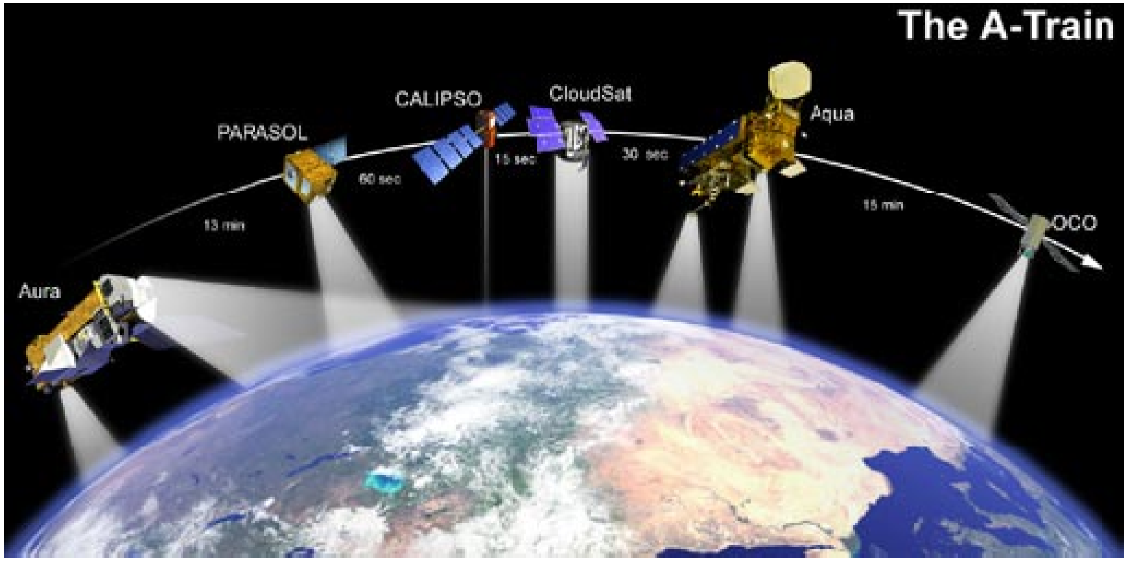
Synergistic cloud retrievals from radar, lidar and radiometers

Robin Hogan
Julien Delanoë, Nicola Pounder, Nicky Chalmers, Thorwald Stein, Anthony Illingworth
University of Reading

Spaceborne radar, lidar and radiometers



The A-Train

- CloudSat 94-GHz radar (launch 2006)
- Calipso 532/1064-nm depol. lidar
- MODIS multi-wavelength radiometer
- CERES broad-band radiometer
- 700-km orbit
- NASA

EarthCARE (launch 2013)

- 94-GHz Doppler radar
- 355-nm HSRL/depol. lidar
- Multispectral imager
- Broad-band radiometer
- 400-km orbit (more sensitive)
- ESA+JAXA

Towards assimilation of cloud radar and lidar

- Before we assimilate radar and lidar into NWP models it is helpful to first develop variational cloud retrievals
  - Need to develop forward models and their adjoints: used by both
  - Refine microphysical and a-priori assumptions
  - Get an understanding of information content from observations
- Progress in our development of synergistic radar-lidar-radiometer retrievals of clouds:
  - Variational retrieval of ice clouds applied to ground-based radar-lidar and the SEVIRI radiometer (Delanoe and Hogan 2008)
  - Applied to >2 years of A-Train data (Delanoe and Hogan 2010)
  - Fast forward models for radar and lidar subject to multiple scattering (Hogan 2008, 2009; Hogan and Battaglia 2009)
  - With ESA & NERC funding, currently developing a "unified" algorithm for retrieving cloud, aerosol and precipitation properties from the EarthCARE radar, lidar and radiometers; will apply to other platforms

Overview

- Retrieval framework
- Minimization techniques: Gauss-Newton vs. Gradient Descent
- Results from CloudSat-Calipso ice-cloud retrieval
- Components of unified retrieval: state variables and forward models
- Multiple scattering radar and lidar forward model
- Multiple field-of-view lidar retrieval
- First results from prototype unified retrieval

Retrieval framework

Ingredients developed before

In progress

Not yet developed

1. New ray of data: define state vector

Use classification to specify variables describing each species at each gate

Ice: extinction coefficient , N_0', lidar extinction-to-backscatter ratio

Liquid: extinction coefficient and number concentration

Rain: rain rate and mean drop diameter

Aerosol: extinction coefficient, particle size and lidar ratio

2. Convert state vector to radar-lidar resolution

Often the state vector will contain a low resolution description of the profile

3. Forward model

3a. Radar model

Including surface return and multiple scattering

3b. Lidar model

Including HSRL channels and multiple scattering

3c. Radiance model

Solar and IR channels

4. Compare to observations

Check for convergence

Not converged

5. Convert Jacobian/adjoint to state-vector resolution

Initially will be at the radar-lidar resolution

6. Iteration method

Derive a new state vector

Either Gauss-Newton or quasi-Newton scheme

Converged

7. Calculate retrieval error

Error covariances and averaging kernel

Proceed to next ray of data

Minimizing the cost function

$$J = \frac{1}{2}\left[\mathbf{y} - H(\mathbf{x})\right]^T \mathbf{R}^{-1}\left[\mathbf{y} - H(\mathbf{x})\right] + \frac{1}{2}\left(\mathbf{x} - \mathbf{a}\right)^T \mathbf{B}^{-1}\left(\mathbf{x} - \mathbf{a}\right)$$

Gradient of cost function (a vector)

$$\nabla_{\mathbf{x}} J = -\mathbf{H}^T \mathbf{R}^{-1}\left[\mathbf{y} - H(\mathbf{x})\right] + \mathbf{B}^{-1}\left(\mathbf{x} - \mathbf{a}\right)$$

and 2nd derivative (the Hessian matrix):

$$\nabla_{\mathbf{x}}^2 J = \mathbf{H}^T \mathbf{R}^{-1}\mathbf{H} + \mathbf{B}^{-1}$$

Gauss-Newton method

$$\mathbf{x}_{i+1} = \mathbf{x}_i - \left(\nabla_{\mathbf{x}}^2 J\right)^{-1} \nabla_{\mathbf{x}} J$$

- Rapid convergence (instant for linear problems)
- Get solution error covariance "for free" at the end
- Levenberg-Marquardt is a small modification to ensure convergence
- Need the Jacobian matrix **H** of every forward model: can be expensive for larger problems as forward model may need to be rerun with each element of the state vector perturbed

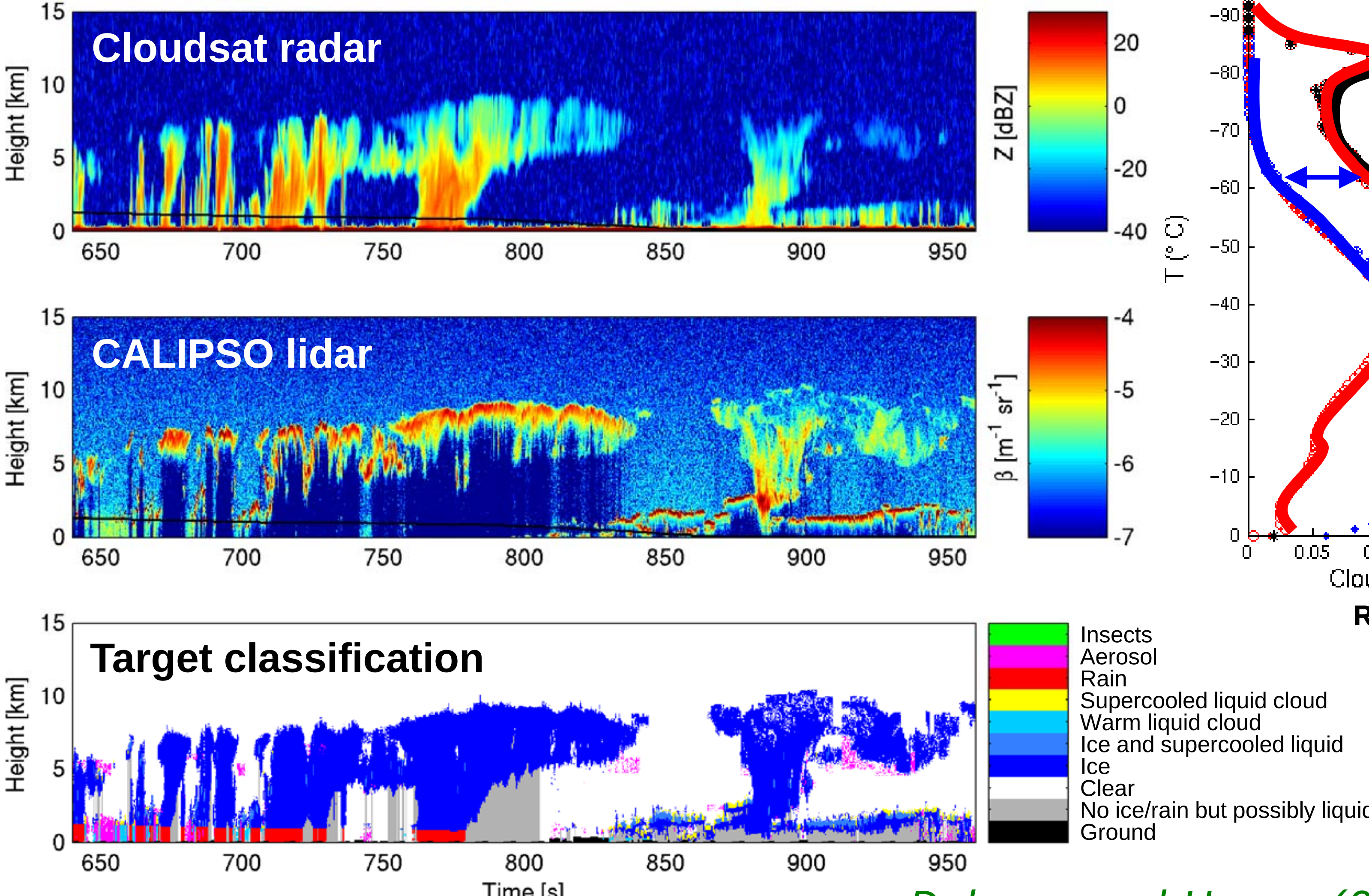
Gradient Descent methods

$$\mathbf{x}_{i+1} = \mathbf{x}_i - \mathbf{A}\nabla_{\mathbf{x}} J$$

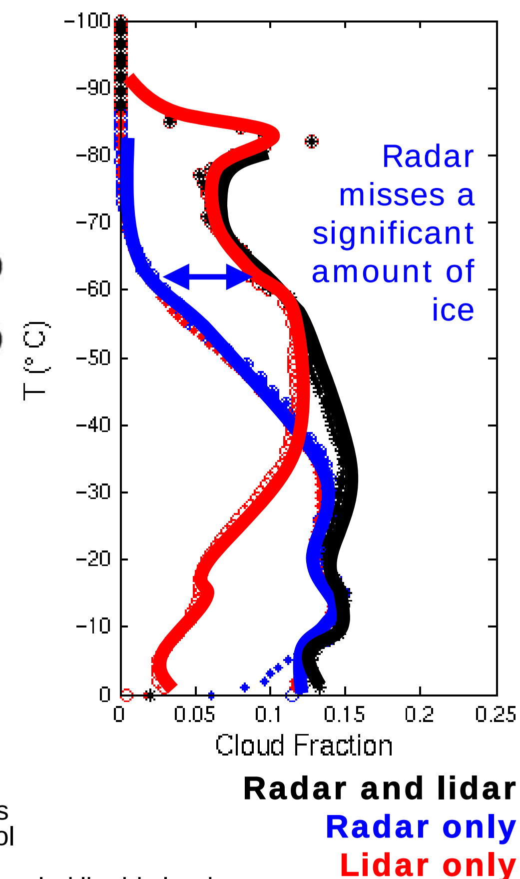
- Fast adjoint method to calculate $\nabla_{\mathbf{x}} J$ means don't need to calculate Jacobian
- Disadvantage: more iterations needed since we don't know curvature of $J(\mathbf{x})$
- Quasi-Newton method to get the search direction (e.g. L-BFGS used by ECMWF): builds up an approximate inverse Hessian **A** for improved convergence
- Scales well for large **x**
- Poorer estimate of the error at the end

Combining radar and lidar…

- Variational ice cloud retrieval using Gauss-Newton method

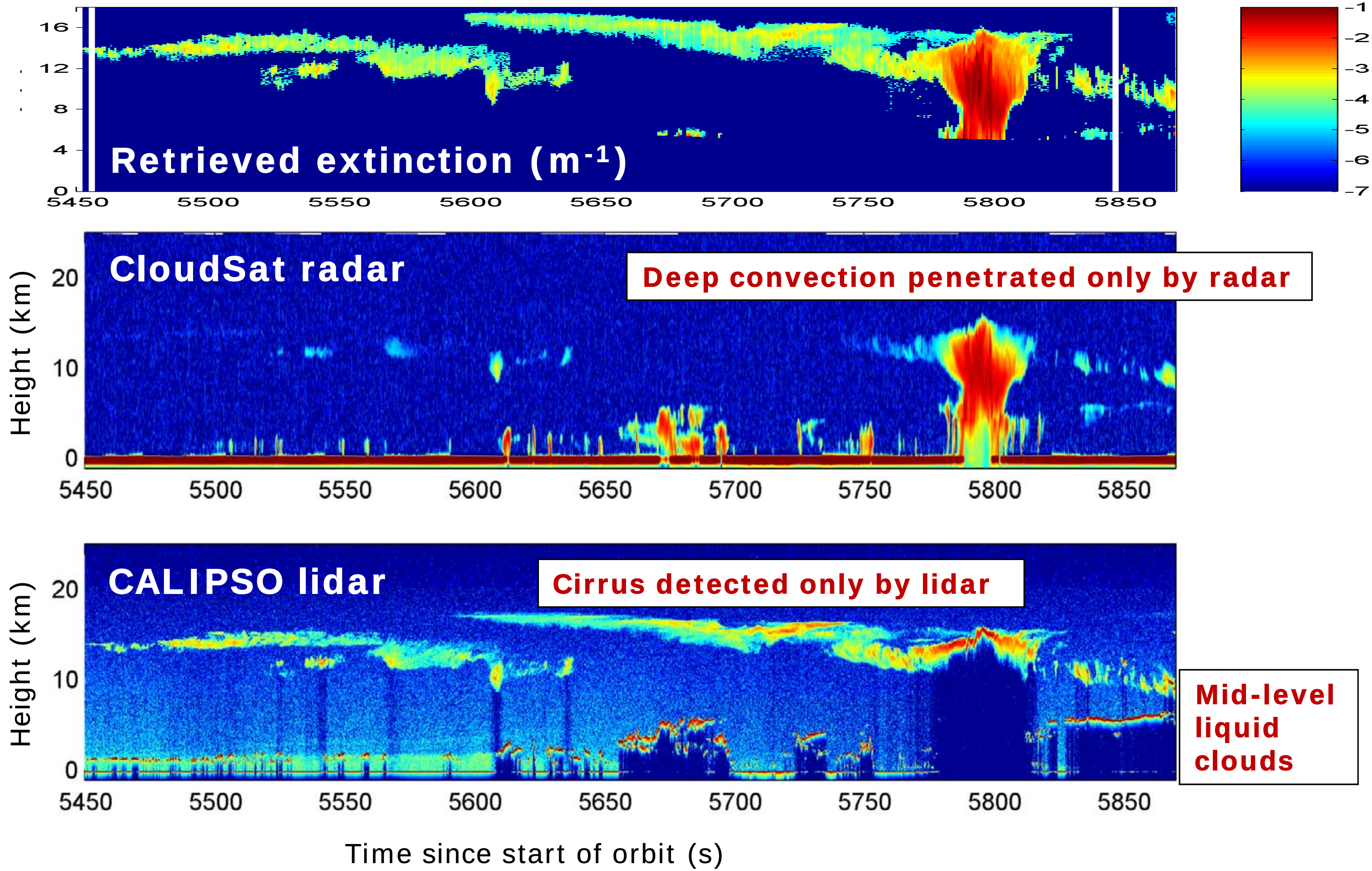


Global-mean cloud fraction



Delanoe and Hogan (2008, 2010)

Example of mid-Pacific convection

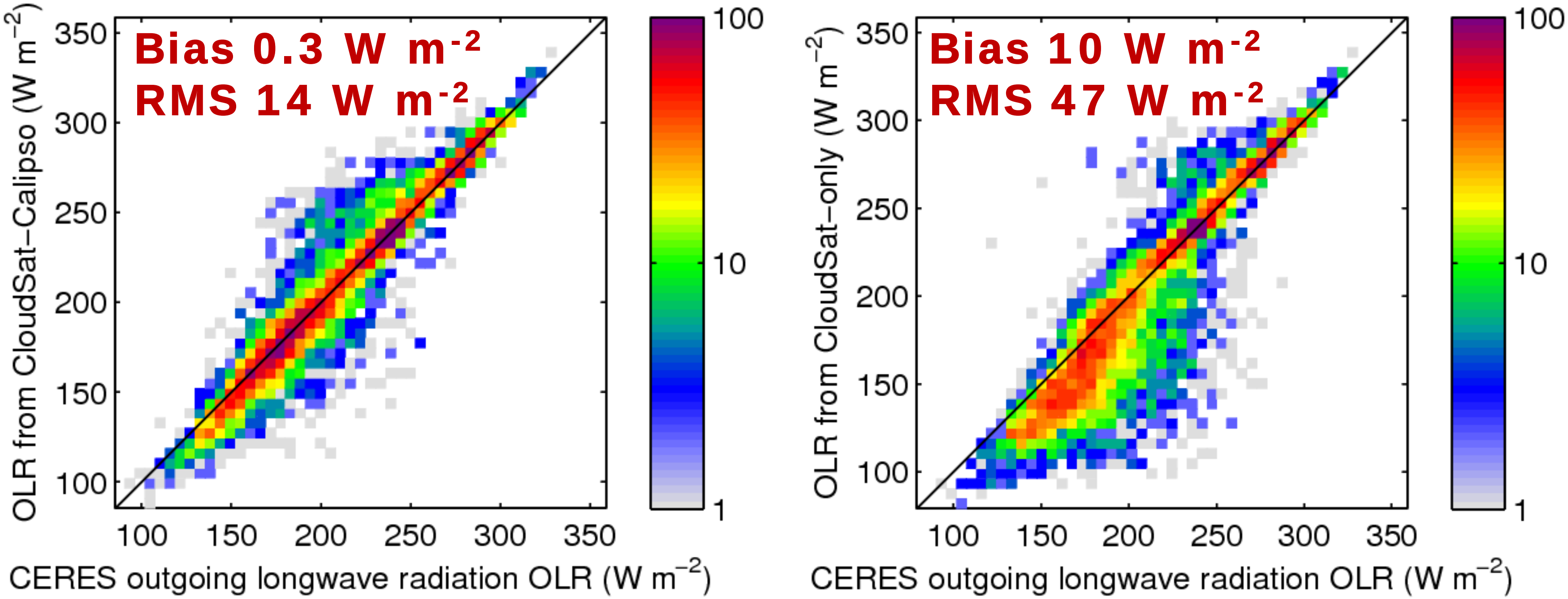


Evaluation using CERES longwave flux

- Retrieved profiles containing only ice are used with Edwards-Slingo radiation code to predict outgoing longwave radiation, and compared to CERES

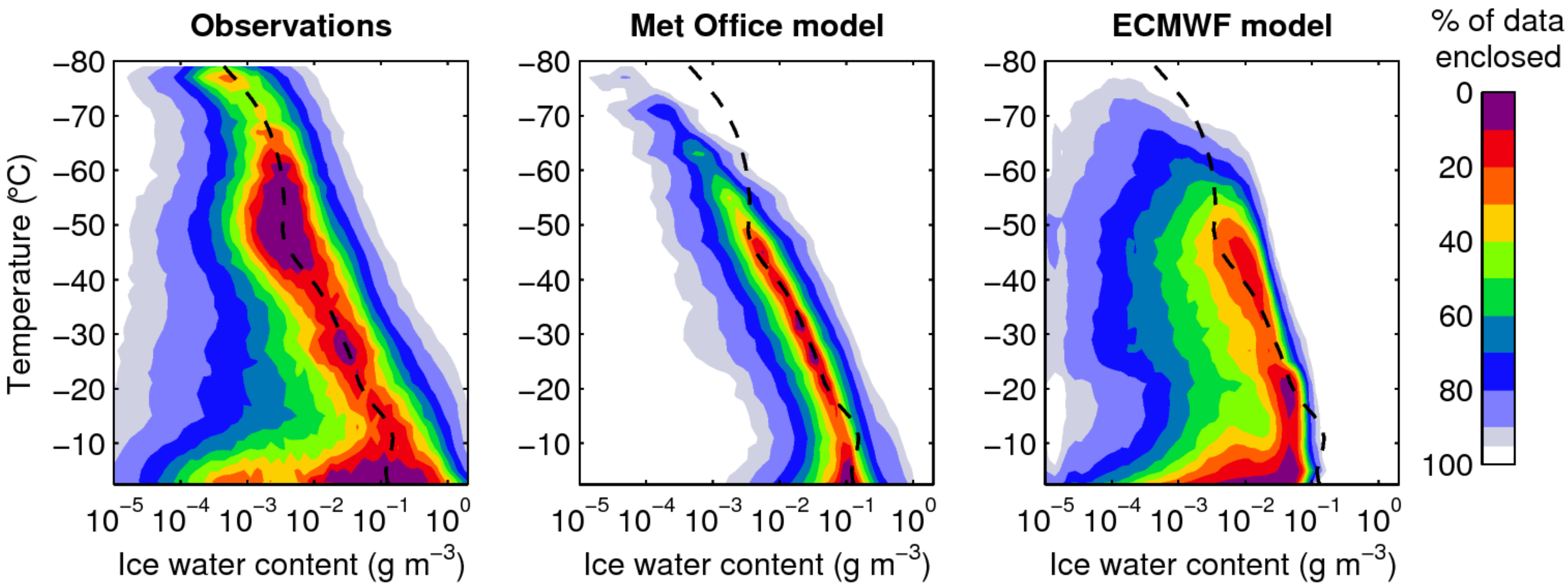
CloudSat-Calipso retrieval (Delanoe & Hogan 2010)

CloudSat-only retrieval (Hogan et al. 2006)



Nicky Chalmers

Evaluation of models



- Comparison of the IWC distribution versus temperature for July 2006
- Met Office model has too little spread
- ECMWF model lacks high IWC values due to snow threshold
- New ECMWF model version remedies this problem

Delanoe et al. (2010)

Unified algorithm: state variables

- Proposed list of retrieved variables held in the state vector **x**

State variable	***Representation with height / constraint***	***A-priori***
Ice clouds and snow		
Visible extinction coefficient	One variable per pixel with smoothness constraint	None
Number conc. parameter	Cubic spline basis functions with vertical correlation	Temperature dependent
Lidar extinction-to-backscatter ratio	Cubic spline basis functions	20 sr
Riming factor	Likely a single value per profile	1
Liquid clouds		
Liquid water content	One variable per pixel but with gradient constraint	None
Droplet number concentration	One value per liquid layer	Temperature dependent
Rain		
Rain rate	Cubic spline basis functions with flatness constraint	None
Normalized number conc. N_w	One value per profile	Dependent on whether from melting ice or coallescence
Melting-layer thickness scaling factor	One value per profile	1
Aerosols		
Extinction coefficient	One variable per pixel with smoothness constraint	None
Lidar extinction-to-backscatter ratio	One value per aerosol layer identified	Climatological type depending on region

Ice clouds follows Delanoe & Hogan (2008); *Snow & riming in convective clouds needs to be added*

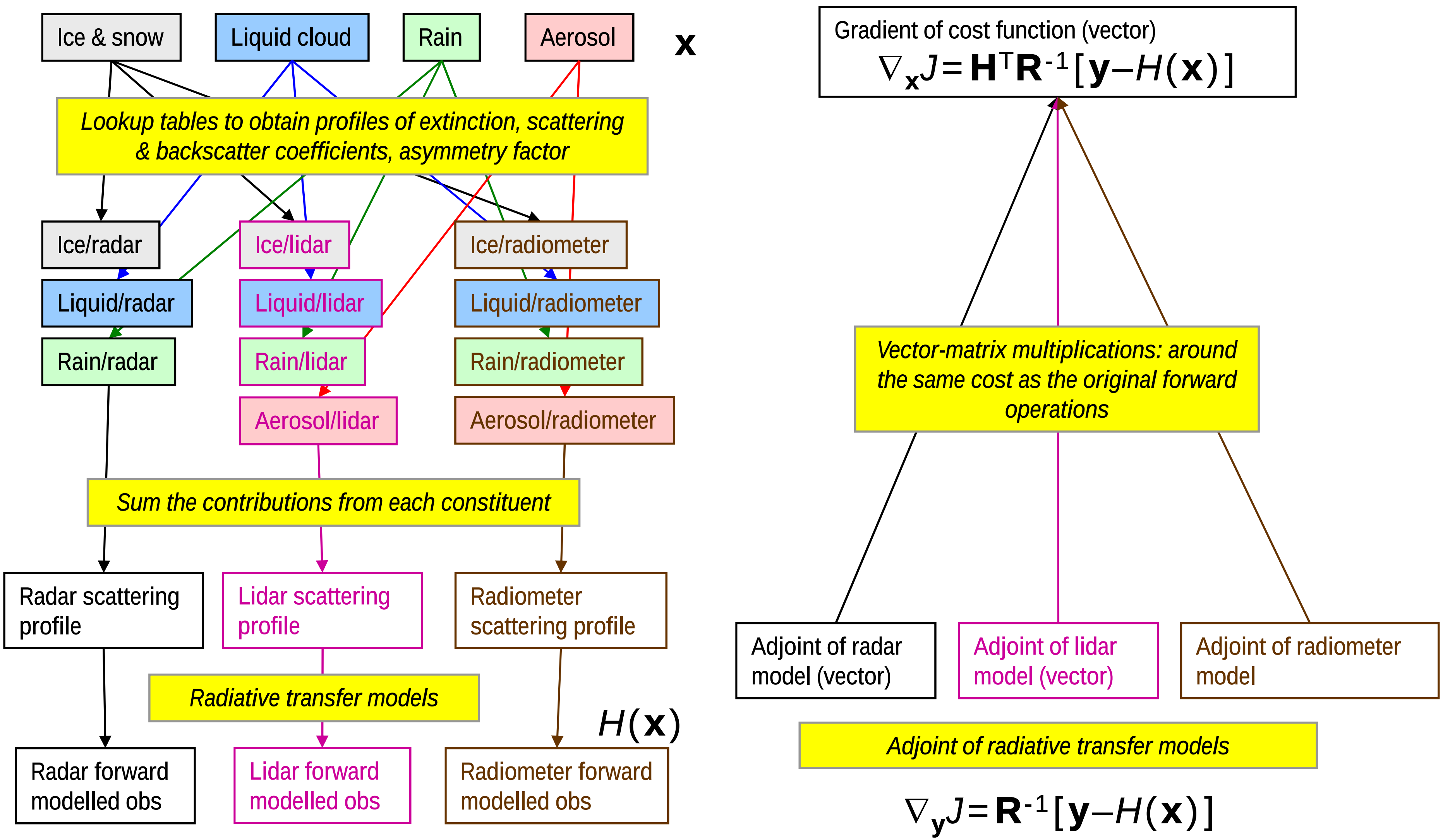
Liquid clouds currently being tackled

Basic rain to be added shortly; *Full representation later*

Basic aerosols to be added shortly; *Full representation via collaboration?*

Forward model components

- From state vector **x** to forward modelled observations $H(\mathbf{x})$...



Scattering models

- First part of a forward model is the *scattering and fall-speed model*
  - Same methods typically used for all radiometer and lidar channels
  - Radar and Doppler model uses another set of methods

Particle type	***Radar (3.2 mm)***	***Radar Doppler***	***Thermal IR, Solar, UV***
Aerosol	*Aerosol not detected by radar*	*Aerosol not detected by radar*	Mie theory, Highwood refractive index
Liquid droplets	Mie theory	Beard (1976)	Mie theory
Rain drops	T-matrix: Brandes et al. (2002) shapes	Beard (1976)	Mie theory
Ice cloud particles	T-matrix (Hogan et al. 2010)	Westbrook & Heymsfield	Baran (2004)
Graupel and hail	Mie theory	**TBD**	Mie theory
Melting ice	Wu & Wang (1991)	**TBD**	Mie theory

- Graupel and melting ice still uncertain

Radiative transfer forward models

- Computational cost can scale with number of points describing vertical profile N; we can cope with an N^2 dependence but not N^3

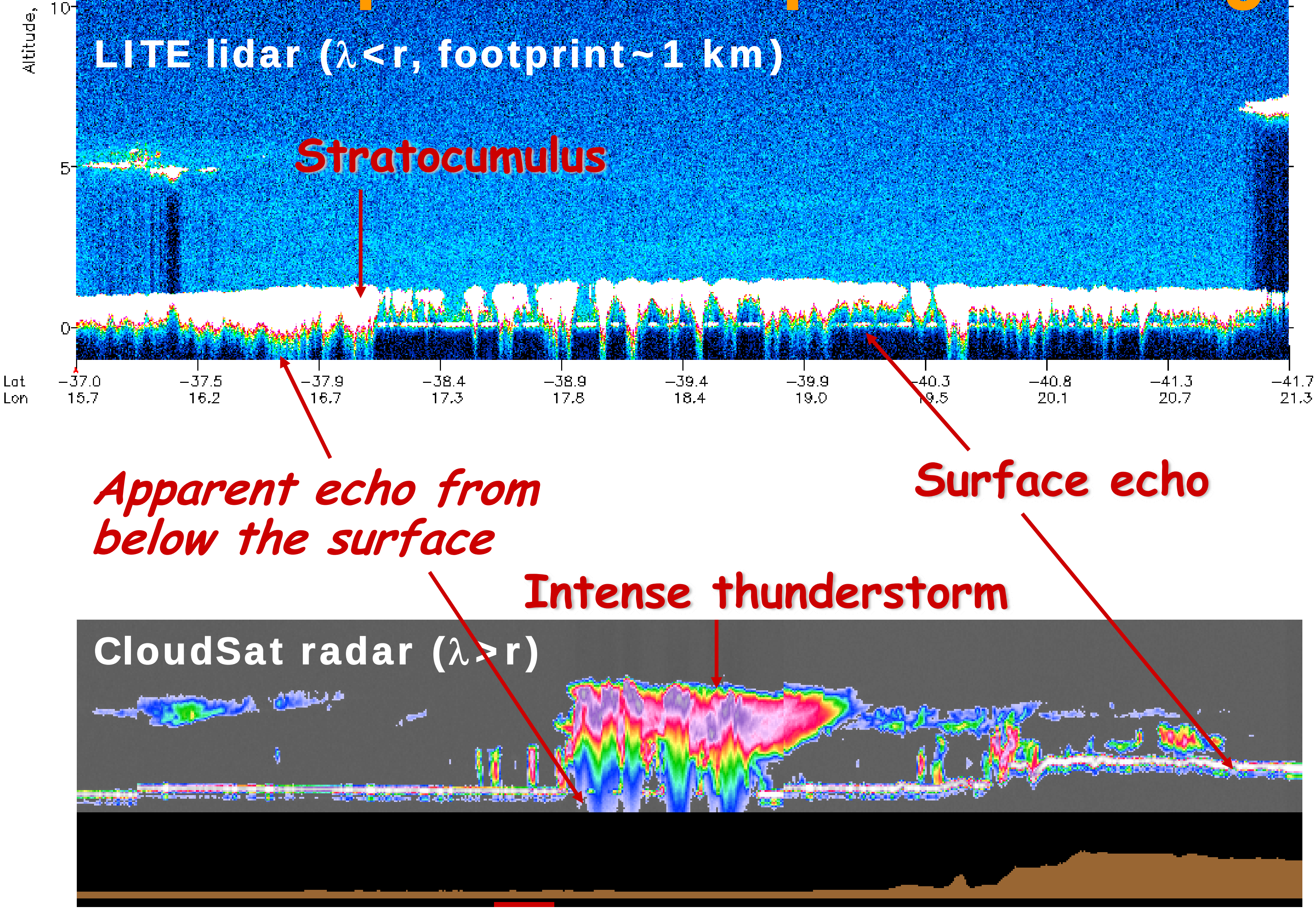
Radar/lidar model	*Applications*	*Speed*	*Jacobian*	*Adjoint*
Single scattering: $\beta'=\beta \exp(-2\tau)$	Radar & lidar, no multiple scattering	N	N^2	N
Platt's approximation $\beta'=\beta \exp(-2\eta\tau)$	Lidar, ice only, crude multiple scattering	N	N^2	N
Photon Variance-Covariance (PVC) method (Hogan 2006, 2008)	Lidar, ice only, small-angle multiple scattering	N or N^2	N^2	N
Time-Dependent Two-Stream (TDTS) method (Hogan and Battaglia 2008)	Lidar & radar, wide-angle multiple scattering	N^2	N^3	N^2
Depolarization capability for TDTS	Lidar & radar depol with multiple scattering	N^2		N^2

- Lidar uses PVC+TDTS (N^2), radar uses single-scattering+TDTS (N^2)
- Jacobian of TDTS is too expensive: N^3
- We have recently coded adjoint of multiple scattering models
- Future work: depolarization forward model with multiple scattering

Radiometer model	*Applications*	*Speed*	*Jacobian*	*Adjoint*
RTTOV (used at ECMWF & Met Office)	Infrared and microwave radiances	N		N
Two-stream source function technique (e.g. Delanoe & Hogan 2008)	Infrared radiances	N	N^2	
LIDORT	Solar radiances	N	N^2	N

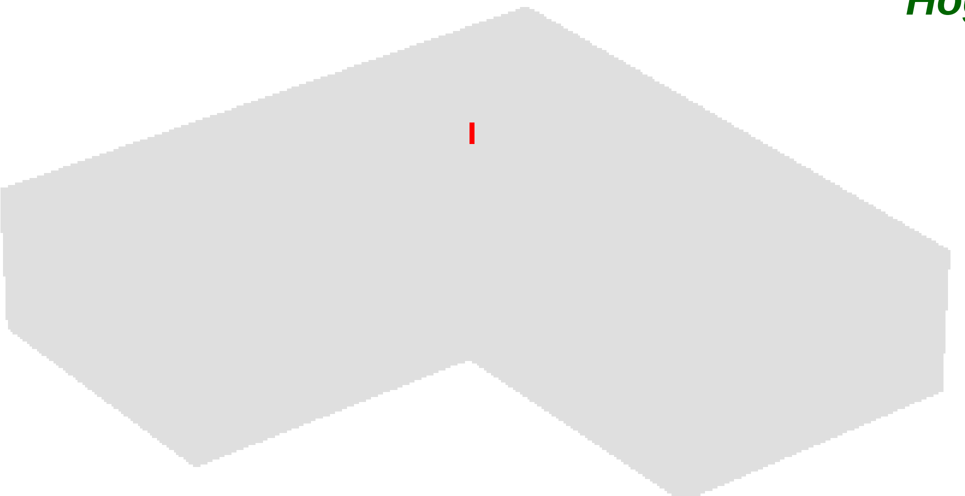
- Infrared will probably use RTTOV, solar radiances will use LIDORT
- Both currently being tested by Julien Delanoe

Examples of multiple scattering



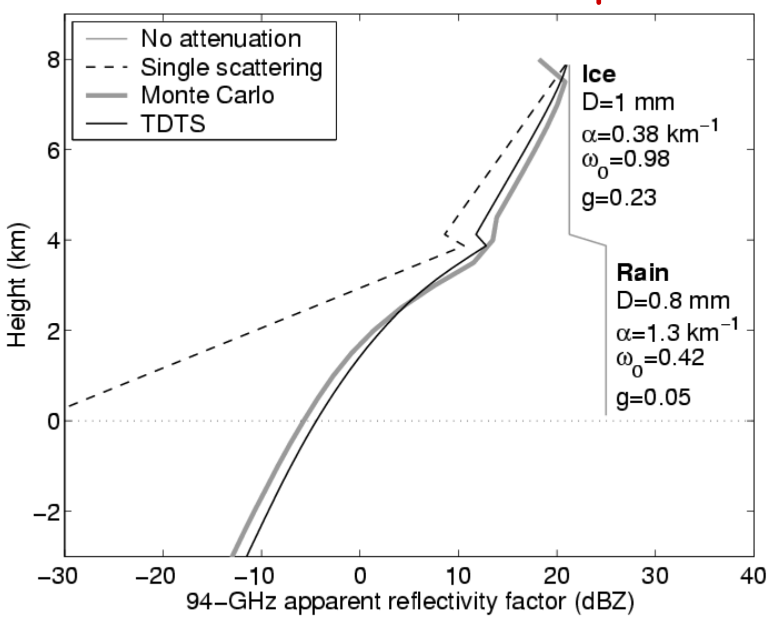
Fast multiple scattering forward model

Hogan and Battaglia (J. Atmos. Sci. 2008)

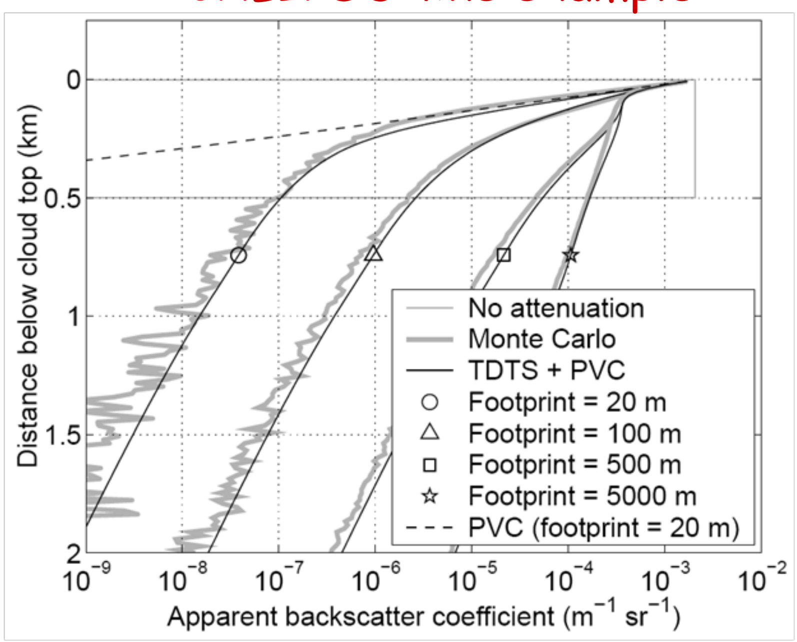


- New method uses the *time-dependent two-stream approximation*
- Agrees with Monte Carlo but ~10^7 times faster (~3 ms)
- Added to CloudSat simulator

CloudSat-like example

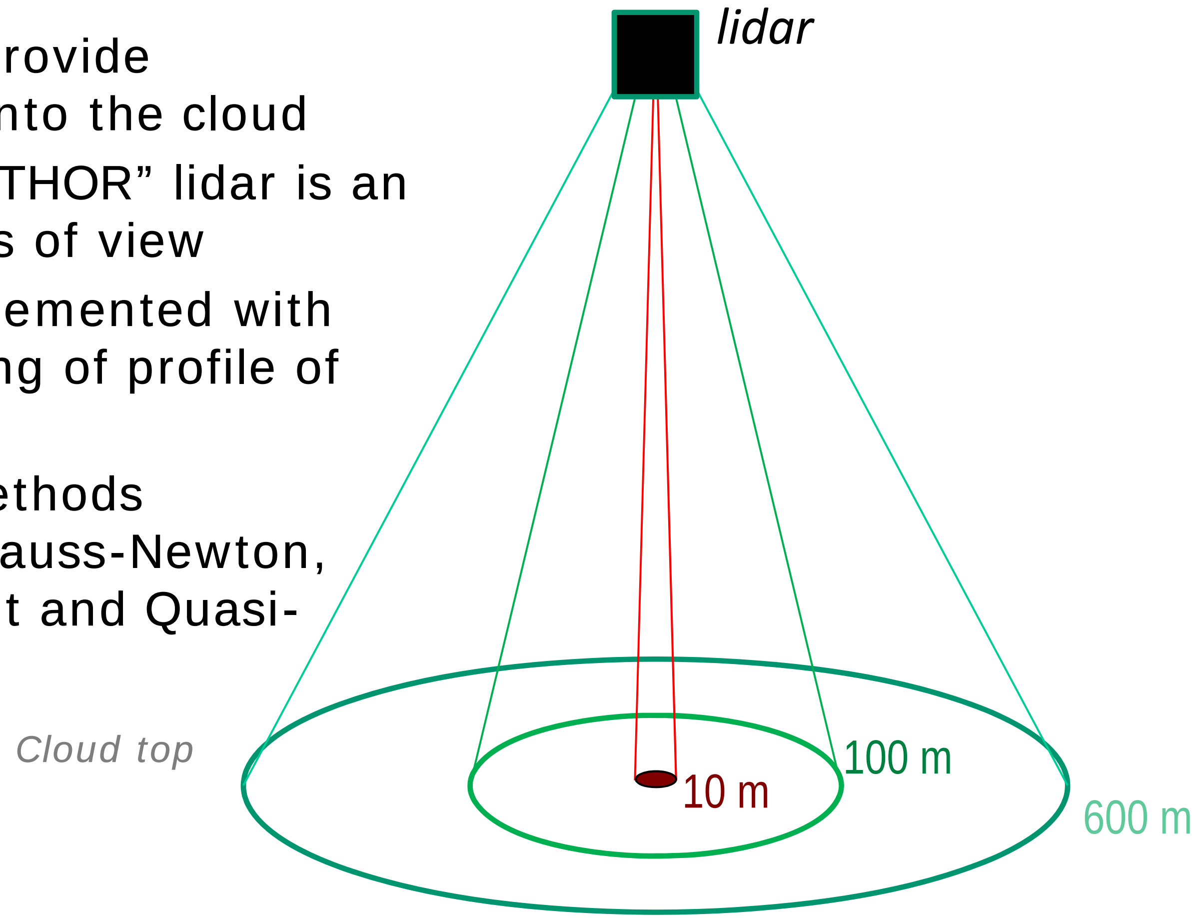


CALIPSO-like example



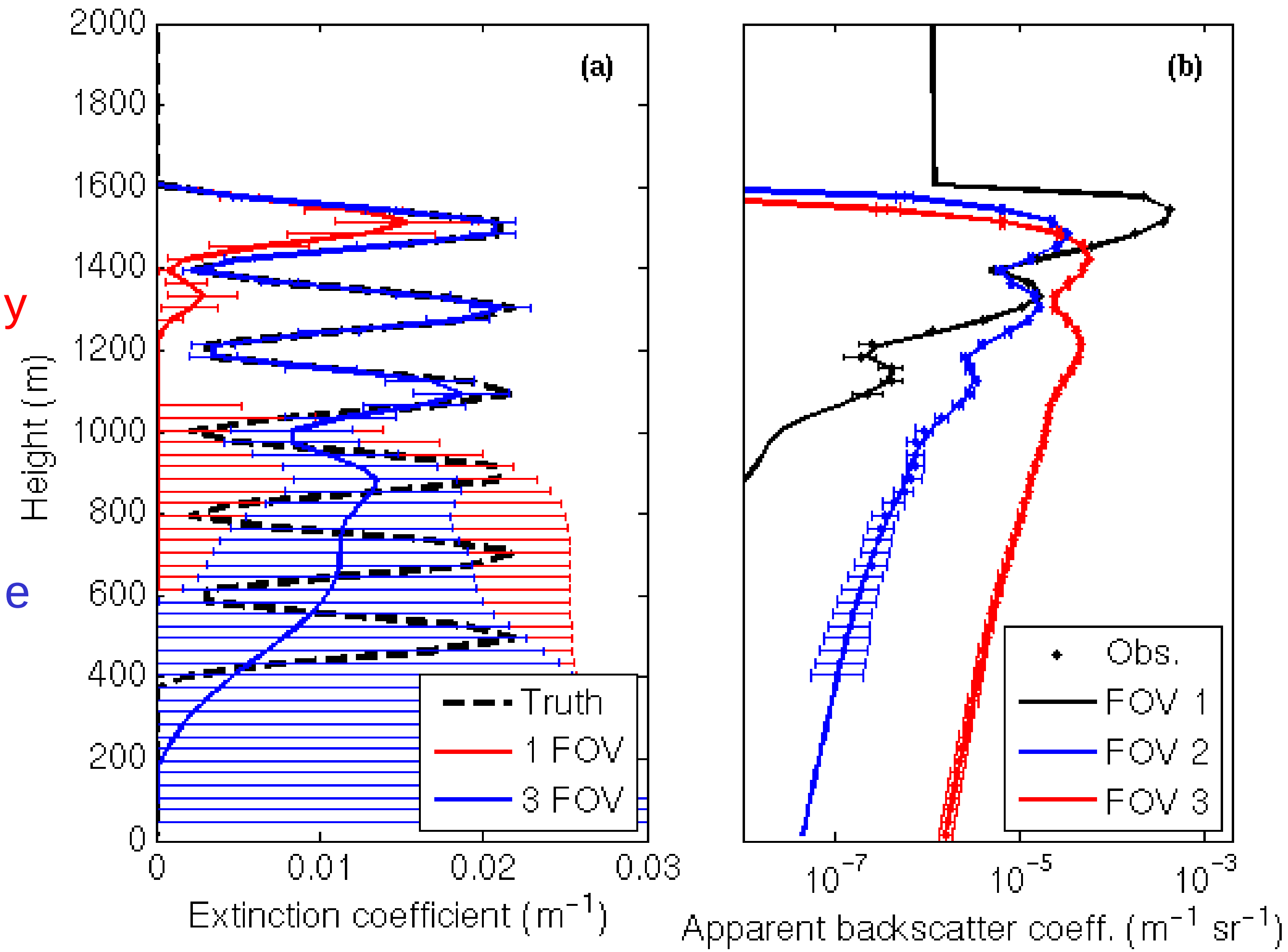
Multiple field-of-view lidar retrieval

- To test multiple scattering model in a retrieval, and its adjoint, consider a multiple field-of-view lidar observing a liquid cloud
- Wide fields of view provide information deeper into the cloud
- The NASA airborne “THOR” lidar is an example with 8 fields of view
- Simple retrieval implemented with state vector consisting of profile of extinction coefficient
- Different solution methods implemented, e.g. Gauss-Newton, Levenberg-Marquardt and Quasi-Newton (L-BFGS)



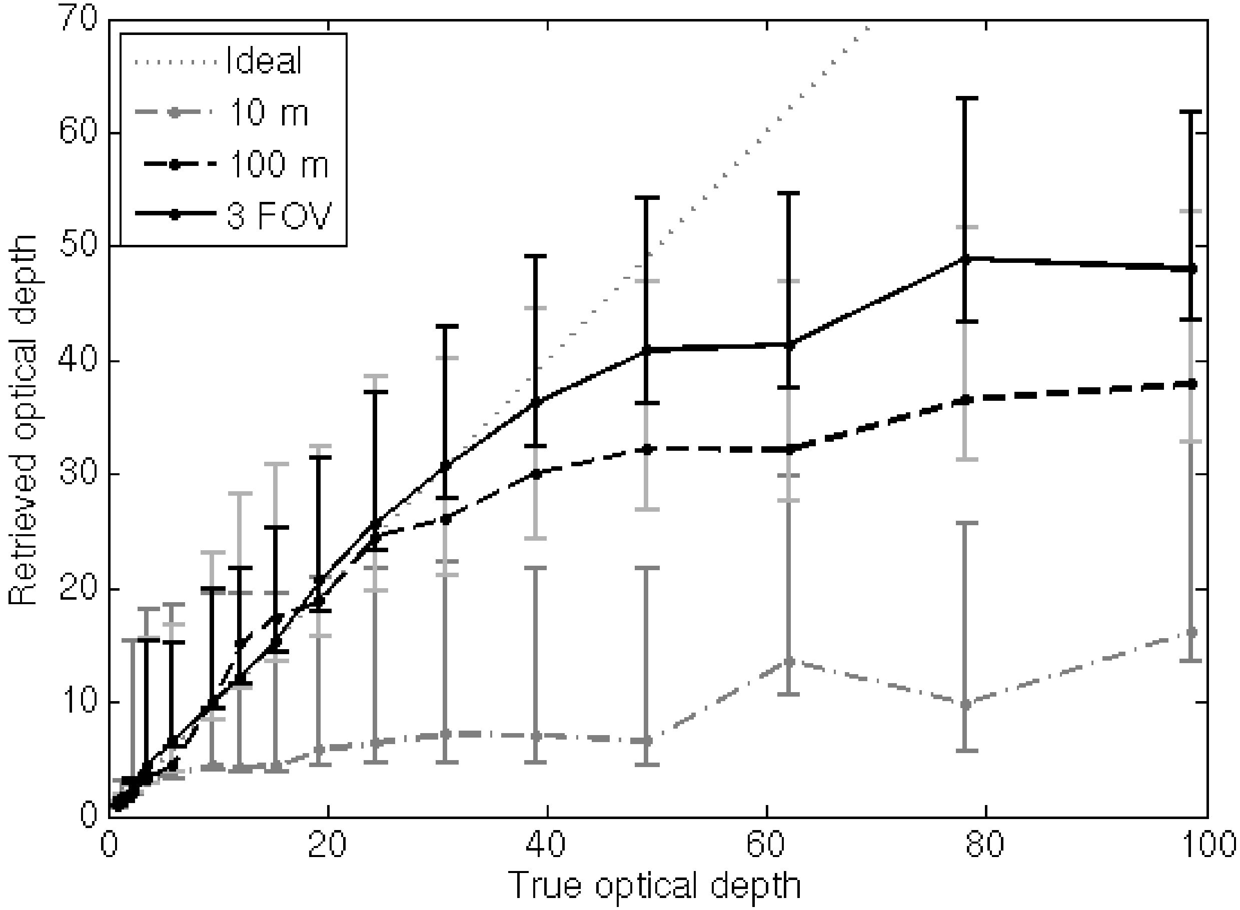
Results for a sine profile

- Simulated test with 200-m sinusoidal structure in extinction
- With one FOV, only retrieve first 2 optical depths
- With three FOVs, retrieve structure of extinction profile down to 6 optical depths
- Beyond that the information is smeared out



Nicola Pounder

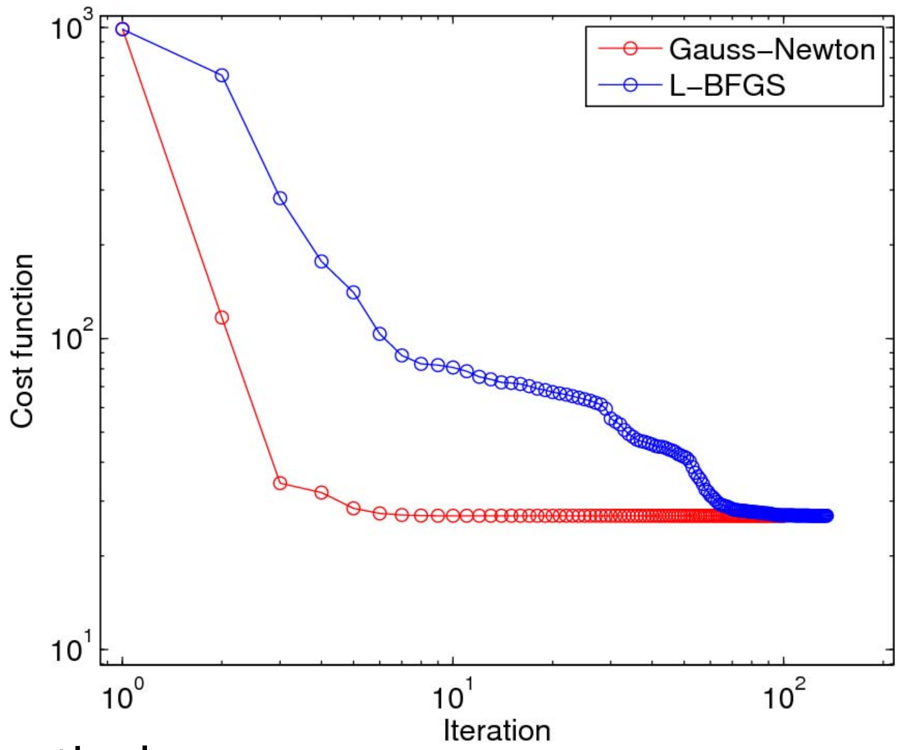
Optical depth from multiple FOV lidar



- Despite vertical smearing of information, the total optical depth can be retrieved to ~30 optical depths
- Limit is closer to 3 for one narrow field-of-view lidar

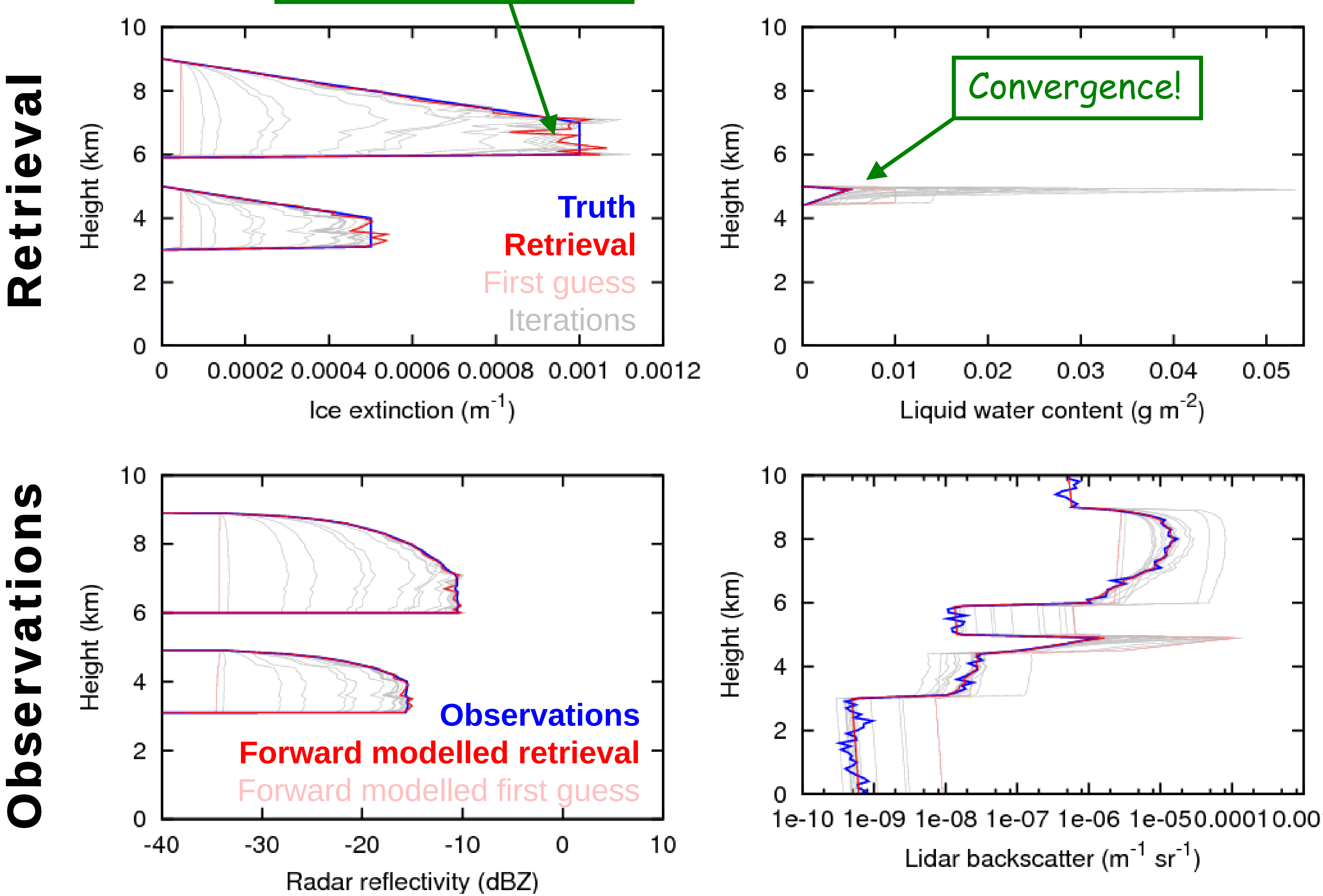
Nicola Pounder

Comparison of convergence rates

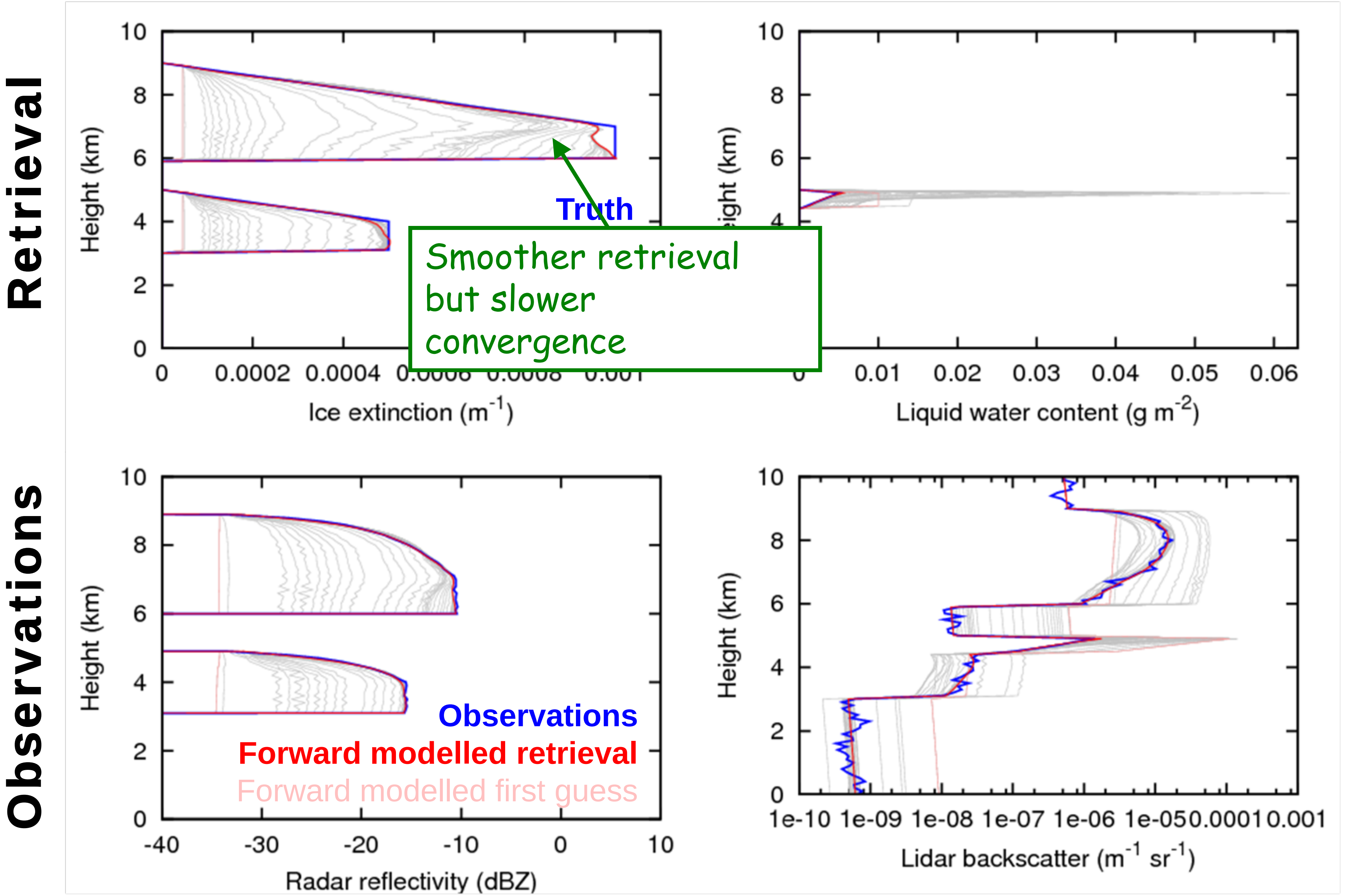


- Solution is identical
- Gauss-Newton method converges in < 10 iterations
- L-BFGS Gradient Descent method converges in < 100 iterations
- Conjugate Gradient method converges a little slower than L-BFGS
- Each L-BFGS iteration >> 10x faster than each Gauss-Newton one!
- Gauss-Newton method requires the Jacobian matrix, which must be calculated by rerunning multiple scattering model multiple times

Unified a… st results for ice+liquid



Add smoothness constraint



Unified algorithm: progress

- Done:
  - Functioning algorithm framework exists
  - C++: object orientation allows code to be completely flexible: observations can be added and removed without needing to keep track of indices to matrices, so same code can be applied to different observing systems
  - Code to generate particle scattering libraries in NetCDF files
  - Adjoint of radar and lidar forward models with multiple scattering and HSRL/Raman support
  - Interface to L-BFGS algorithm in GNU Scientific Library
- In progress / future work:
  - Debug adjoint code (so far we are using numerical adjoint - slow)
  - Implement full ice, liquid, aerosol and rain constituents
  - Estimate and report error in solution and averaging kernel
  - Interface to radiance models
  - Test on a range of ground-based, airborne and spaceborne instruments, particularly the A-Train and EarthCARE satellites
  - Assimilation?