Use of ground-based radar and lidar to evaluate model clouds

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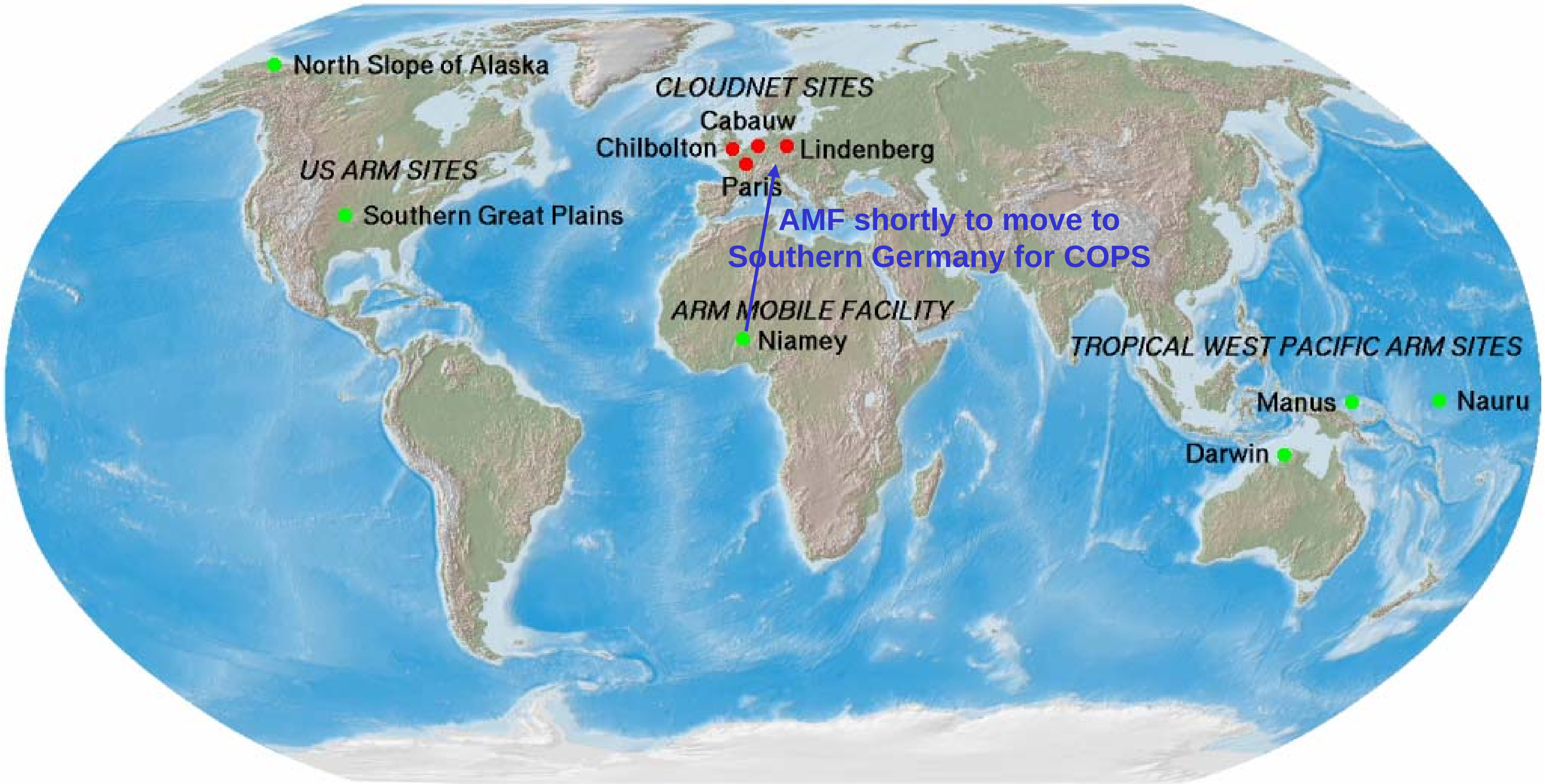
Overview

- Cloud radar and lidar sites worldwide
- Cloud evaluation over Europe as part of Cloudnet
  - Identifying targets in radar and lidar data (cloud droplets, ice particles, drizzle/rain, aerosol, insects etc)
  - Evaluation of cloud fraction
  - Liquid water content
  - Ice water content
  - Forecast evaluation using skill scores
  - Drizzle rates beneath stratocumulus
- The future: variational methods
  - Optimal combination of many instruments

Continuous cloud-observing sites



- Key cloud instruments at each site:
  - Radar, lidar and microwave radiometers

The Cloudnet methodology

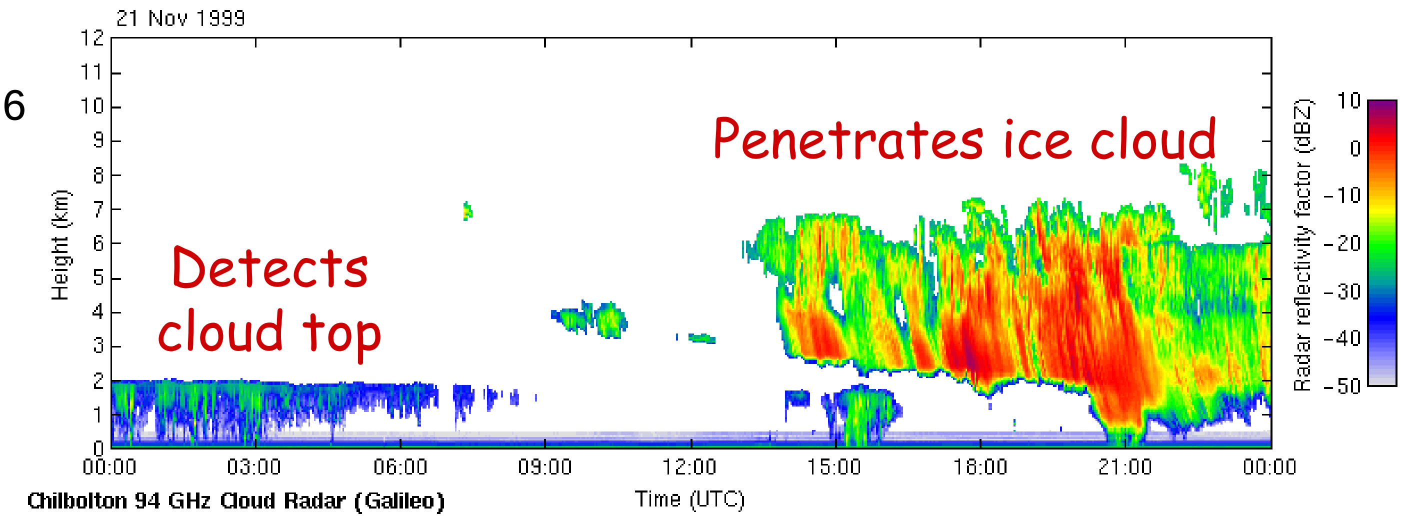
Recently completed EU project; www.cloud-net.org

- Aim: to retrieve and evaluate the crucial cloud variables in forecast and climate models
  - *Models:* Met Office (4-km, 12-km and global), ECMWF, Météo-France, KNMI RACMO, Swedish RCA model, DWD
  - *Variables:* target classification, cloud fraction, liquid water content, ice water content, drizzle rate, mean drizzle drop size, ice effective radius, TKE dissipation rate
  - *Sites:* 4 Cloudnet sites in Europe, 6 ARM including the mobile facility
  - *Period:* Several years near-continuous data from each site
- Crucial aspects
  - Common formats (including errors & data quality flags) allow all algorithms to be applied at all sites to evaluate all models
  - Evaluate for months and years: avoid unrepresentative case studies

Basics of radar and lidar

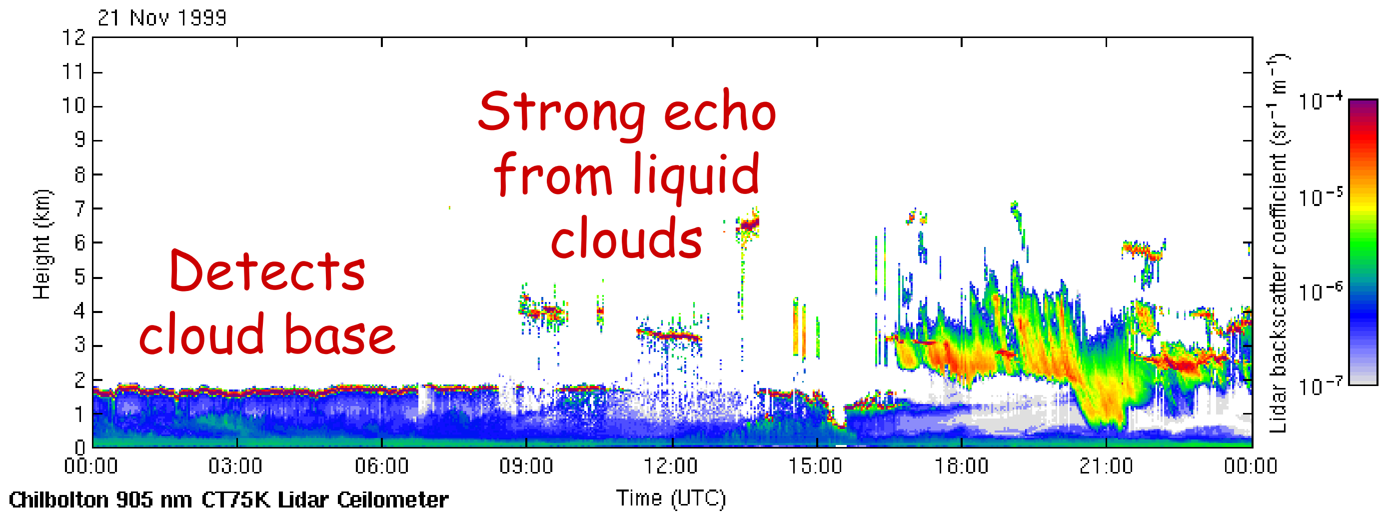
Radar: $Z \sim D^6$

Sensitive to large particles (ice, drizzle)



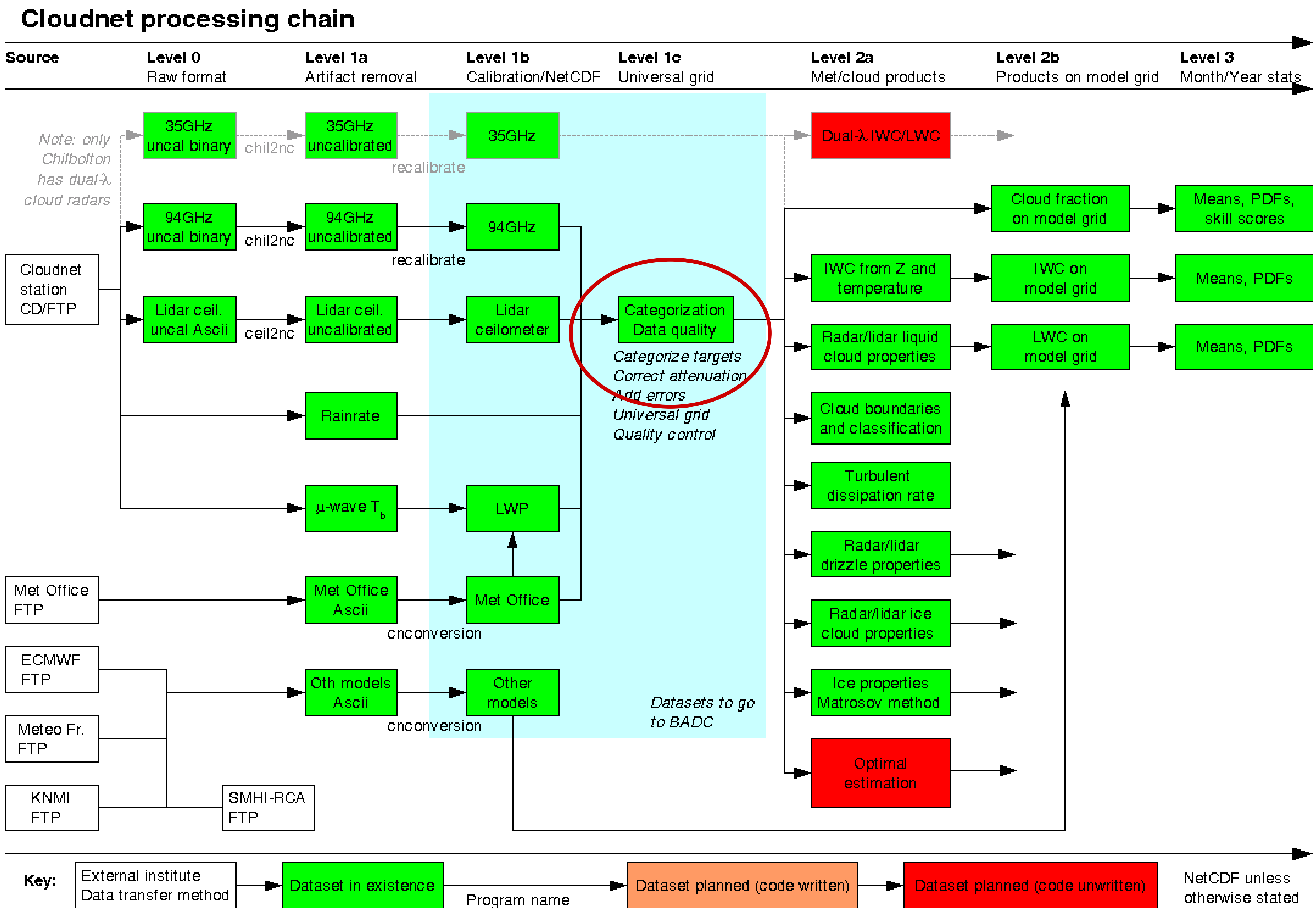
Lidar: $\beta \sim D^2$

Sensitive to small particles (droplets, aerosol)



Radar/lidar ratio provides information on particle size

← Level 0-1: *observed quantities* →|← Level 2-3: *cloud products* →

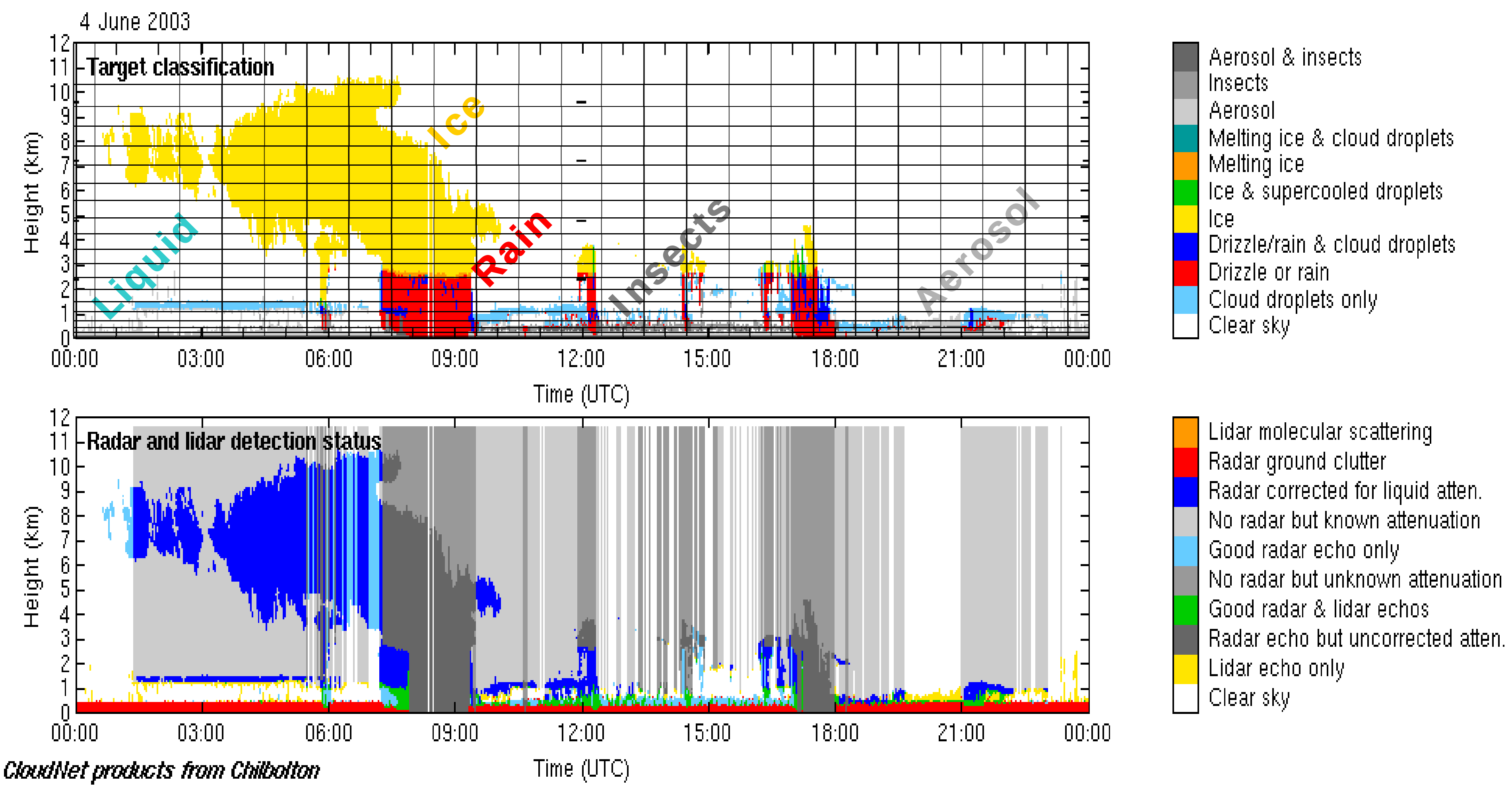


The Instrument synergy/ Target categorization product

- Makes multi-sensor data much easier to use:
  - Combines radar, lidar, model, raingauge and μ-wave radiometer
  - ***Identical format*** for each site (based around NetCDF)
- Performs common pre-processing tasks:
  - Interpolation on to the same grid
  - Ingest model data (many algorithms need temperature & wind)
  - Correct radar for ***attenuation*** (gas and liquid)
- Provides essential extra information:
  - Random and systematic ***measurement errors***
  - Instrument ***sensitivity***
  - Categorization of targets: ***droplets/ice/aerosol/insects*** etc.
  - ***Data quality flags:*** when are the observations unreliable?

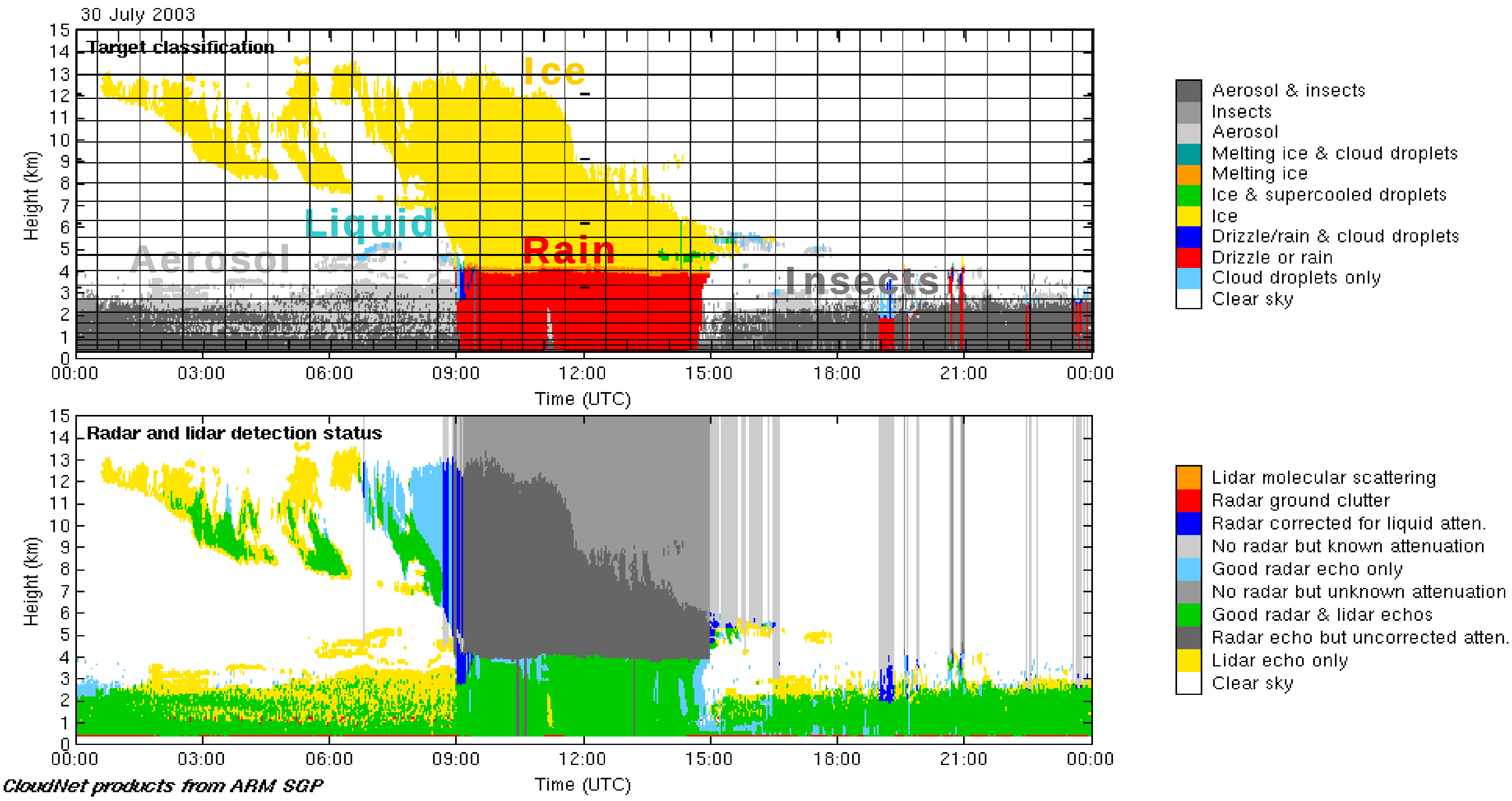
Target categorization

- Combining radar, lidar and model allows the type of cloud (or other target) to be identified
- From this can calculate cloud fraction in each model gridbox

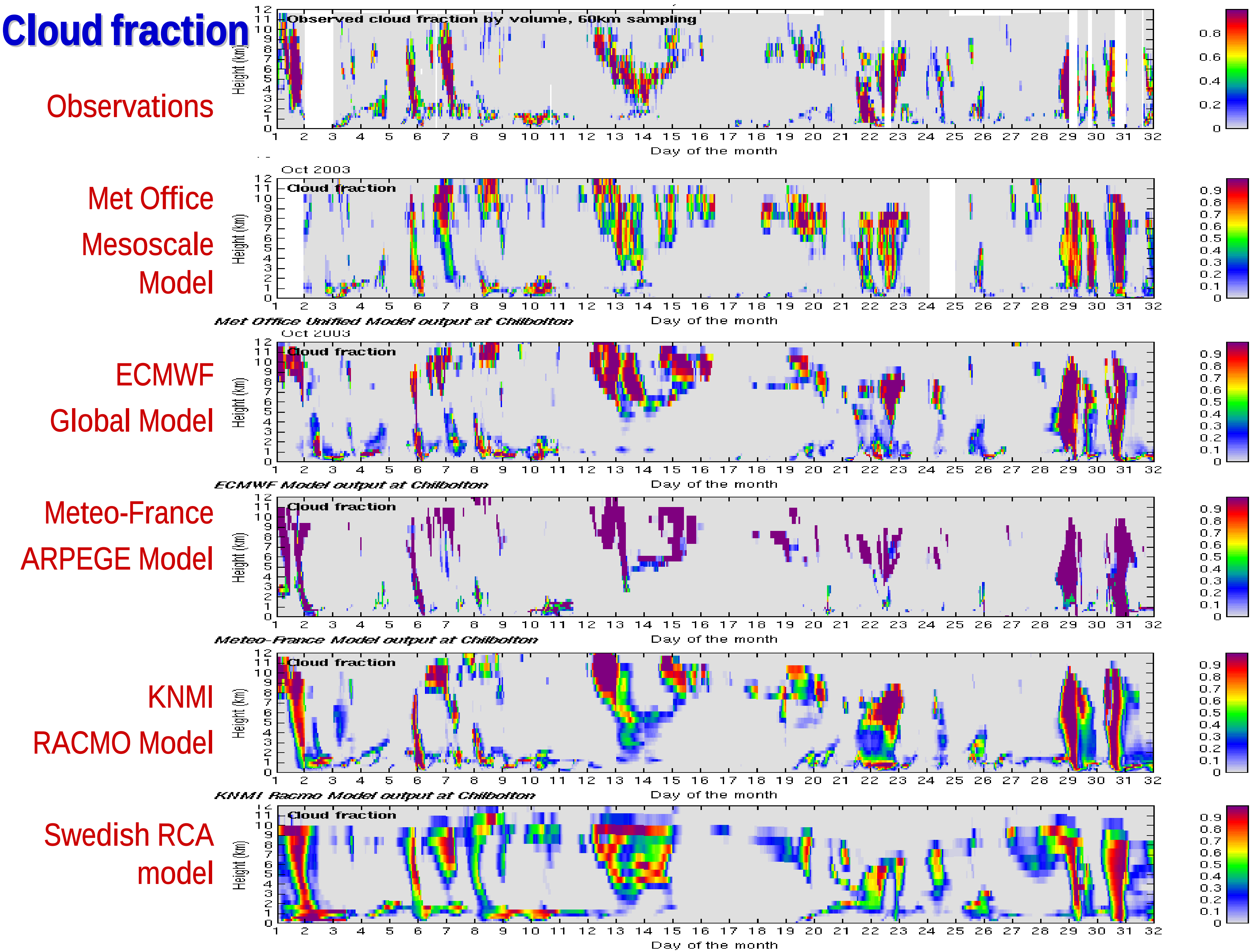


First step: target classification

- Combining radar, lidar and model allows the type of cloud (or other target) to be identified
- From this can calculate cloud fraction in each model gridbox

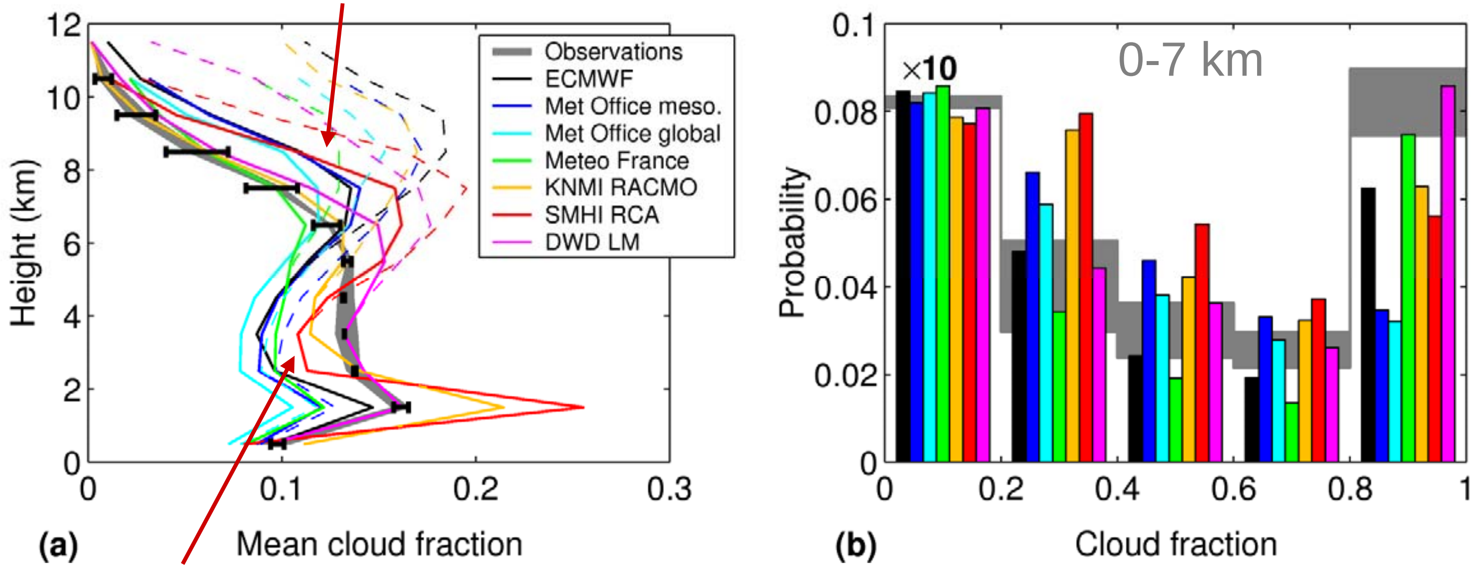


Cloud fraction



Cloud fraction in 7 models

- Mean & PDF for 2004 for Chilbolton, Paris and Cabauw
  - Uncertain above 7 km as must remove undetectable clouds in model

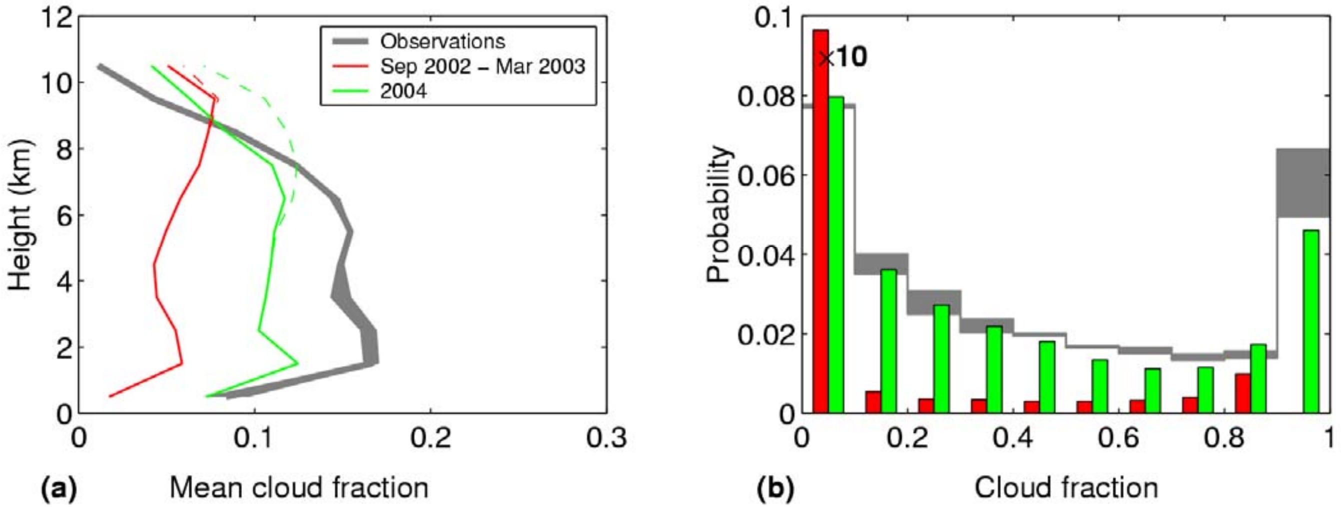


  - All models except DWD underestimate mid-level cloud; some have separate "radiatively inactive" snow (ECMWF, DWD); Met Office has combined ice and snow but still underestimates cloud fraction
  - Wide range of low cloud amounts in models

Illingworth, Hogan, O'Connor et al., submitted to BAMS

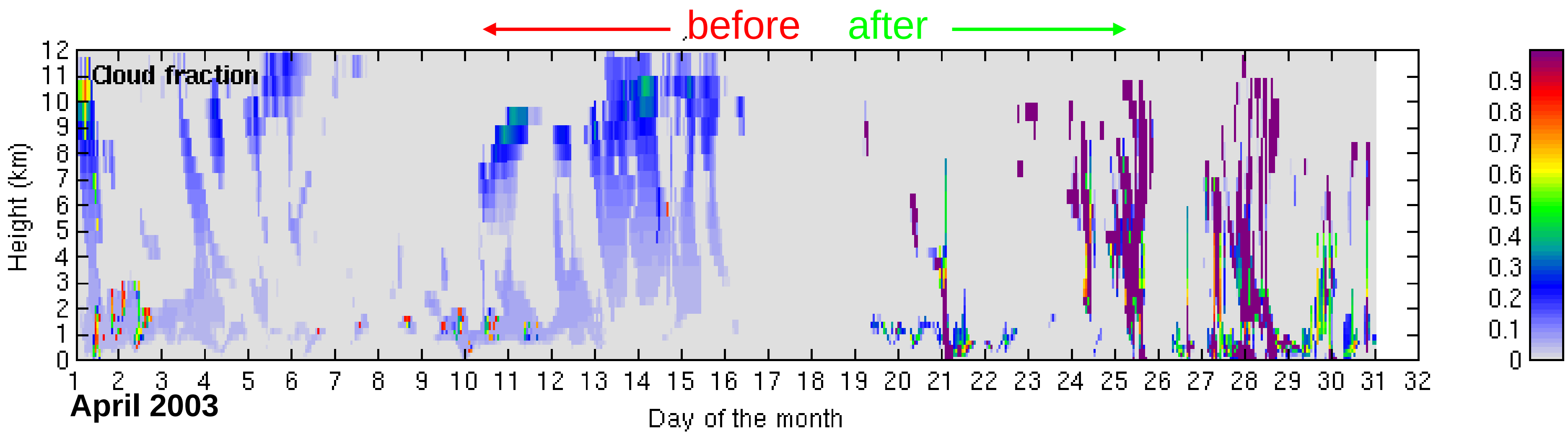
A change to Meteo-France cloud scheme

- Compare cloud fraction to observations before and after April 2003
- Note that cloud fraction and water content are entirely diagnostic



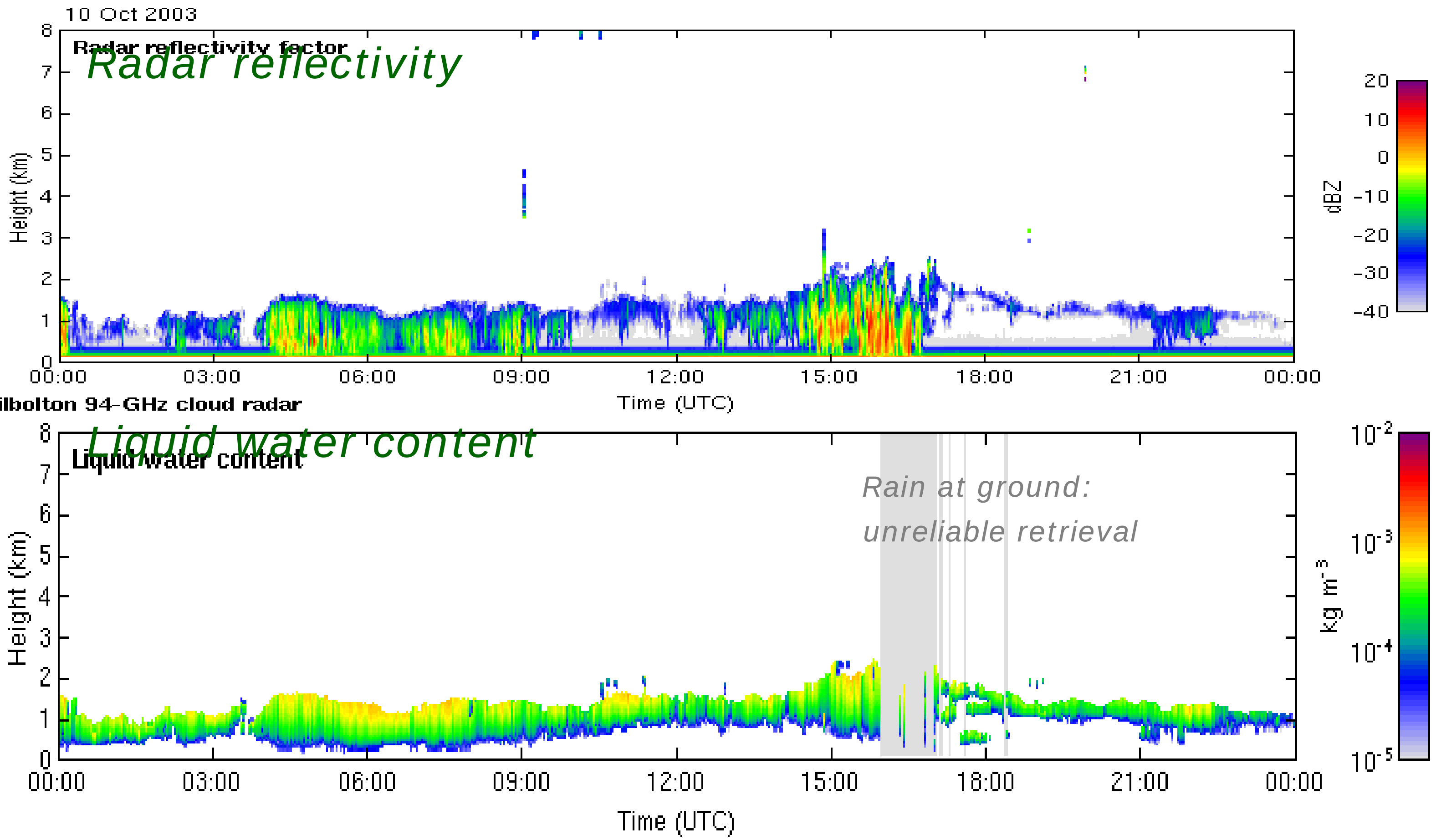
But human obs. indicate model now **underestimates** mean cloud-cover!

Compensation of errors: overlap scheme changed from random to maximum-random



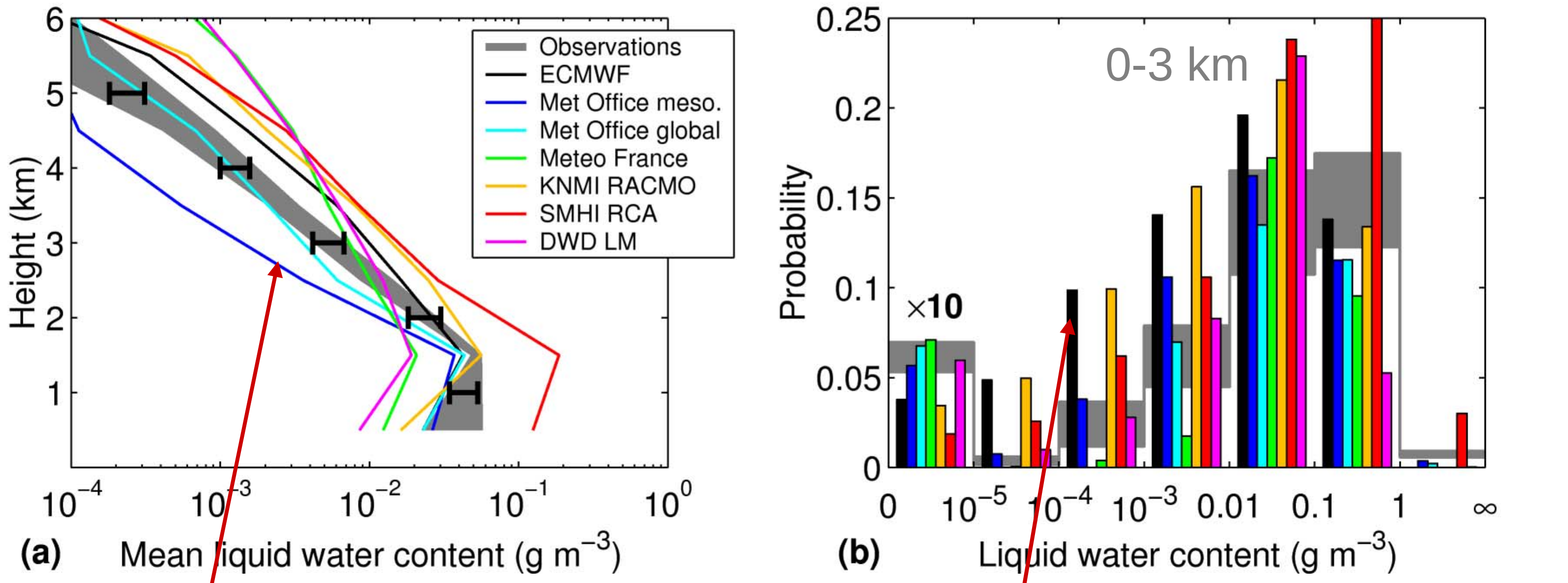
Liquid water content

- Can't use radar Z for LWC: often affected by drizzle
  - Simple alternative: lidar and radar provide cloud boundaries
  - Model temperature used to predict "adiabatic" LWC profile
  - Scale with LWP (entrainment often reduces LWC below adiabatic)



Liquid water content

- LWC derived using the *scaled adiabatic method*
  - Lidar and radar provide cloud boundaries, adiabatic LWC profile then scaled to match liquid water path from microwave radiometers

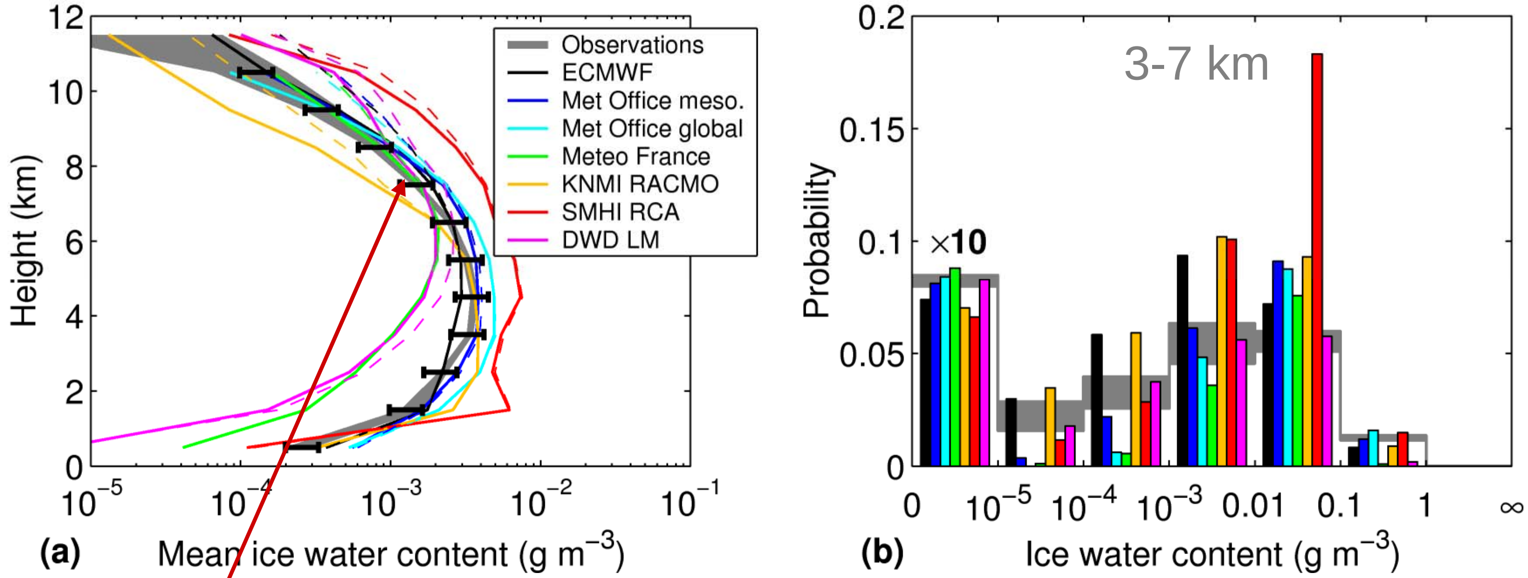


- Met Office mesoscale tends to underestimate supercooled water occurrence

- ECMWF has far too great an occurrence of low LWC values
- KNMI RACMO identical to ECMWF: same physics package!

Ice water content

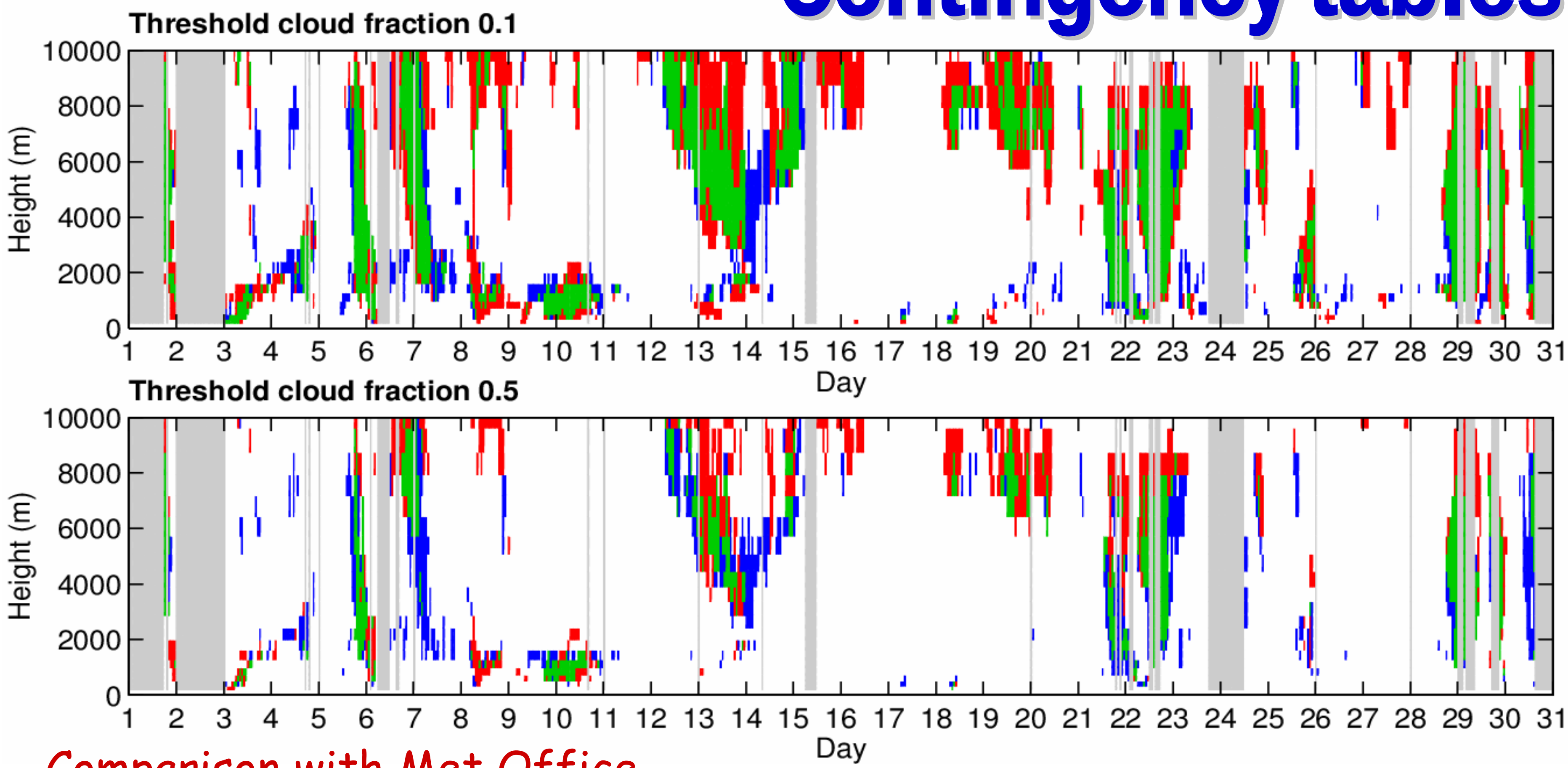
- IWC estimated from radar reflectivity and temperature
  - Rain events excluded from comparison due to mm-wave attenuation
  - For IWC above rain, use cm-wave radar (e.g. Hogan et al., JAM, 2006)



- ECMWF and Met Office within the observational errors at all heights
- Encouraging: AMIP implied an error of a factor of 10!

- Be careful in interpretation: mean IWC dominated by occasional large values so PDF more relevant for radiative properties

Contingency tables



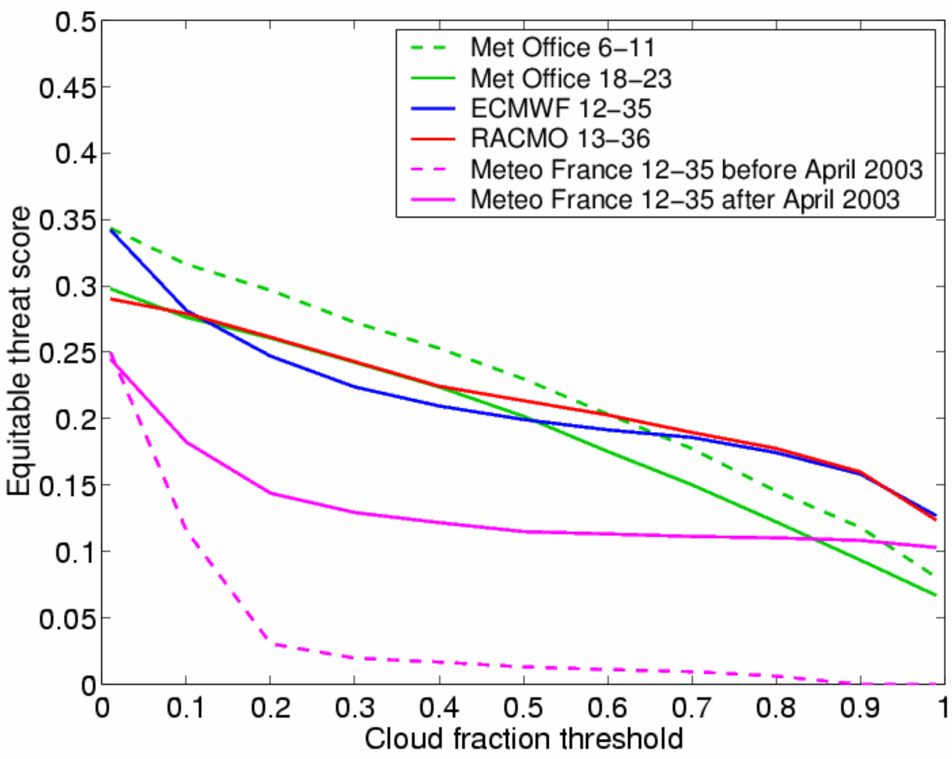
Comparison with Met Office model over Chilbolton October 2003

	Observed cloud	Observed clear-sky
Model cloud	A: Cloud hit	B: False alarm
Model clear-sky	C: Miss	D: Clear-sky hit

Equitable threat score

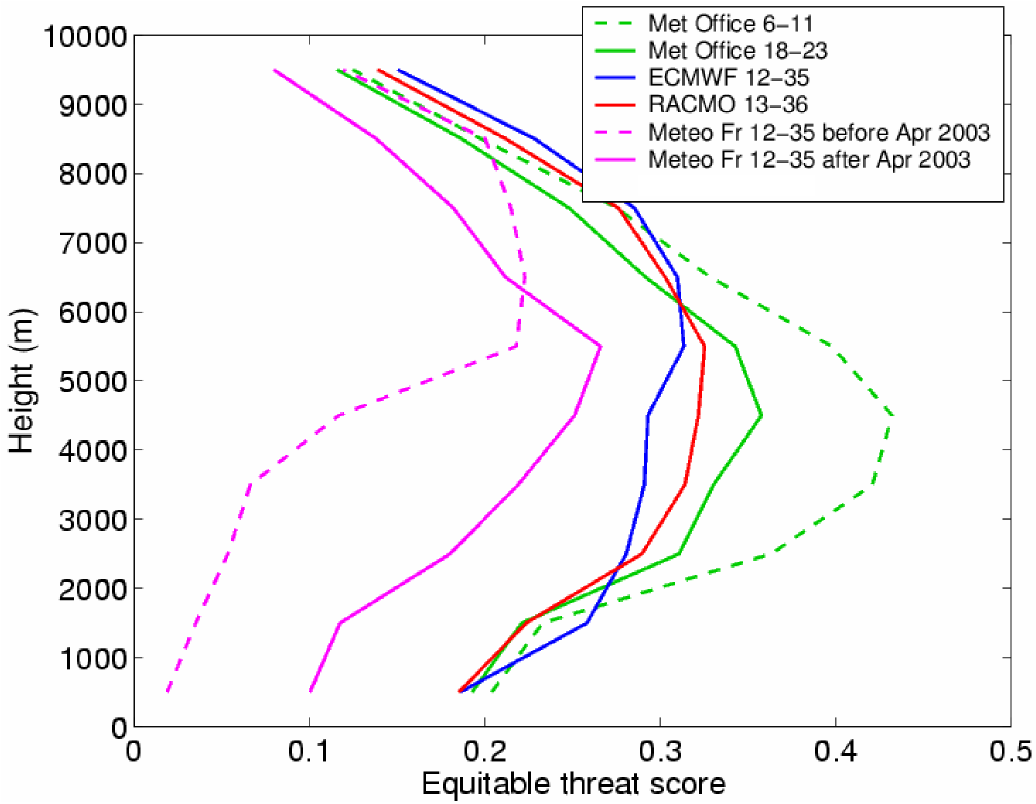
- Definition: **ETS =** (A-E)/(A+B+C-E)
- E removes those hits that occurred by chance:

  E=[(A+B)(A+C)]/[A+B+C+D]
- 1 = perfect forecast, 0 = random forecast



From now on we use Equitable Threat Score with threshold of 0.1

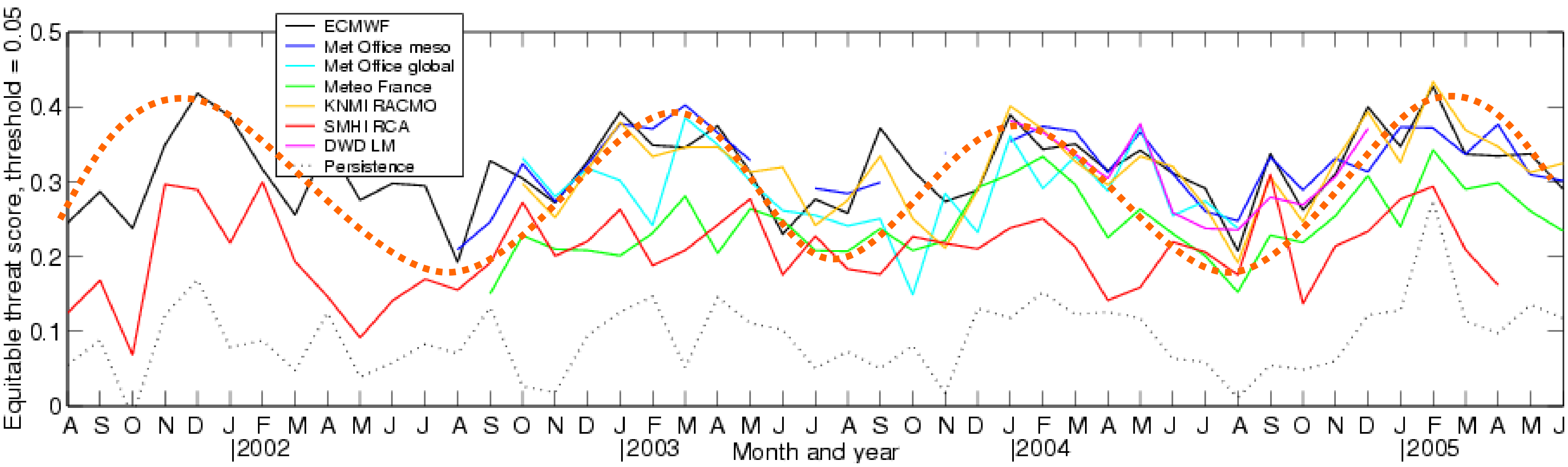
Skill versus height



- Model performance:
  - ECMWF, RACMO, Met Office models perform similarly
  - Météo France not so well, much worse before April 2003
  - Met Office model significantly better for shorter lead time
- Potential for testing:
  - New model parameterisations
  - Global versus mesoscale versions of the Met Office model

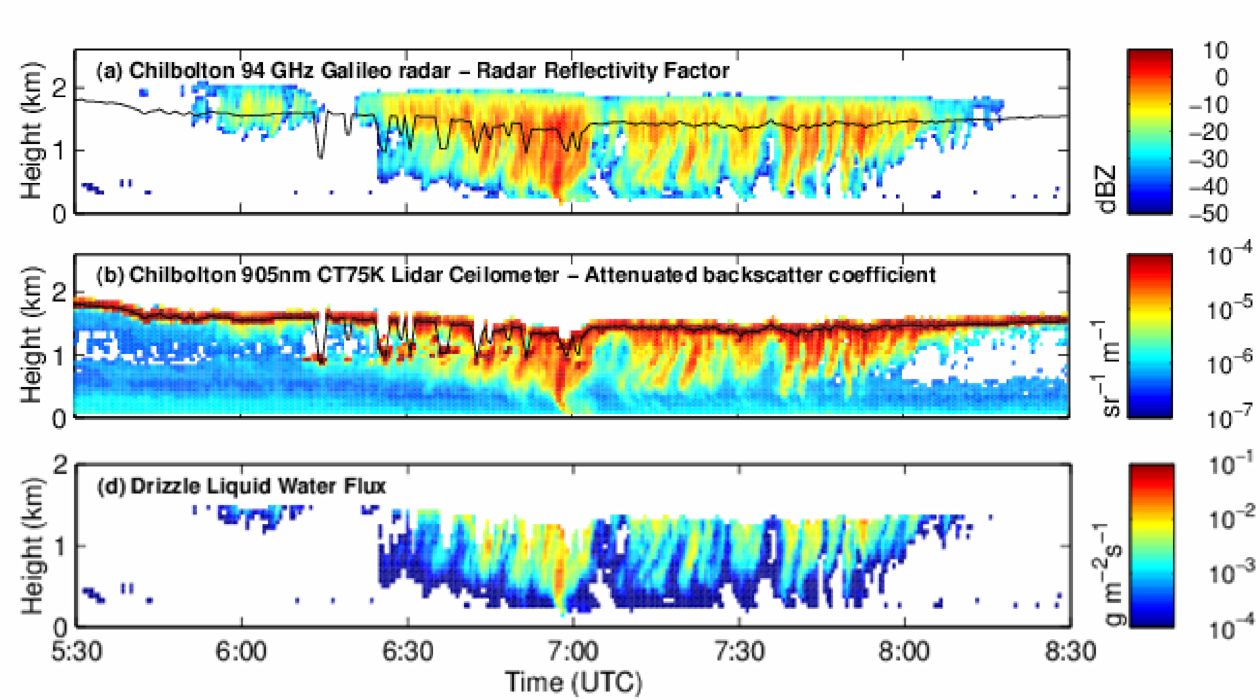
Equitable threat score

- Definition: **ETS =** (A-E)/(A+B+C-E)
  - E removes those hits that occurred by chance
  - 1 = perfect forecast, 0 = random forecast
- Measure of the skill of forecasting cloud fraction>0.05
  - *Assesses the weather of the model not its climate*
  - Persistence forecast is shown for comparison



- Lower skill in summer convective events

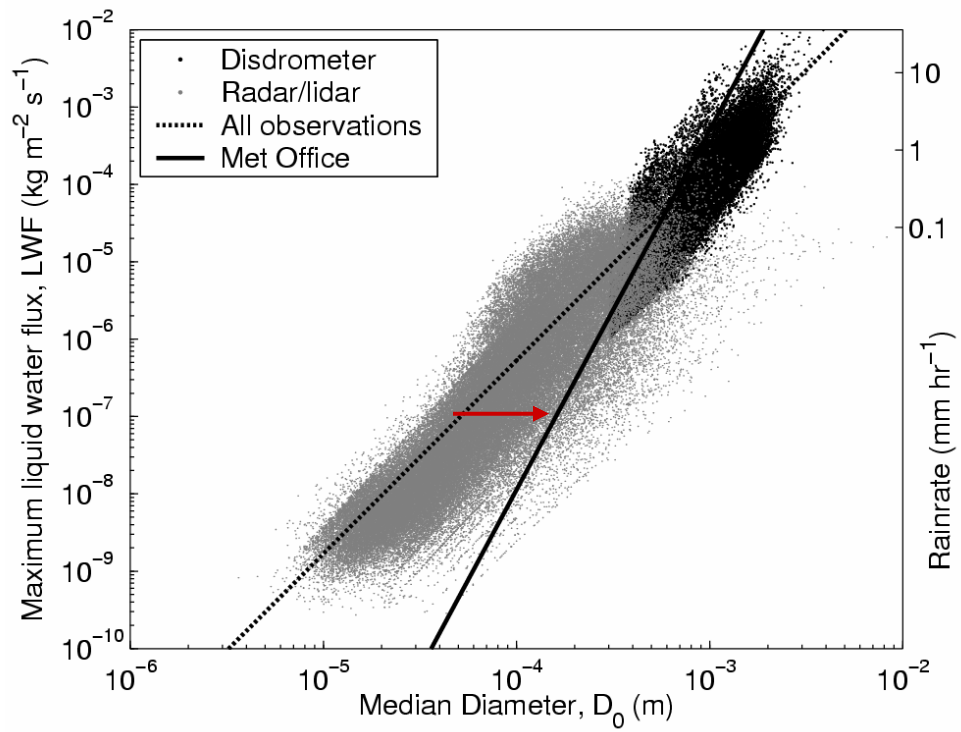
Drizzle!



- Radar and lidar used to derive drizzle rate below stratocumulus
- Important for cloud lifetime in climate models

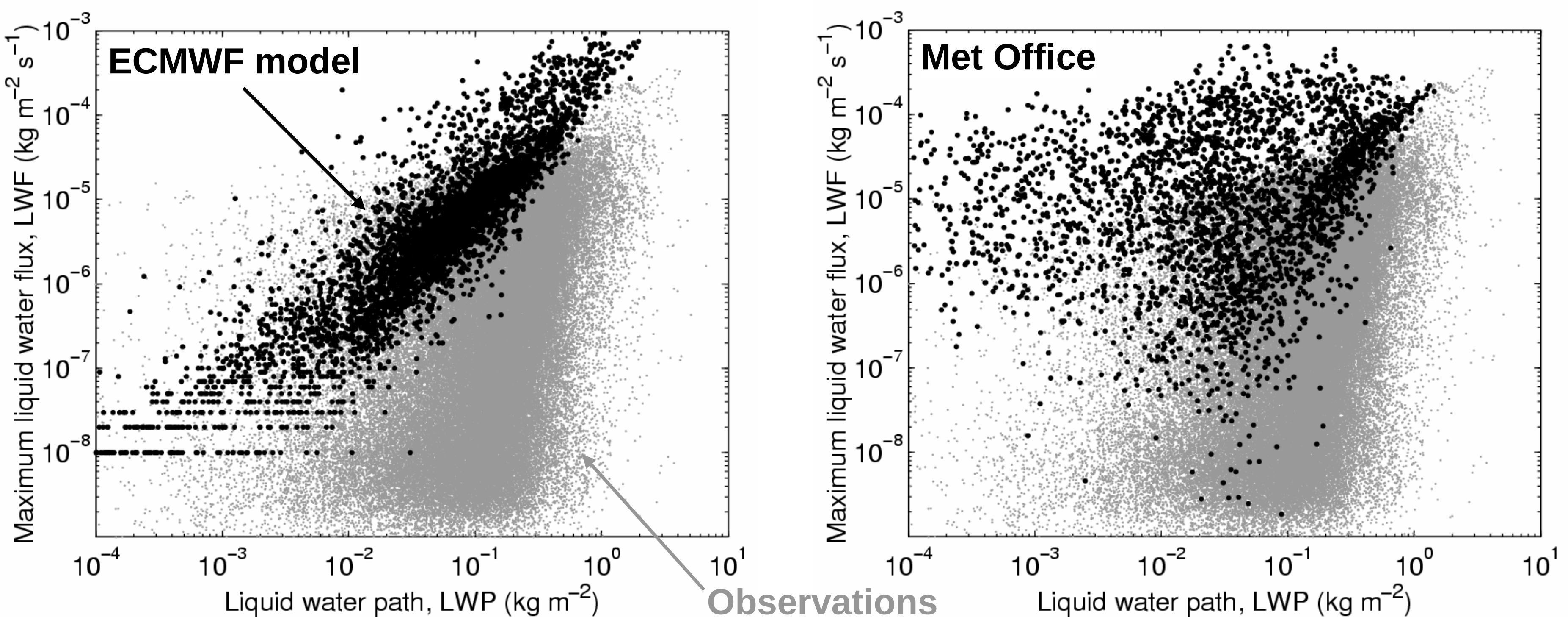
O'Connor et al. (2005)

- Met Office uses Marshall-Palmer distribution for all rain
  - *Observations show that this tends to* ***overestimate*** *drop size in the lower rain rates*
- Most models (e.g. ECMWF) have no explicit raindrop size distribution



1-year comparison with models

- ECMWF, Met Office and Meteo-France overestimate drizzle rate
  - Problem with auto-conversion and/or accretion rates?
- Larger drops in model fall faster so too many reach surface rather than evaporating: drying effect on boundary layer?



O'Connor et al., submitted to J. Climate

Variational retrieval

- The retrieval guy's dream is to do everything *variationally*:
  - Make a first guess of the profile of cloud properties
  - Use forward models to predict observations that are available (e.g. radar reflectivity, Doppler velocity, lidar backscatter, microwave radiances, geostationary TOA infrared radiances) and the Jacobian
  - Iteratively refine the cloud profile to minimize the difference between the observations and the forward model in a least-squares sense
- Existing methods only perform retrievals where both the radar and lidar detect the cloud
  - A variational method (1D-VAR) can spread information vertically to regions detected by just the radar or the lidar
- We have done this for ice clouds (liquid clouds to follow)
  - Use fast lidar multiple scattering model that incorporates high orders of scattering (Hogan, Appl. Opt., 2006)
  - Use the two-stream source function method for the SEVIRI radiances
  - Use extinction coefficient and "normalized number concentration parameter" as the state variables…

Solution method

- Find **x** that minimizes a cost function *J* of the form

  J = deviation of **x** from a-priori

  + deviation of observations from forward model

  + curvature of extinction profile

New ray of data

Locate cloud with radar & lidar

Define elements of **x**

First guess of **x**

Forward model

Predict measurements **y** from state vector **x** using forward model $H(\mathbf{x})$

Also predict the *Jacobian* **H**

Has solution converged?

χ^2 convergence test

No

Gauss-Newton iteration step

Predict new state vector:

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \mathbf{A}^{-1}\{\mathbf{H}^T\mathbf{R}^{-1}[\mathbf{y}-H(\mathbf{x}_i)] - \mathbf{B}^{-1}(\mathbf{x}_i-\mathbf{x}^a) - \mathbf{T}\mathbf{x}_i\}$$

where the *Hessian* is

$$\mathbf{A} = \mathbf{H}^T\mathbf{R}^{-1}\mathbf{H} + \mathbf{B}^{-1} + \mathbf{T}$$

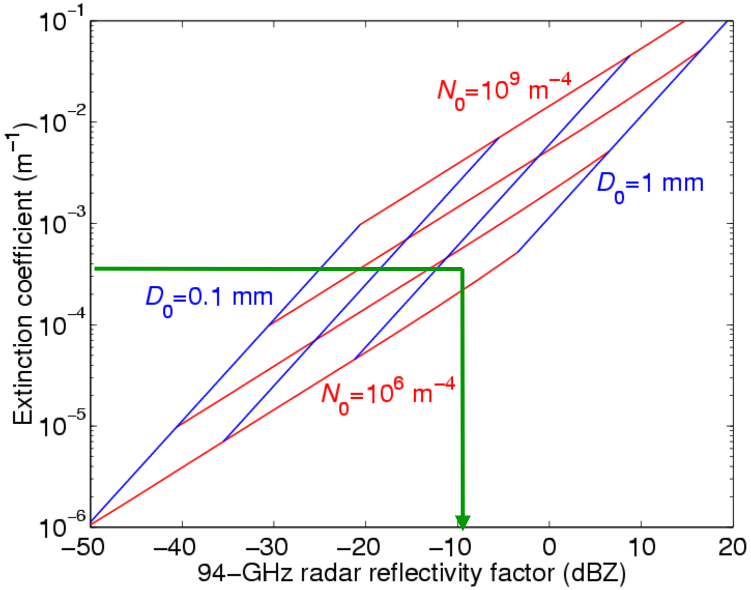
Yes

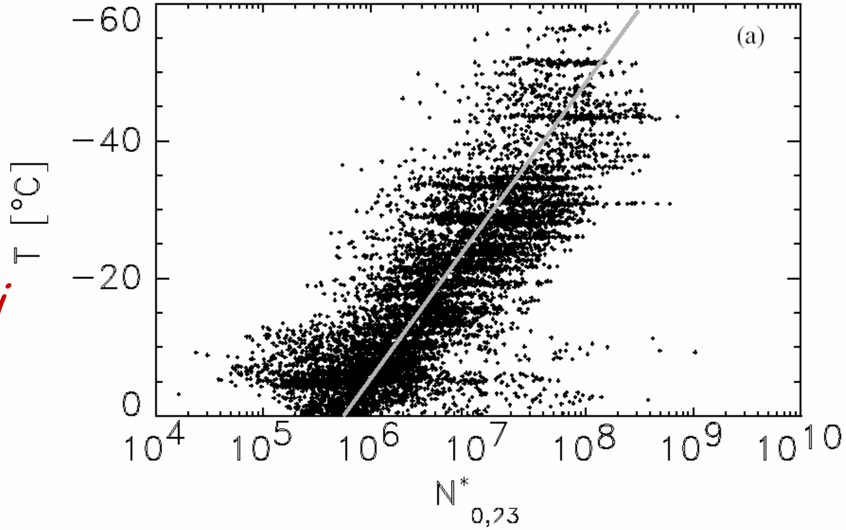
Calculate error in retrieval

Proceed to next ray

Radar forward model and *a priori*

- Create lookup tables
  - Gamma size distributions
  - Choose mass-area-size relationships
  - Mie theory for 94-GHz reflectivity
- Define *normalized number concentration parameter* N_0*
  - "The N_0 that an exponential distribution would have with same IWC and D_0 as actual distribution"
  - Forward model predicts Z from the state variables (extinction and N_0*)
  - Effective radius from lookup table
- N_0 has strong T dependence
  - Use Field et al. power-law as *a-priori*
  - When no lidar signal, retrieval relaxes to one based on Z and T (Liu and Illingworth 2000, Hogan et al. 2006)

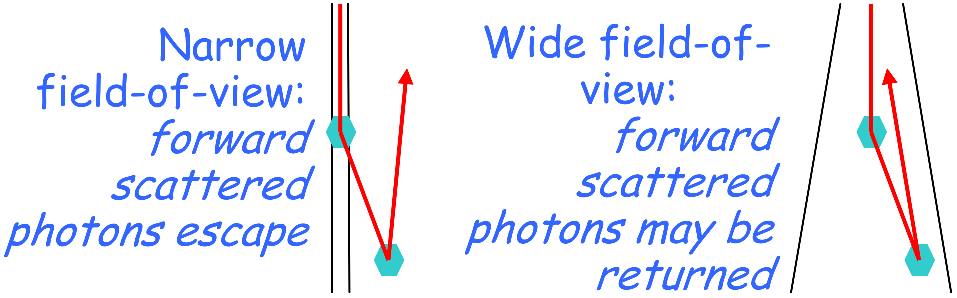


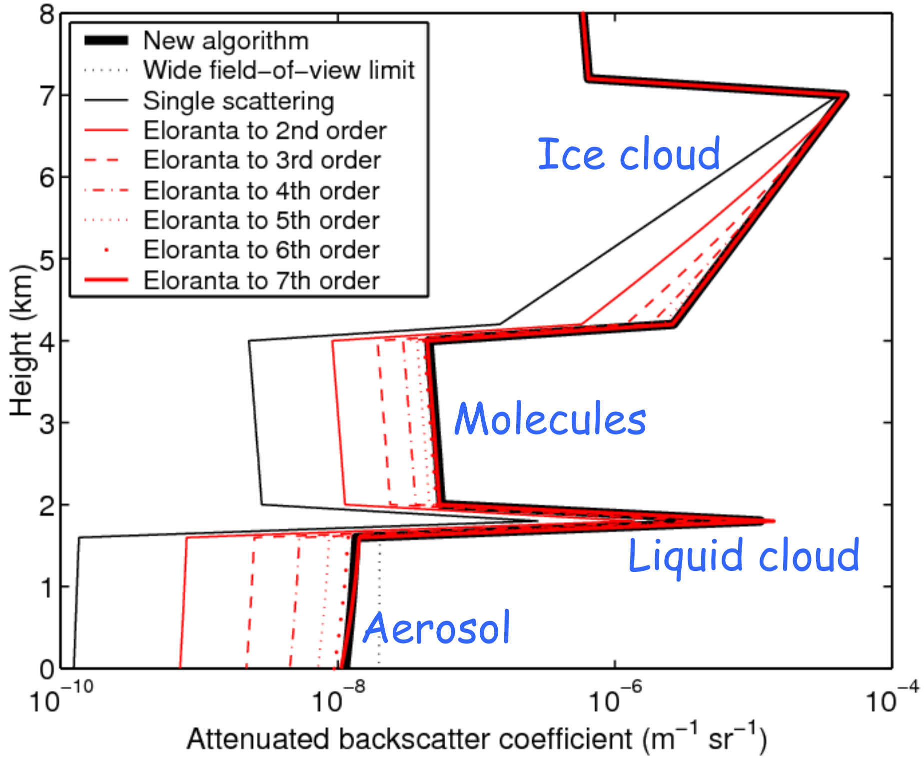


Field et al. (2005)

Lidar forward model: multiple scattering

- Degree of multiple scattering increases with field-of-view
- Eloranta's (1998) model
  - $O(N^m/m!)$ efficient for N points in profile and m-order scattering
  - Too expensive to take to more than 3rd or 4th order in retrieval (not enough)
- *New method:* treats third and higher orders together
  - $O(N^2)$ efficient
  - As accurate as Eloranta when taken to ~6th order
  - 3-4 orders of magnitude faster for N=50 (~ 0.1 ms)





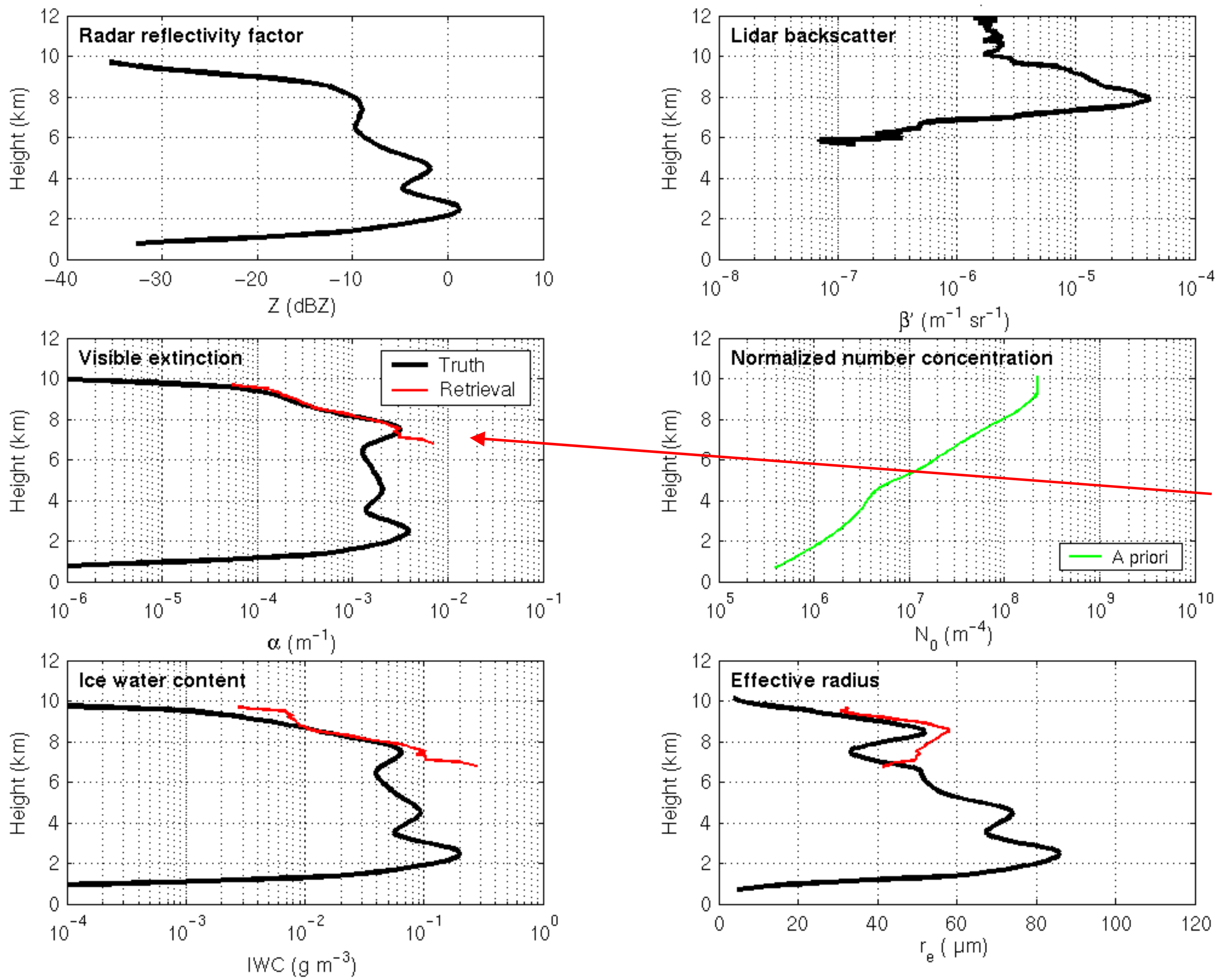
Hogan (Applied Optics, 2006). Code: www.met.rdg.ac.uk/clouds

Ice cloud: non-variational retrieval

Observations

State variables

Derived variables



Aircraft-simulated profiles with noise (from Hogan et al. 2006)

Retrieval is accurate but not perfectly stable where lidar loses signal

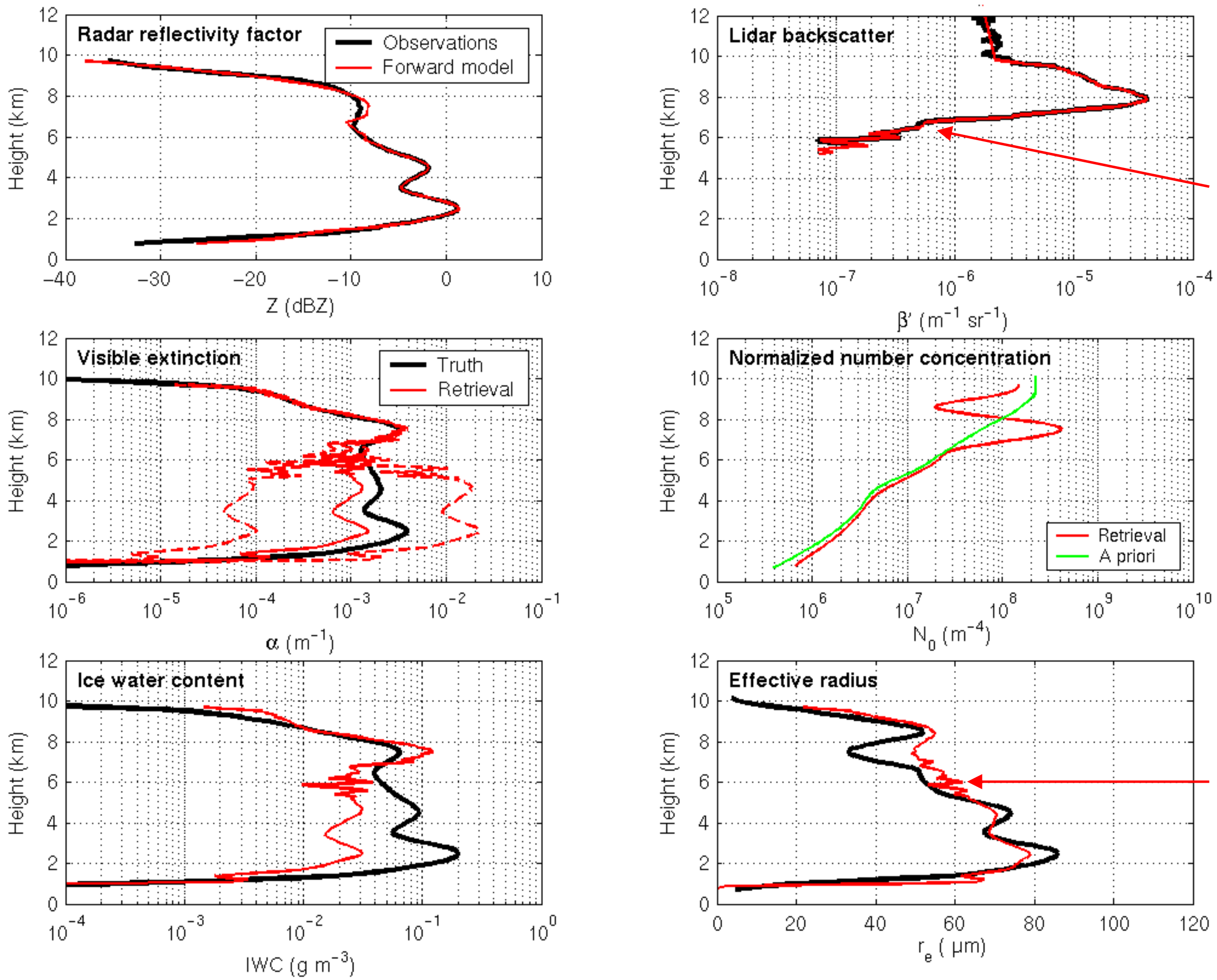
- Existing algorithms can only be applied where both lidar and radar have signal

Variational radar/lidar retrieval

Observations

State variables

Derived variables



Lidar noise matched by retrieval

Noise feeds through to other variables

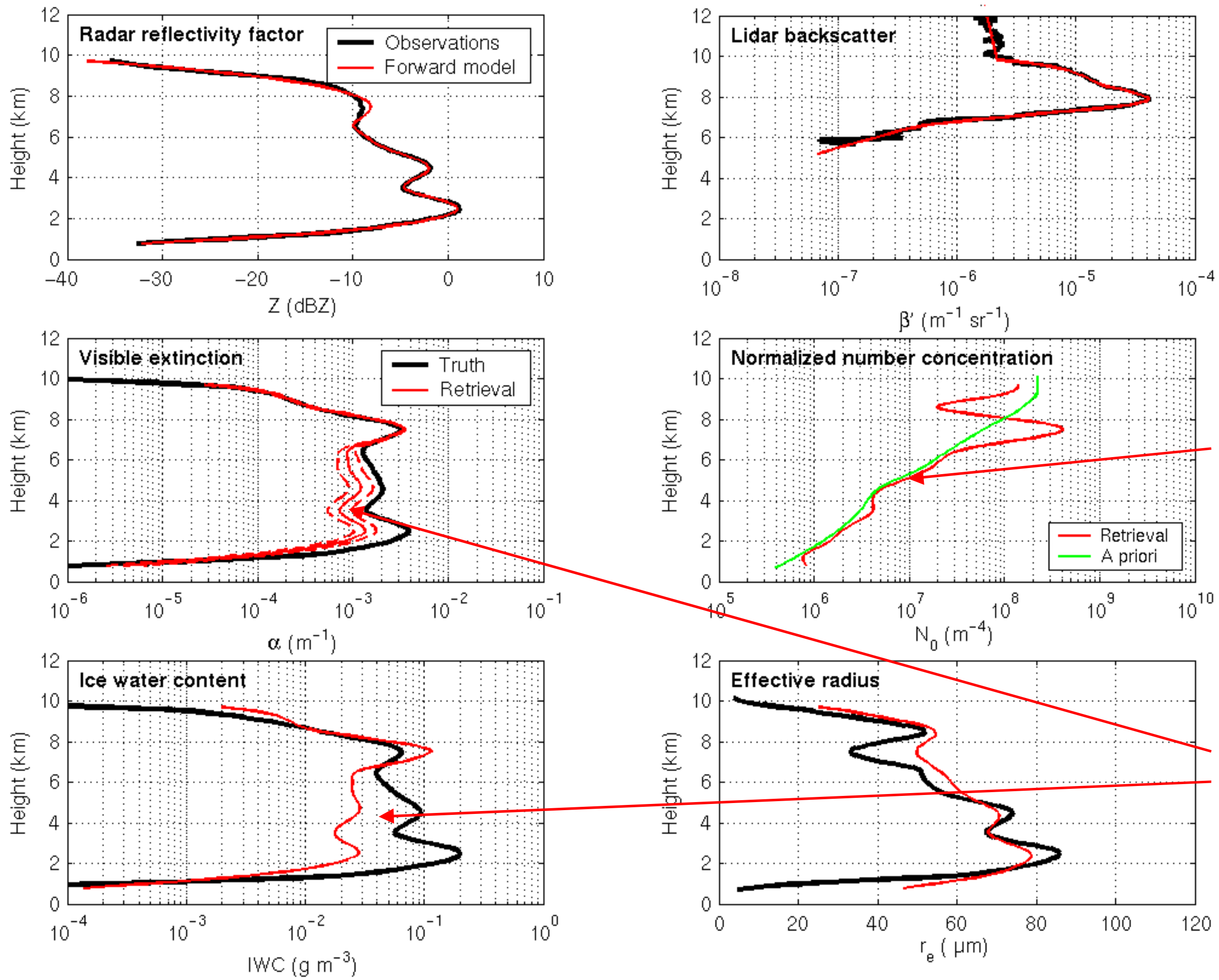
- Noise in lidar backscatter feeds through to retrieved extinction

...add smoothness constraint

Observations

State variables

Derived variables



Retrieval reverts to a-priori N_0

Extinction and IWC too low in radar-only region

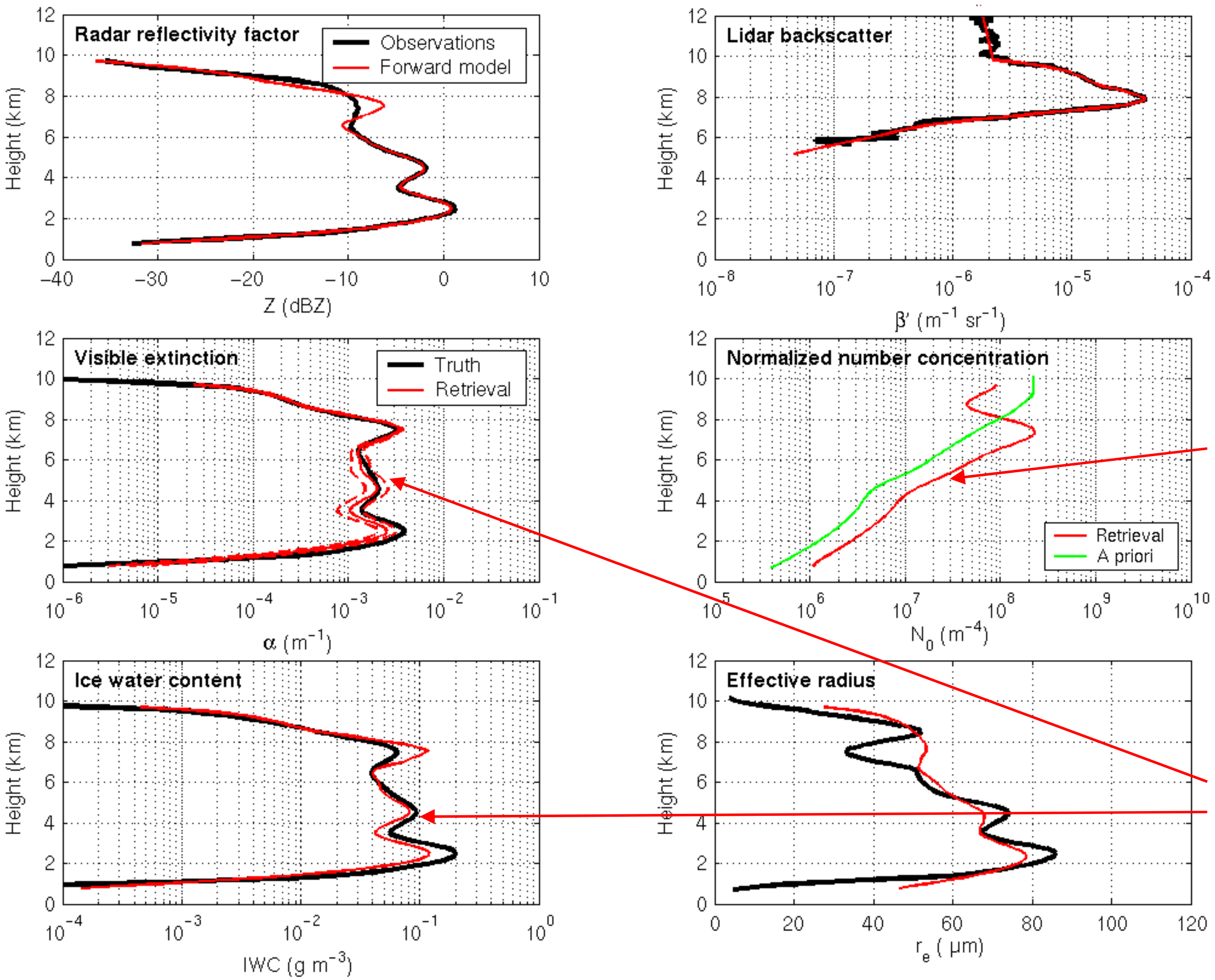
- Smoothness constraint: add a term to cost function to penalize curvature in the solution ($J' = \lambda \Sigma_i\, d^2\alpha_i/dz^2$)

...add a-priori error correlation

Observations

State variables

Derived variables



Vertical correlation of error in N_0

Extinction and IWC now more accurate

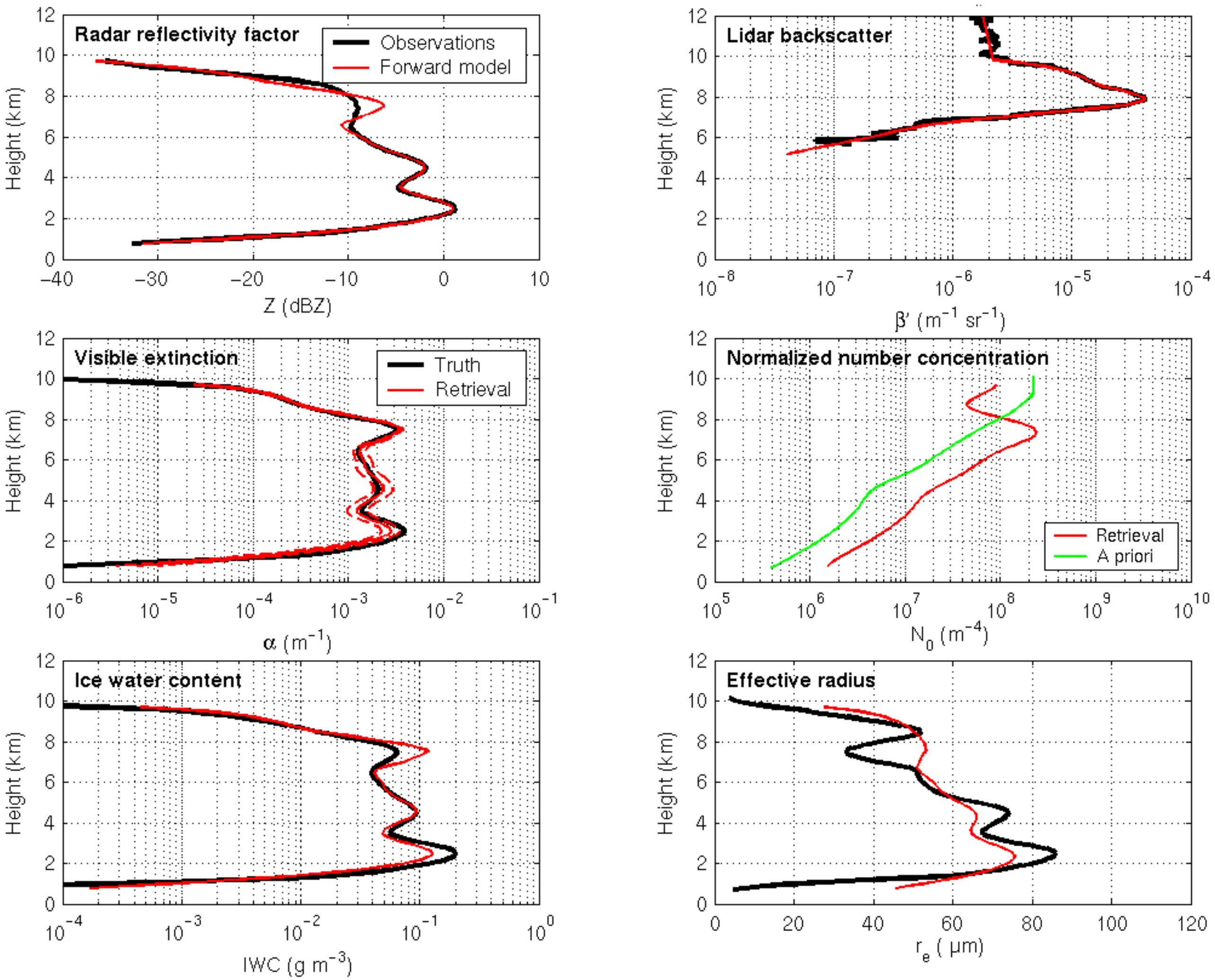
- Use **B** (the a priori error covariance matrix) to smooth the N_0 information in the vertical

...add visible optical depth constraint

Observations

State variables

Derived variables



Slight refinement to extinction and IWC

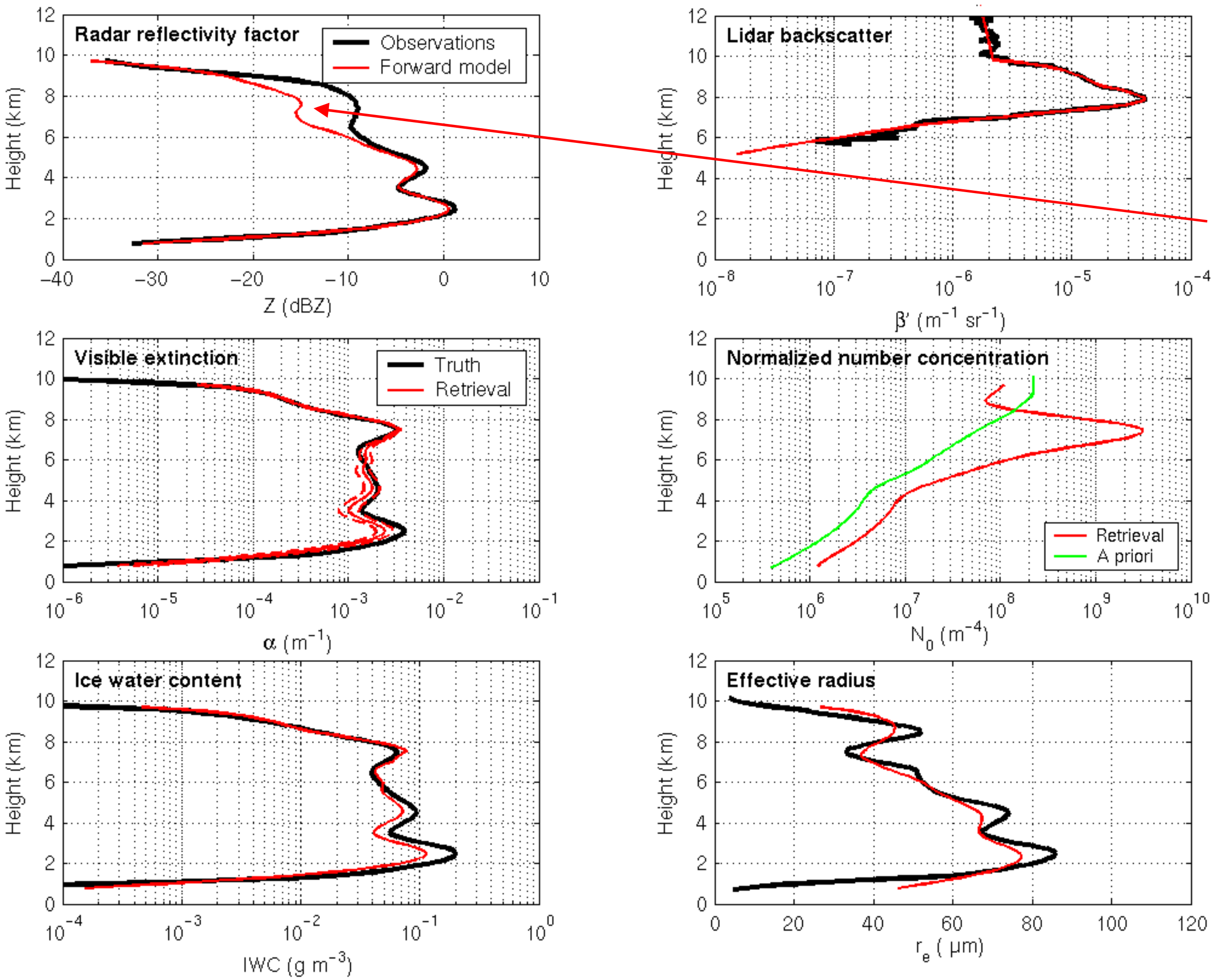
- Integrated extinction now constrained by the MODIS-derived visible optical depth

...add infrared radiances

Observations

State variables

Derived variables



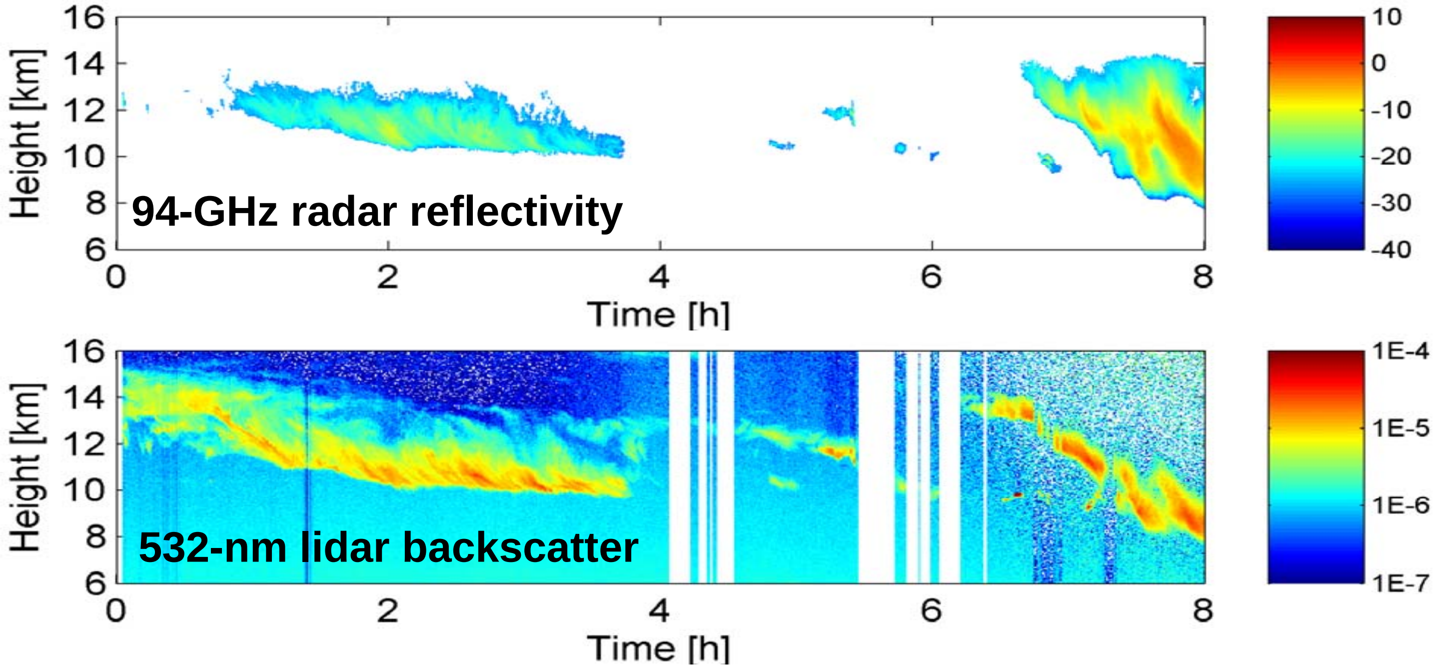
Poorer fit to Z at cloud top: information here now from radiances

- Better fit to IWC and r_e at cloud top

Example from the AMF in Niamey

ARM Mobile Facility observations from Niamey, Niger, 22 July 2006

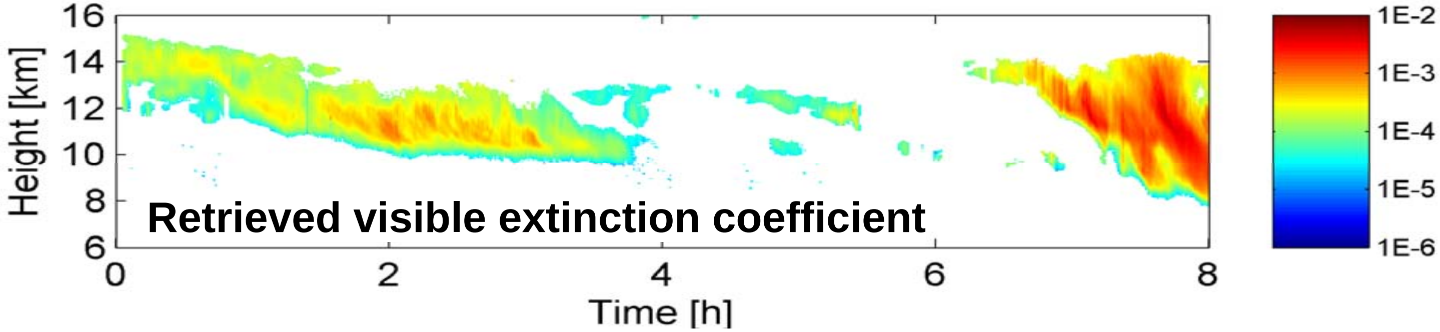
Also use SEVIRI channels at 8.7, 10.8, 12μm

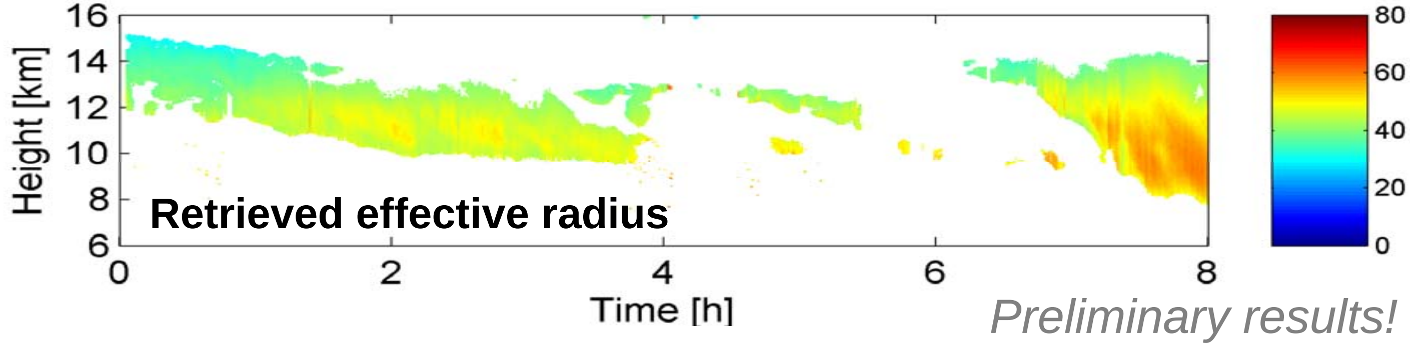


Results

Radar+lidar only

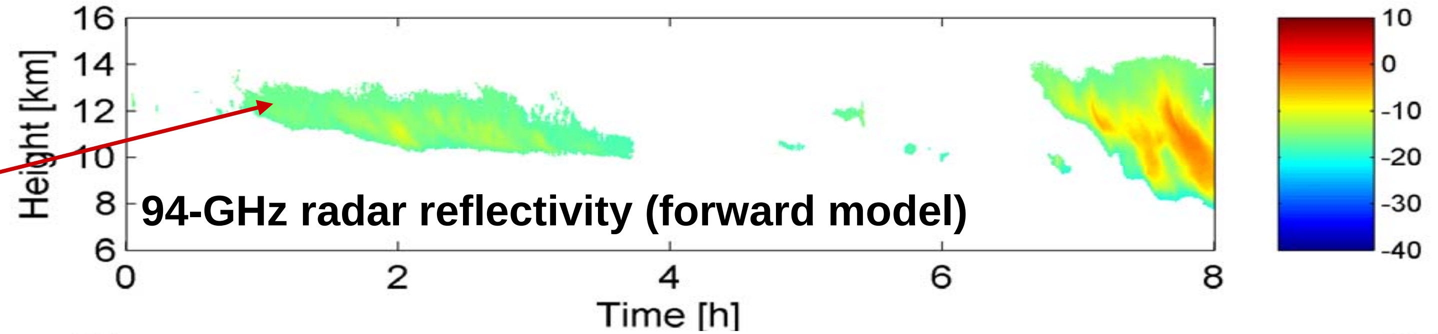
Retrievals in regions where only the radar or lidar detects the cloud

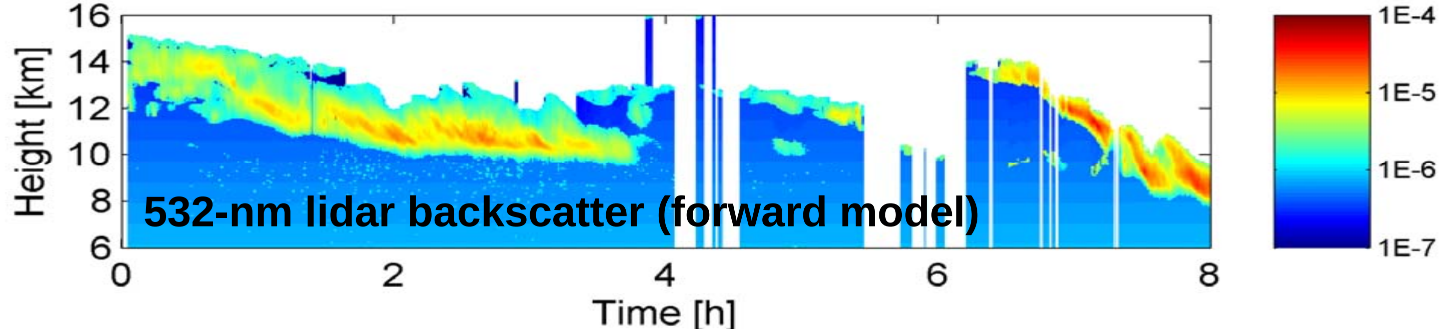




Preliminary results!

By forward modelling radar instrument noise, we use the fact that a cloud is below the instrument sensitivity as a constraint





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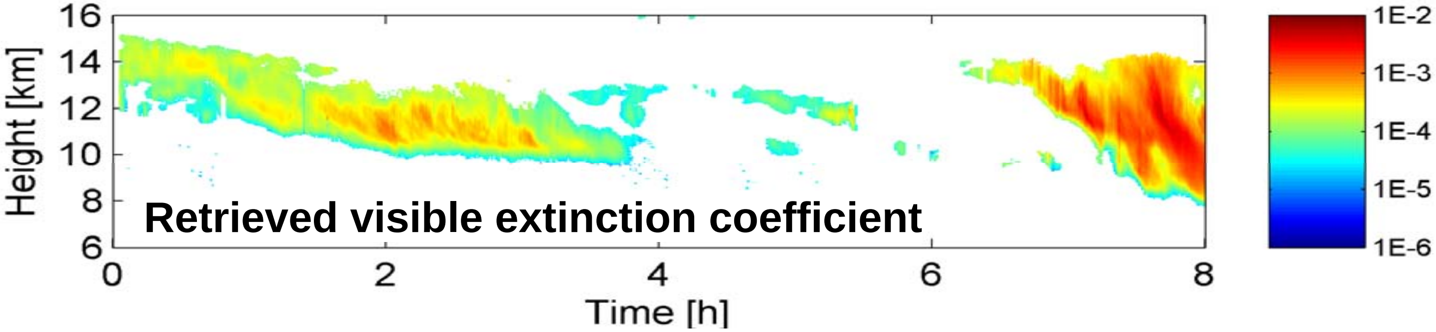
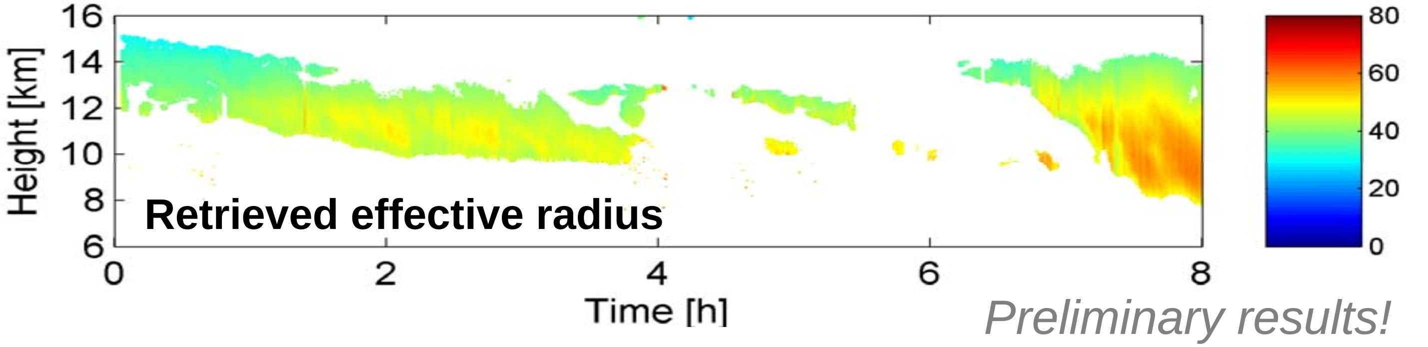
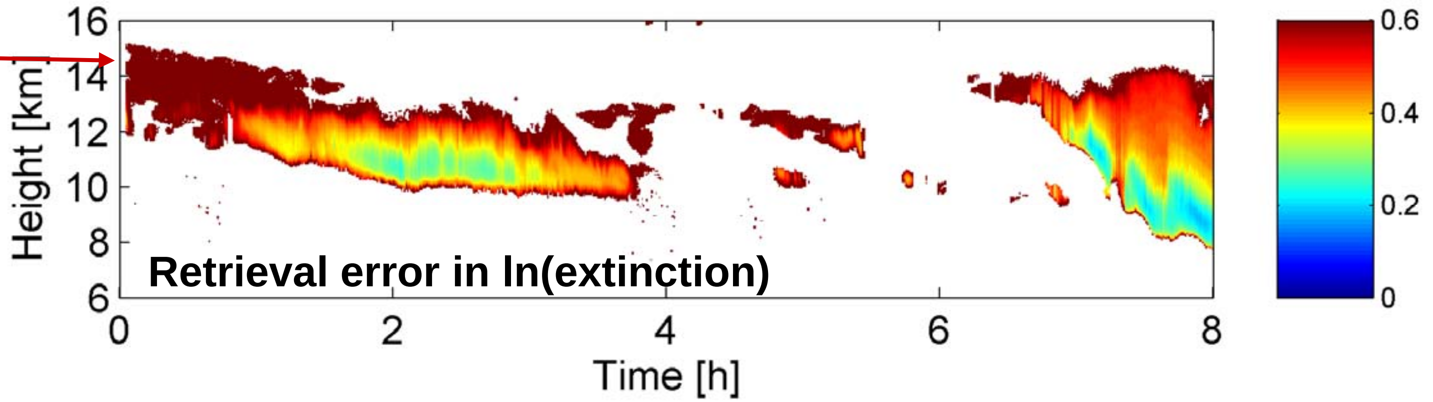




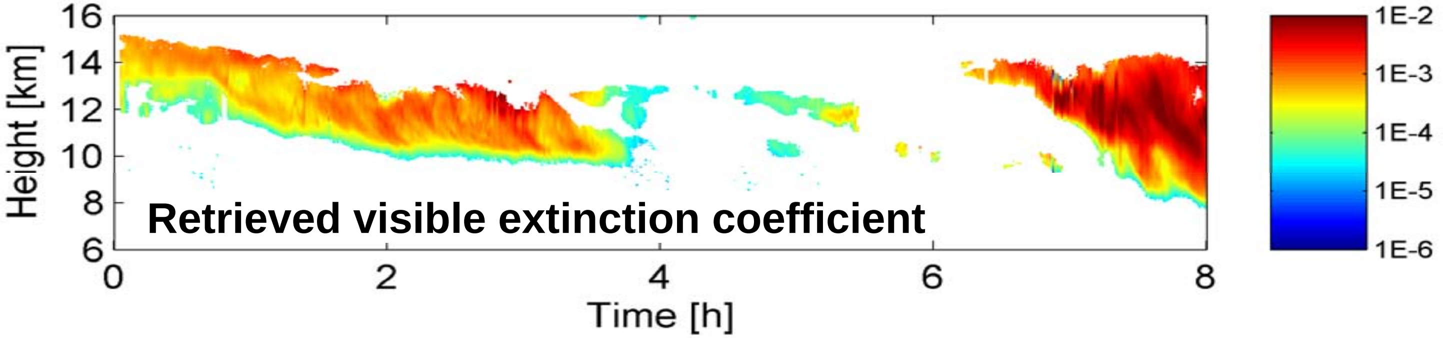
Preliminary results!

Large error where only one instrument detects the cloud

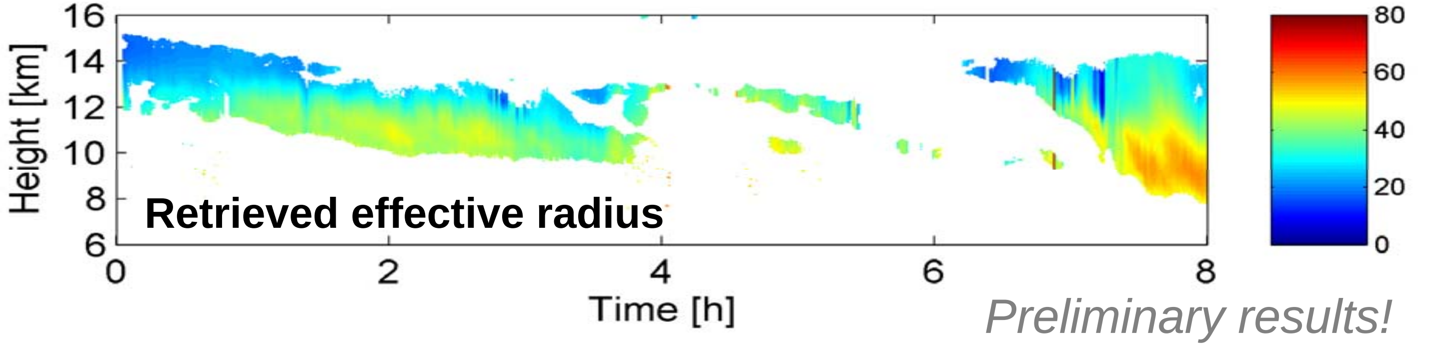


Results

Radar, lidar, SEVERI radiances

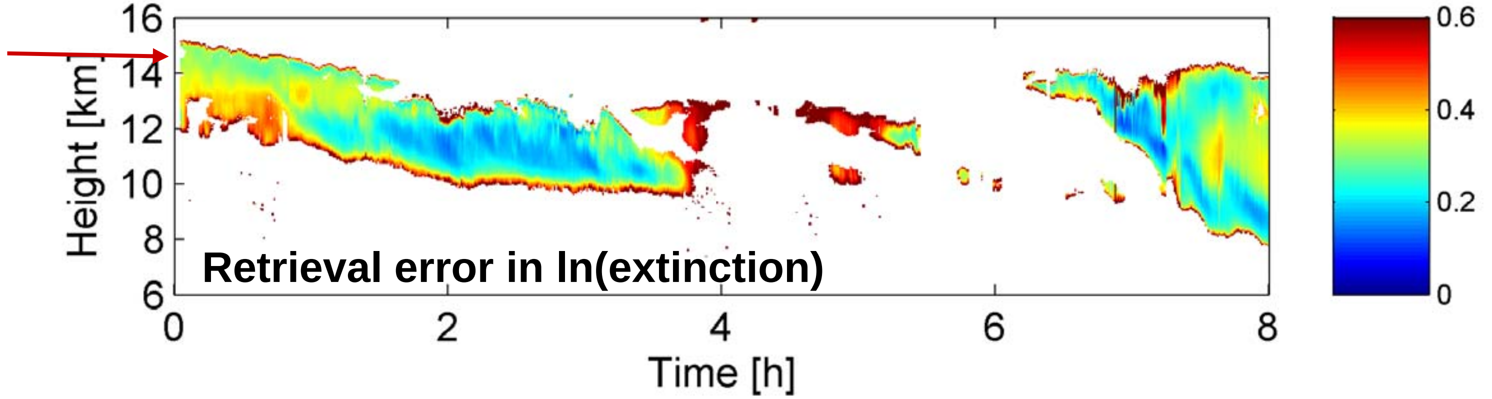


TOA radiances increase the optical depth and decrease particle size near cloud top



Preliminary results!

Cloud-top error is greatly reduced



Future work

- Ongoing Cloudnet-type evaluation of models
  - A large quantity of ARM data already processed
  - Would like to be able to evaluate model clouds in near real time (within a few days) to inform model update cycles
  - ***BUT need to establish continued funding for this activity!***

For quicklooks and further information:

www.cloud-net.org

- Variational retrieval method
  - Apply to more ground-based data
  - Apply to CloudSat/Calipso/MODIS (when Calipso data released)
  - New forward model including wide-angle multiple scattering for both radar and lidar
  - Evaluate ECMWF and Met Office models under CloudSat
  - Could form the basis for radar and lidar assimilation