WP5–NA5: Clouds and aerosol quality-controlled observations

Deliverable D5.9: Implementation of variational technique

Objectives

The development of new techniques in Task 5.3 of WP5 explicitly requires that quantified errors are provided with all derived parameters. Quantified errors are essential for utilising observed parameters in:

- process studies,
- climatological studies,
- model evaluation,
- data assimilation.

Analytical retrievals for individual products should be designed to provide uncertainties together with their products; this is already standard practice for all analytical retrievals currently implemented within the Cloudnet framework (Illingworth et al., 2007).

However, the retrieval of separate products independently does not necessarily imply consistency between the products and their errors, even when derived from the same set of instruments. Certain products may require other parameters as input variables, i.e. one parameter must be calculated prior to their inclusion within another retrieval algorithm. One such example is the use of liquid water content retrievals for correcting the radar reflectivity profile for attenuation before calculating ice properties.

The advantage of a variational framework is that, in principle, all products could be retrieved simultaneuously within a unified algorithm. All retrieved products would be consistent, as would their errors. Such a framework can be expanded to include the retrieval of new parameters through the inclusion of an appropriate forward model.

Principles of variational retrieval techniques

The basic principle of the variational technique is to use forward models to find the combination of micro-physical variables that best match the observations in a least-squares sense (also known as `optimal estimation` theory; Rodgers, 2000).

Within the variational scheme, the parameters to be retrieved are represented by a state vector and the observed variables by an observation vector. The state vector is initialised with a prior, or first guess. Each element in the observation vector is then predicted from the state vector using a forward model. Comparison of the predicted observation with the actual observation is used to refine the state vector; a new prediction is then made from the updated state vector. This process iterates until convergence; where the difference in the observations and the forward-modelled observation vector is minimised in a least-squares sense, realised through the use of a cost function.

Once the iteration has converged to provide a solution, the uncertainties in the derived parameters (terms in the state vector) are obtained as error covariances from the inverse of the Hessian matrix, a square matrix of the second-order partial derivatives (Rodgers, 2000).

A prerequisite for such schemes is suitable *a priori* information, to provide a reasonable first guess. Additionally, it is assumed that the nature of the errors in each instrument, whether random or systematic, correlated or uncorrelated, are known and can be adequately represented in the forward model.

Variational retrieval in ice cloud

The variational ice retrieval algorithm of Delanoë and Hogan (2008) has been implemented as a test product within Cloudnet. The method utilises a combination of Doppler cloud radar and lidar to provide profiles of a number of ice properties. Inclusion of satellite radiances, from an infra-red radiometer such as SEVIRI, can improve the retrieval further if available. Necessary ancillary information, such as temperature, pressure and humidity profiles, is obtained from radiosoundings or the output from weather forecast models.

The variational retrieval technique requires forward models. The forward model for the radar reflectivity includes non-Rayleigh scattering for large particles at millimetre wavelengths. The forward model for attenuated lidar backscatter includes molecular and multiple scattering.

Algorithm basis

The technique builds on the knowledge that it should be possible to retrieve profiles of the microphysical properties of ice clouds from the combination of radar reflectivity and lidar attenuated backscatter coefficient, since these two instruments are sensitive to very different moments of the particle size distribution.

Algorithm inputs

The following observables together with their uncertainties:

- Radar reflectivity profile
- Lidar attenuated backscatter coefficient profile
- Thermodynamic profile (temperature, pressure and humidity)
- (Optional) Infra-red radiometer

Algorithm outputs

Profiles of the following ice cloud properties together with their uncertainties:

- visible extinction coefficient
- ice water content
- effective radius
- normalized number concentration parameter, N_0*

Algorithm procedure

The procedure is outlined in Fig. 1. The procedure starts from the Cloudnet target categorization product (Hogan and O`Connor, 2004), which provides the input variables and their associated uncertainties.

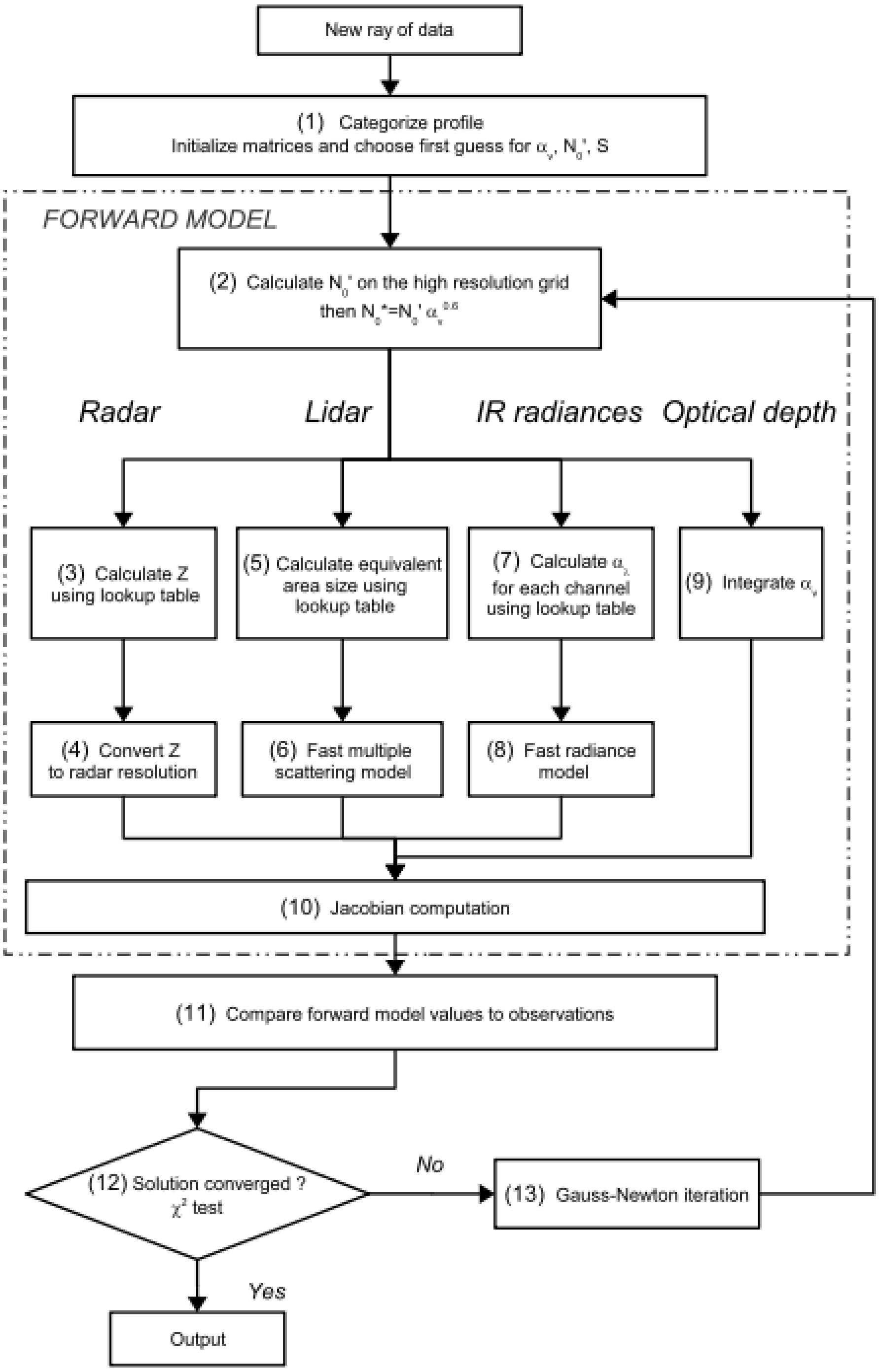

Figure 1: Flowchart detailing VarCloud variational retrieval procedure. Taken from Delanoë and Hogan (2008).

Example

Some examples of the application of the variational procedure described in Delanoë and Hogan (2008) are now described. The observed radar reflectivity, radar Doppler velocity, and lidar attenuated backscatter coefficient profiles are shown in Fig. 2. An initial check on the performance of the radar and lidar forward models can be made by direct comparison of the observations (Fig 2.) with their predicted parameters (Fig 3.). Note that, for efficiency reasons, only profiles diagnosed as containing cloud are processed, and that profiles containing rain or liquid are not yet processed, hence the gaps in Fig 3. The aerosol layers evident in the observed lidar attenuated backscatter are not yet taken into account within the scheme, but otherwise it is clear that the forward model predictor has converged quite close to the observations.

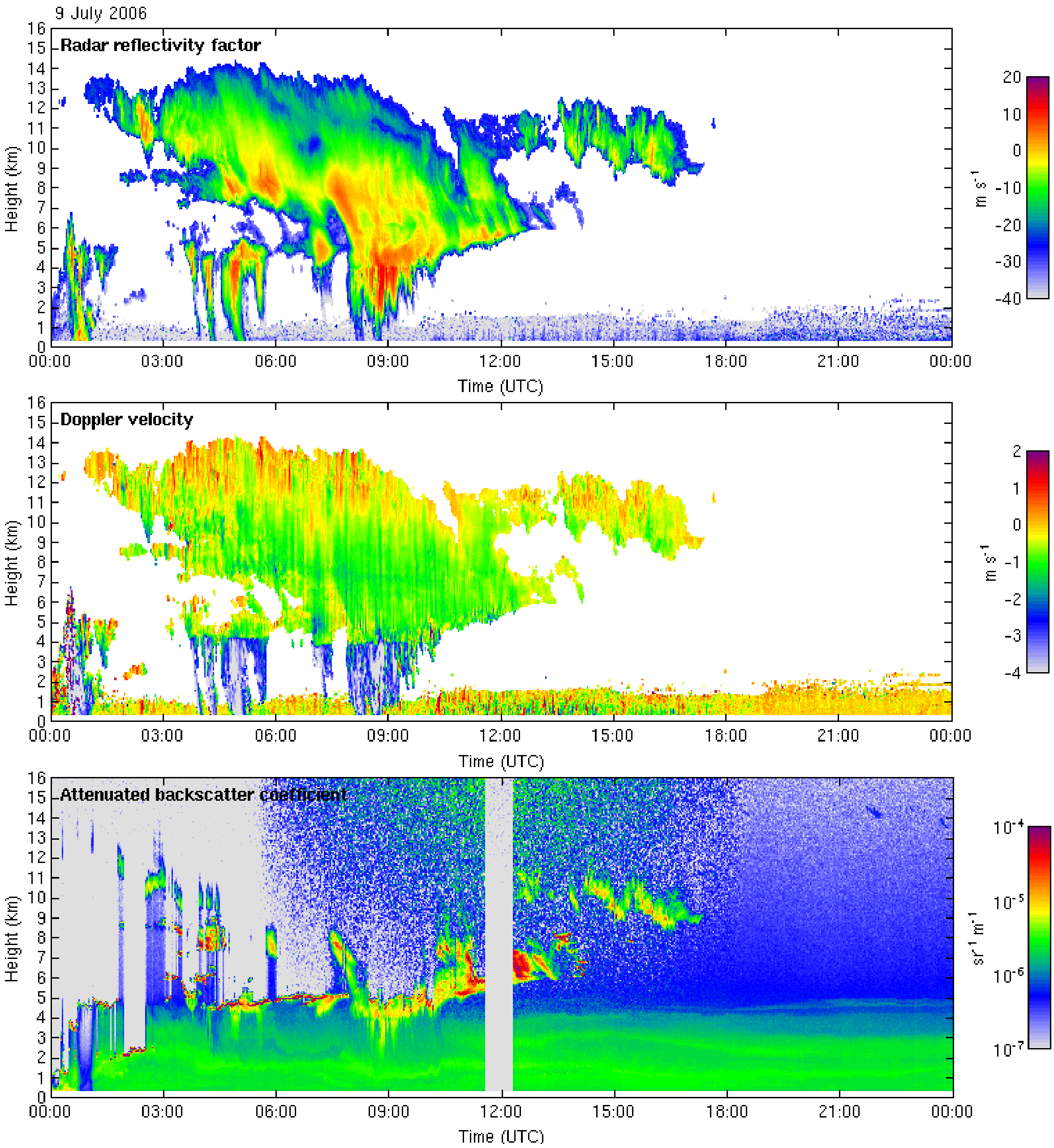

Figure 2: Time-height plots of observed radar reflectivity (top panel), radar Doppler velocity (centre panel), and attenuated lidar backscatter (lower panel) for 7th July 2006 over Niamey, Niger.

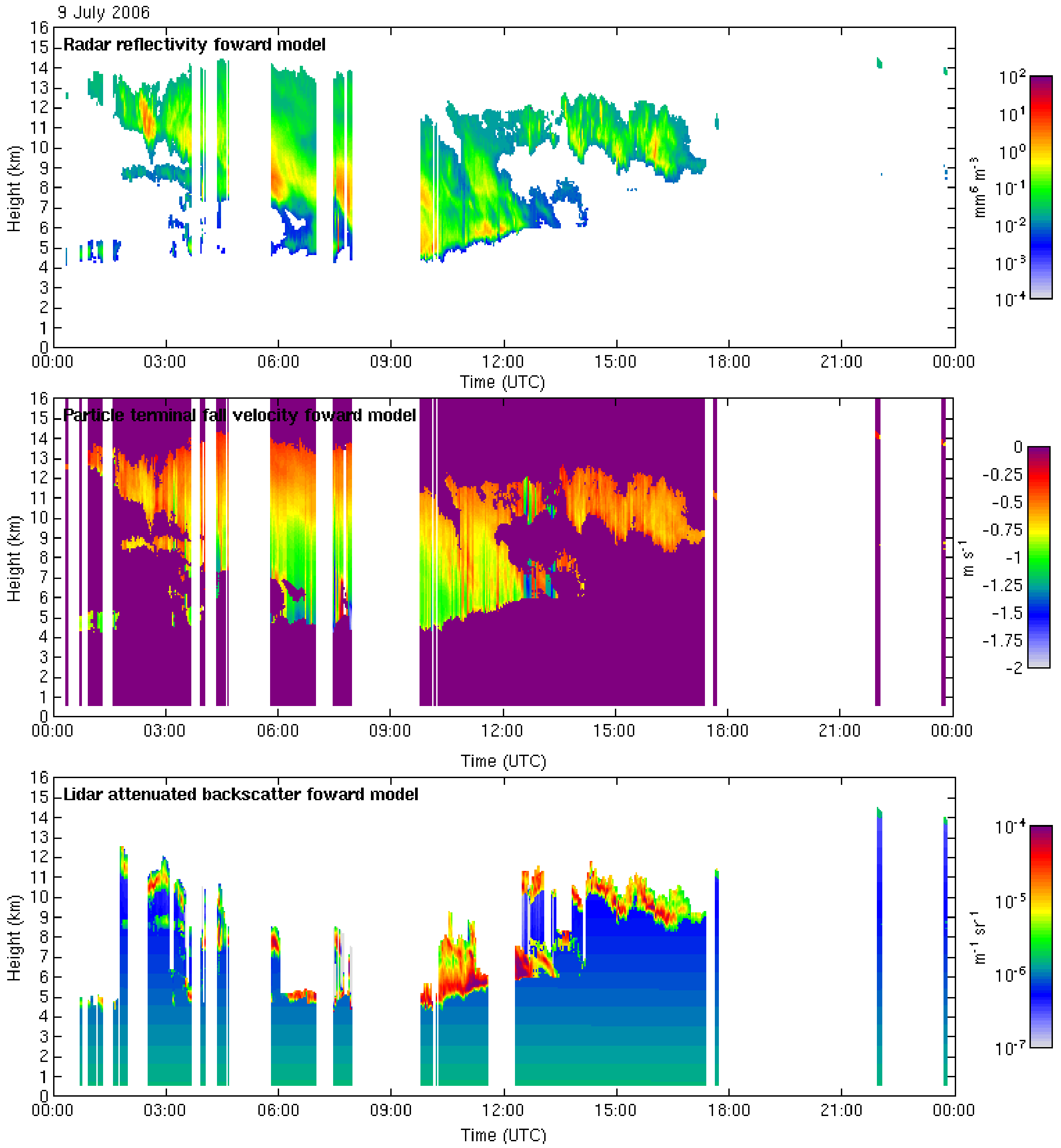

Figure 3: Foward-modelled instrument parameters for the same period as Fig. 2. For efficiency, only those profiles diagnosed as containing ice cloud have been processed. No retrieval is performed when rain or liquid layers are present in the profile.

The retrieved ice water content, IWC, is shown in Fig 4, together with IWC derived using the standard Cloudnet method given in Hogan et al. (2006). Both methods provide similar values, although it should be noted that the *a priori* for the variational technique is taken from Hogan et al. (2006), where IWC is a function of radar reflectivity and temperature.

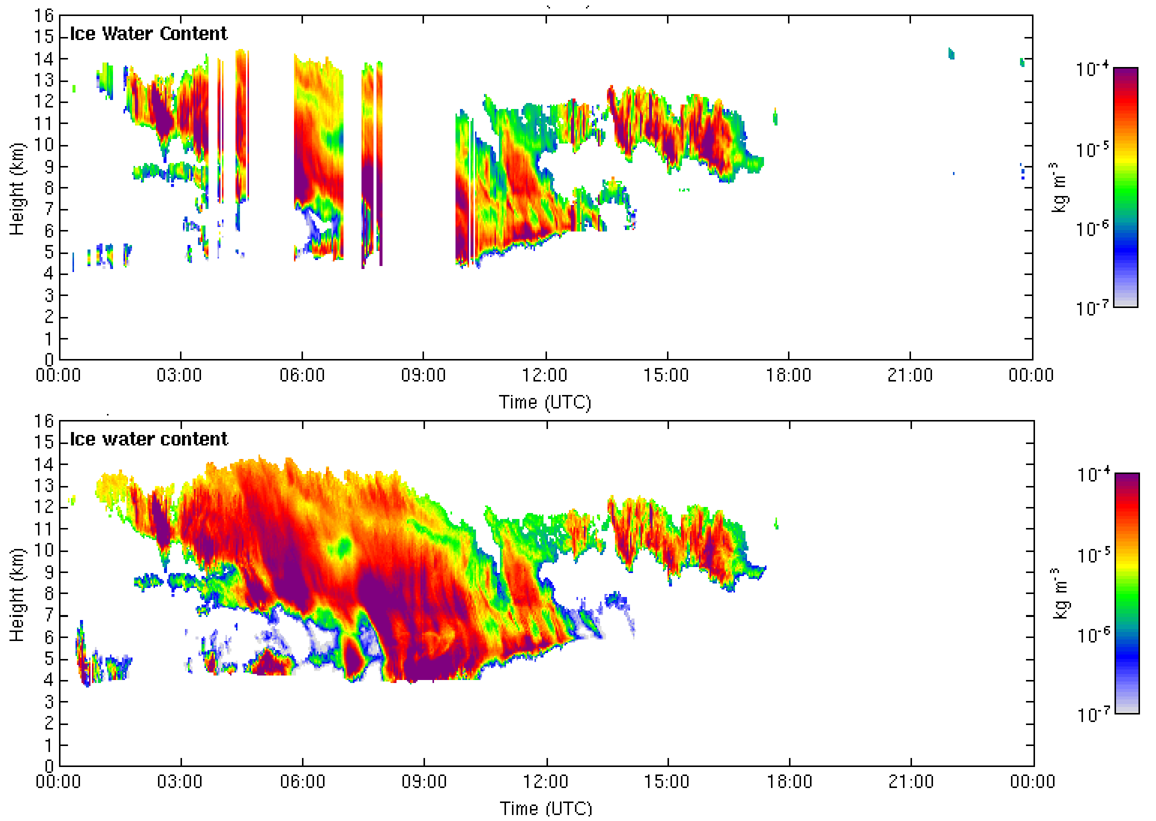

Figure 4: IWC from the variational technique (top panel) and from the standard Cloudnet produxt where IWC is a function of radar reflectivity and temperature (lower panel), for the same period as in Figs. 2-3.

Additional ice parameters retrieved by the variational technique are displayed in Fig5. Note that the standard Cloudnet product given by Hogan et al. (2006) only provides bulk IWC and does not provide these extra microphysical parameters. The variational technique provides uncertainty estimates for each retrieved parameter; Fig. 6 shows the corresponding fractional uncertainty in visible extinction coefficient. Note how the uncertainty increases once the lidar signal has been completely extinguished and there is only radar reflectivity information present.

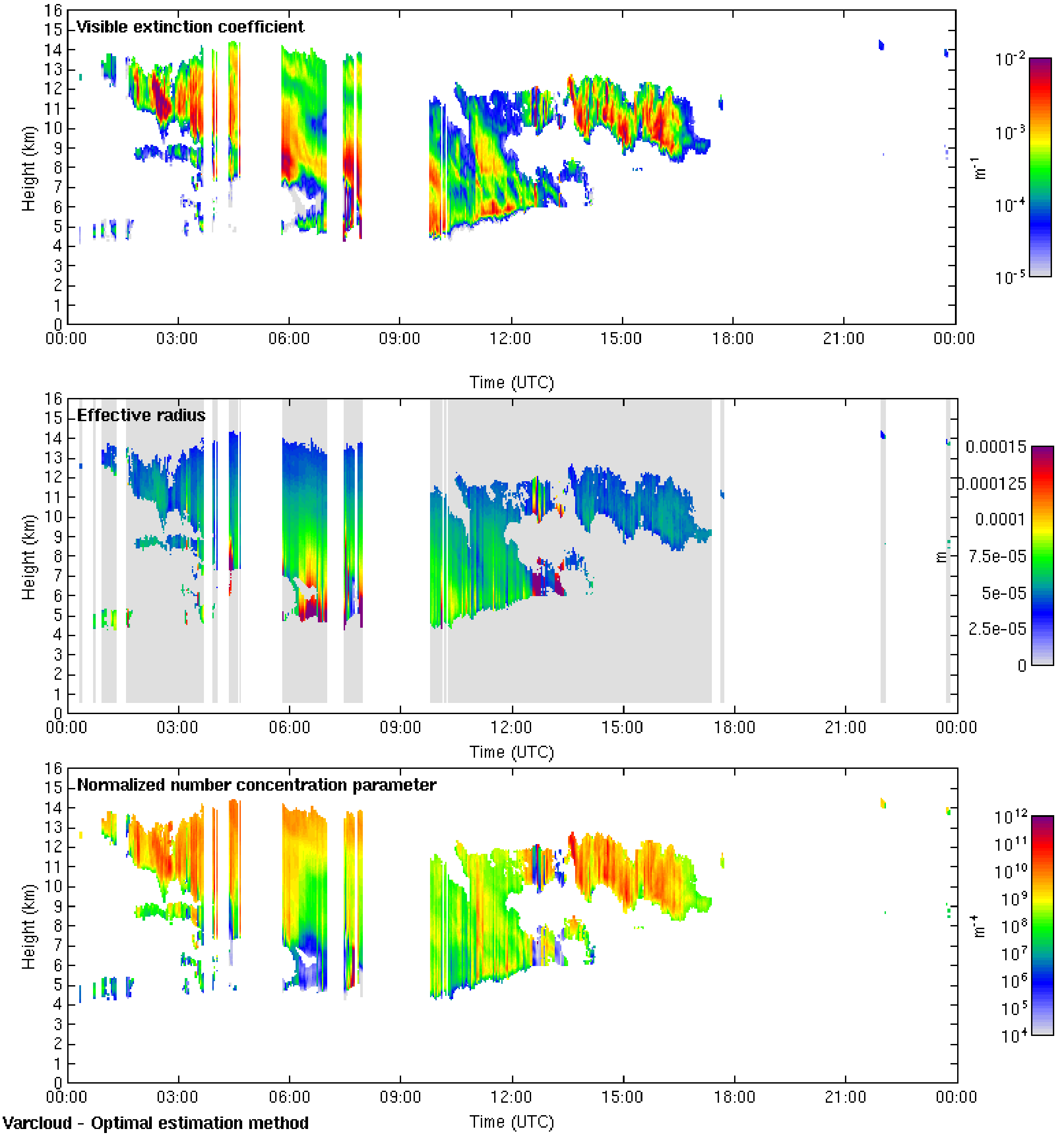

Figure 5: Additional ice microphysical parameters provided by the variational technique, for the same period as in Figs. 2-4.

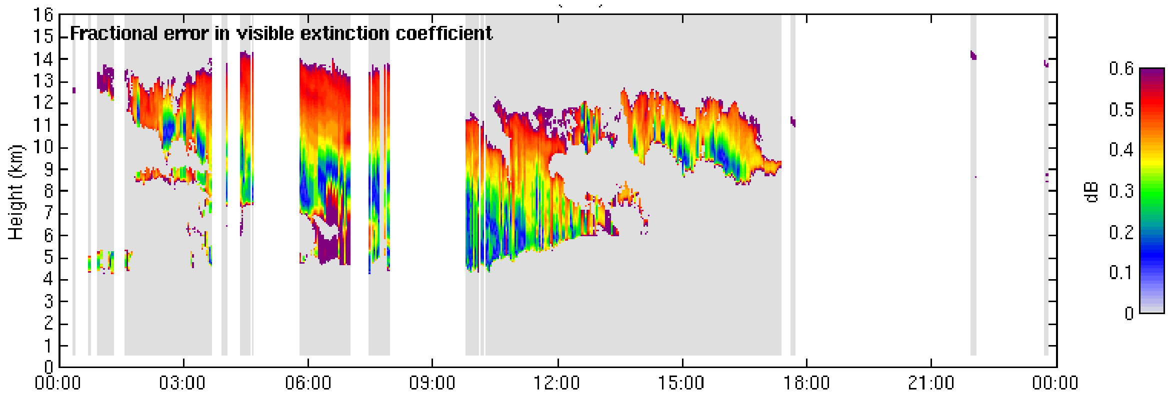

Figure 6: An example of the fractional error in the retrieved visible extinction coefficient for the same period as in Figs. 2-5.

Conclusions

The variational technique has been implemented and tested within the Cloudnet framework. The procedure is flexible, being able to utilise additional observations and constraints. The advantage of this technique is that it can provide smoothly varying retrievals through the entire cloud profile, with no sudden jumps between regions where one instrument only is available, and regions where both radar and lidar are available.

When certain observations are not available, the algorithm will automatically tend towards the relationships from existing algorithms:

- Radar only - IWC from radar reflectivity and temperature (Hogan et al., 2006)
- Radar and visible optical depth - Benedetti et al. (2003)
- Lidar and infrared radiances - Chiriaco et al. (2004).

The variational framework will be expanded to include forward models for liquid layers, including additions to the lidar forward model, and inclusion of observations from a dual/multi-channel microwave radiometer. The potential for combining microwave radiometer brightness temperatures and radar reflectivity profiles has already been demonstrated by Loehnert et al. (2007) in their integrated profiling technique, IPT; a method for the simultaneous retrieval of profiles of the following atmospheric state parameters: temperature, humidity, and liquid water content.

References

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