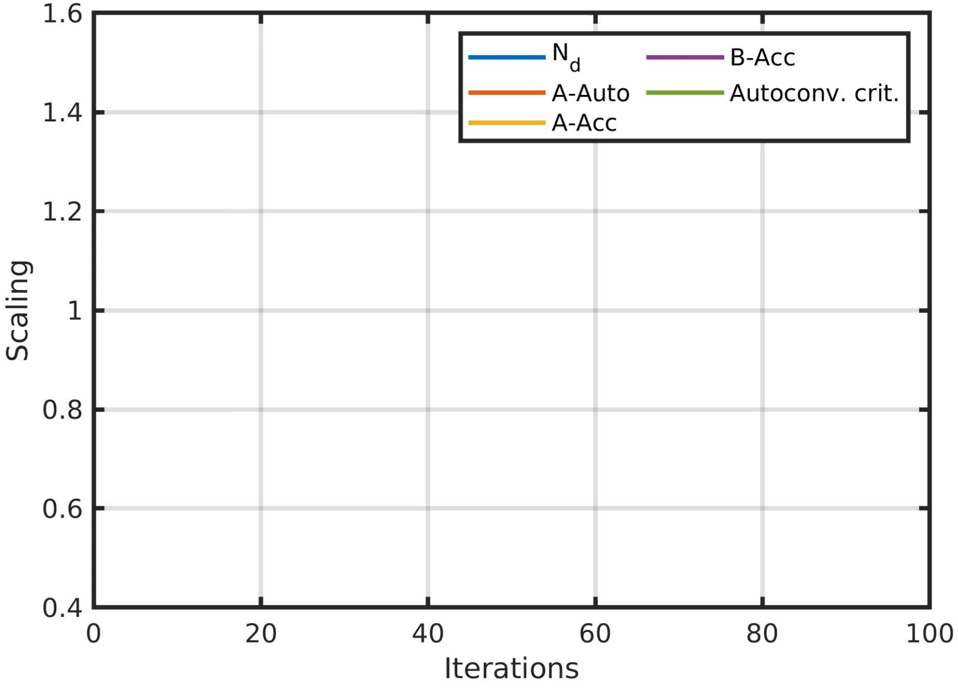
$$\left(\frac{\partial q_r}{\partial t}\right)_{\mathrm{auto}} = 1350\, \boxed{q_c^{2.47}}\, \boxed{N_c^{-1.79}},$$

+ Critical threshold

$$\left(\frac{\partial q_r}{\partial t}\right)_{\mathrm{accr}} = \boxed{67}\,(q_c q_r)^{\boxed{1.15}}.$$

Khairoutdinov and Kogan (2000)



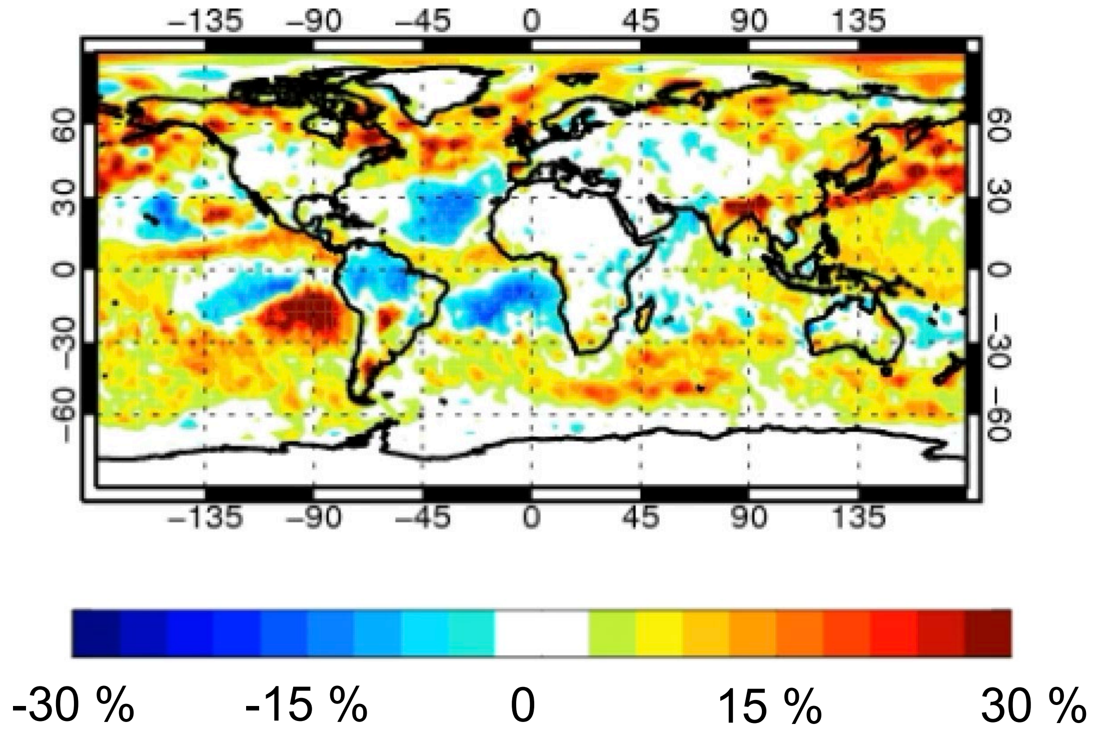


- *Minimize fit to observations via Nelder-Mead method*

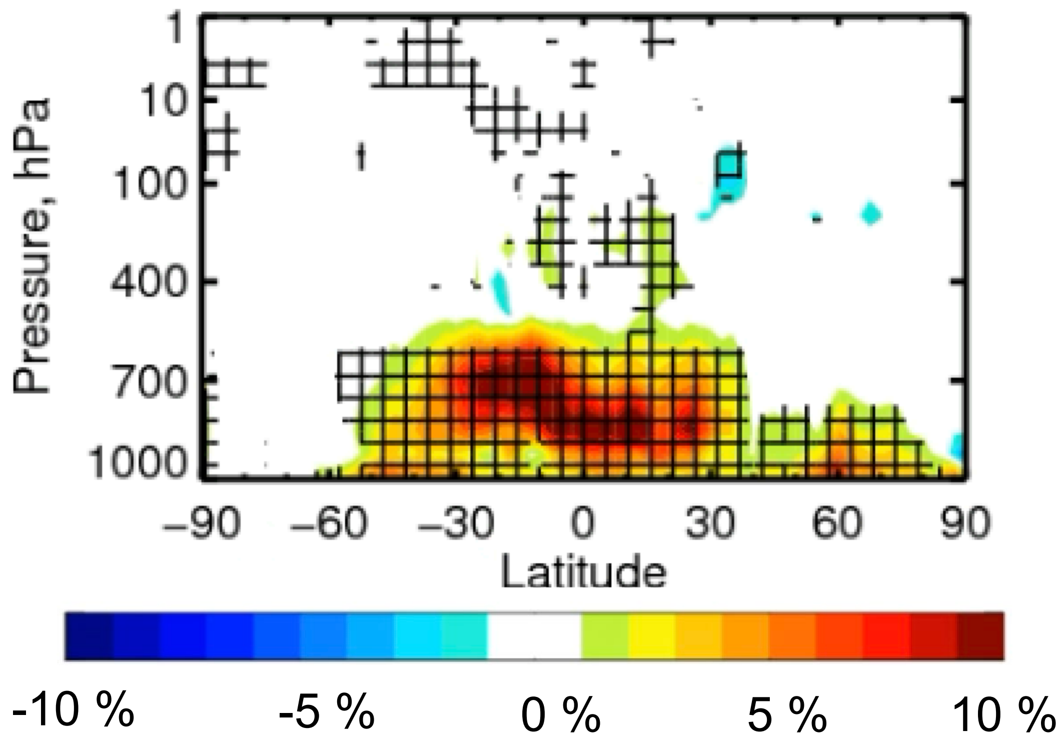
… and applying them to global NWP forecasts

Verification of relative humidity against operational forecast normalised by control

RMS at 1000 hPa, T+24



RMS, T+24

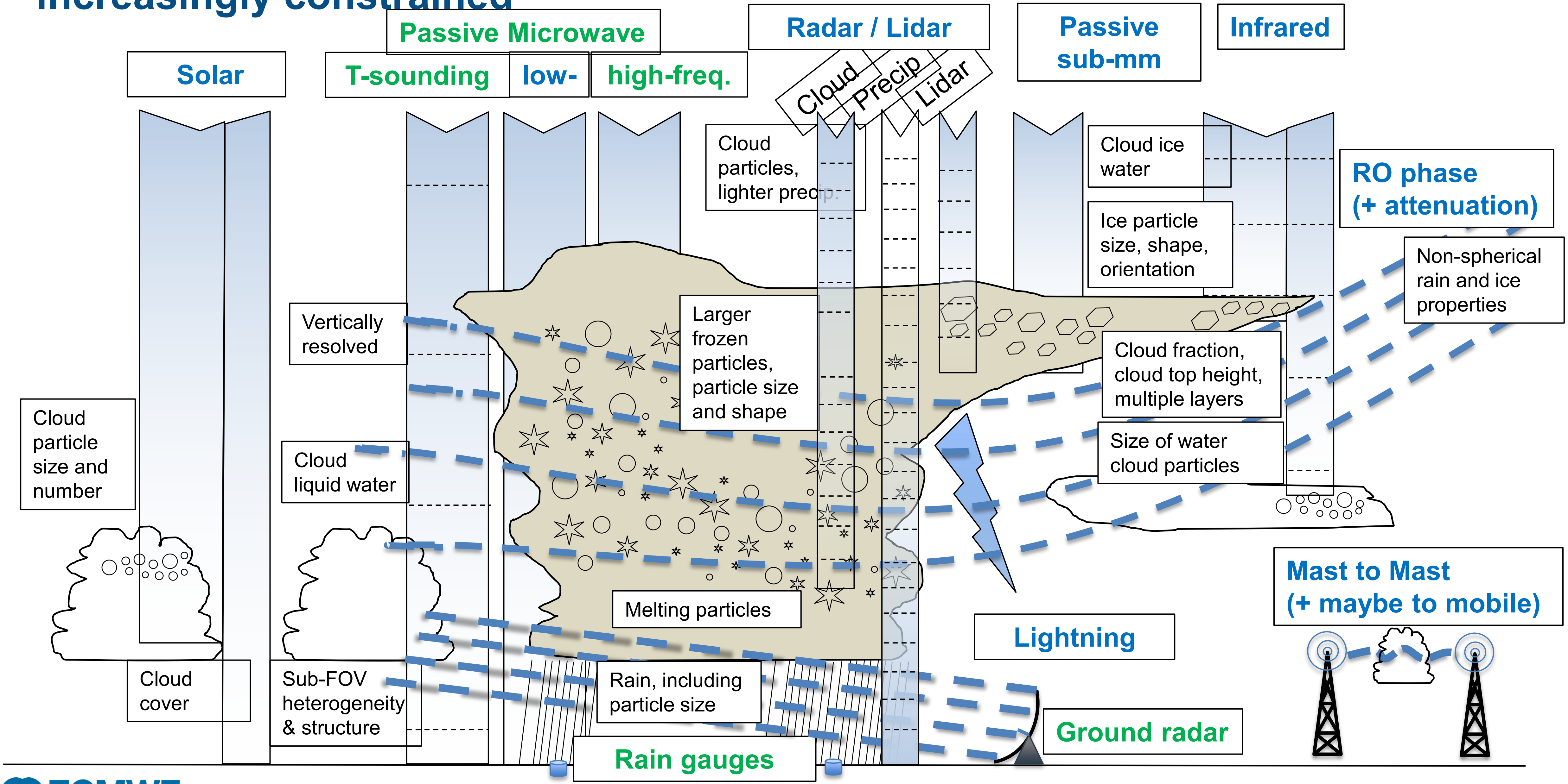


➢ **Not advisable to tune global parameters on individual cases!**

Can we use data assimilation techniques for global parameter estimation?

- Theoretically possible to simultaneously estimate large-scale atmospheric state and model parameters using data assimilation techniques (e.g., 4D-Var: Solar constant estimation at ECMWF, Lopez 2013; LETKF: Autoconversion and shallow convection *Kotsuki et al.*, 2018; roughness-length, *Ruckstuhl and Janjić*, 2020).
- Similar approach to VarBC and weak-constraint 4D-Var. For example, satellite radiance and observation operator biases have been estimated operationally since 2006 via VarBC (*Auligne et al.*, 2007).
- Practically, a huge challenge! (e.g., *Schirber et al.*, 2013)
  - Do we need to estimate all uncertain parameters at once? How to avoid unphysical parameters? Potential correlations between parameters, requires same model in DA as full non-linear model…
  - Danger of attributing model biases or errors to microphysical parameters

But… with increasingly diverse observing system, parameters are increasingly constrained



Summary

- Data assimilation system can be viewed as a unified observational framework for evaluating and improving models.
- Advances in observational capability, such as the imminent launch of EarthCARE satellite, opens new possibilities for cloud physics development.
- Combined state and parameter estimation could create a step-change in the representation of physical processes in NWP, but many hurdles to overcome!