

COMBINING DATA FROM GROUND-BASED MICROWAVE RADIOMETERS AND OTHER INSTRUMENTS IN TEMPERATURE AND HUMIDITY PROFILE RETRIEVALS

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ABSTRACT

Ground-based microwave radiometry offers a new opportunity to automate upper air observations by providing information on temperature and humidity profiles as well as the integrated water vapour and liquid water amounts with high time resolution. To improve their relatively poor vertical resolution and provide a more complete picture of the vertical profile, radiometer observations can be combined with other instruments making up an *Integrated Profiling Station*.

This paper describes a variational method of combining observations from different instruments with background from Numerical Weather Prediction (NWP) models in a statistically optimal way, accounting for their error characteristics. This method is illustrated using microwave and infrared radiometers and surface sensors as an example showing the requirement for a forward model of each observation and an estimate of their error covariance. Methods to exploit the high time-resolution of ground-based observations while assimilating them into NWP are discussed, as these may compensate for the geographic sparsity of a future network of *Integrated Profiling Stations*.

1. INTRODUCTION

This section introduces the general benefits of ground-based remote sensing systems and the concept of combining them as part of an *Integrated Profiling Station* (IPS) to meet user requirements for temperature and humidity profiling. A variational technique is introduced in the following section to retrieve these profiles by combining observations with Numerical Weather Prediction (NWP) model data. This uses the example of a microwave radiometer, which is considered as a cornerstone of the IPS because of its ability to provide information on the basic temperature and humidity profile, which can be further improved by adding observations from other instruments. The final section outlines possible methods by which this may be achieved.

a) User requirements

The stated requirements of all the users of upper air observations were reviewed by Stringer [2006]. These are expressed in terms of the accuracy, vertical and horizontal resolution, observing cycle and delay required of temperature in the boundary layer and lower troposphere, humidity in the lower troposphere and column integrated water vapour for climate monitoring, global and regional NWP, synoptic, aeronautical and nowcasting applications. The requirements are defined in terms of the *minimum* threshold for an observations to have any impact on each application, the *breakthrough* threshold at which the observations could provide a significant advance in forecast capability (relative to that currently available), and the *maximum* threshold, above which no significant benefit will be felt. All observing systems have strengths and weaknesses – none meet the breakthrough levels for all aspects (accuracy, vertical and horizontal resolution, observation cycle and delay). The best that can be expected is to achieve this level of performance from a combination of systems. The user requirements are shown in Table 1 for regional NWP.

Regional NWP needs observations with better accuracy, vertical and horizontal resolution than global NWP. It is here that observations from ground-based remote sensing systems are expected to have most impact, because their information is concentrated in the boundary layer, which often has high temporal variability that may be well captured by their high frequency observations. Better temperature accuracy, vertical and horizontal resolution is required in the boundary layer than the rest of the lower troposphere due to its greater variability in space and time.

Table 1 User requirements of temperature and humidity profiles for Regional NWP – minimum, breakthrough and maximum thresholds

NWP Regional	Temperature (K) Boundary Layer			Temperature (K) Lower Troposphere			Relative Humidity (%) Lower Troposphere			Integrated Water Vapour (kg/m ³)		
	Min.	Brk.	Max.	Min.	Brk.	Max.	Min.	Brk.	Max.	Min.	Brk.	Max.
Accuracy	1.5		0.5	1.5		0.5	10		5	5		1
Vertical Resolution (km)	0.5	0.3	0.01	2	1	0.1	2	1	0.1	N/A	N/A	N/A
Horizontal Resolution (km)	50	10	1	200	30	3	200	30	3	100		10
Observing Cycle (hr)	3	1	0.166	12	3	0.5	12	3	0.5	1		0.5
Delay in Availability (hr)	3		0.083	5		0.25	5		0.25	0.5		0.1

However, if the user requirement for the *minimum* horizontal resolution of boundary layer temperature profiles is taken at face value, then observations will have no impact in regional NWP, unless they can be deployed in a dense network of ~100 in the UK. It would be prohibitively expensive to deploy a network of ground-based instruments that essentially take spot measurements (i.e. do not cover a significant area) capable of exceeding the stated *minimum* threshold for horizontal resolution of regional NWP. However, it may be possible to exploit the observations' high time-resolution as a proxy for horizontal sampling within 4D-VAR (section 4).

b) Expected benefits of ground-based remote sensing

There are a diverse set of ground-based remote sensing systems capable of providing observations on a range of atmospheric variables at different stages of operational implementation. For example, microwave radiometers, wind profiling radars, laser ceilometers, cloud radars provide information on the temperature, humidity and cloud profiles and, when combined at a common location, have the potential to provide a complete picture of the atmospheric profile at that point.

The geometry of ground-based observations typically means their information is concentrated in the planetary boundary layer. This is particularly beneficial to NWP as it complements the information available from aircraft and satellites over land, whose application near the surface is limited by variable emissivity and surface temperature in the case of microwave sounders, and extinction by cloud for infrared sounders. For this reason, ground-based observations are expected to have most impact on short-range NWP. And because of the high time-resolution available from ground-based remote sensing systems, they are able to detect variability on convective scales, which is only resolvable by the latest generation of high resolution NWP models.

c) Integrated Profiling Station Concept

The *Integrated Profiling Station* (IPS) concept describes a combination of co-located ground-based remote sensing systems operating continuously to provide a complete picture of the vertical atmospheric profile. These instruments should be able to operate automatically, requiring minimal manual intervention. Profiles of atmospheric temperature, humidity and cloud can be retrieved by integrating observations from different systems to exploit their relative strengths. This paper discusses a variational method to combine observations with an NWP background.

It is proposed that a number of IPSs may, in the future, form part of the operational upper air network, including radiosondes and profiles from commercial aircraft. This network would provide observations to complement satellite soundings. Until now it has been difficult to fully exploit observations in the boundary layer due to its great spatial and temporal variability. However, this is expected to change in the next few years with the advent of 4-Dimensional Variational assimilation (4D-VAR) in convective scale NWP models.

2. VARIATIONAL RETRIEVALS (1D-VAR)

A 1-Dimensional Variational (1D-VAR) retrieval method is developed using data from the Radiometrics TP/WVP-3000 microwave radiometer [Ware *et al.*, 2003] as an example. This method provides the basis of the *Integrated Profiling System* as it retrieves profiles of temperature and humidity, albeit with poor vertical resolution, as well as the Integrated Liquid Water (ILW). However, the retrievals are *ill posed* as there are many possible profiles that fit a given set of observations. To resolve this ambiguity requires *a priori* information, which are provided as background information from short-range NWP forecasts for the variational retrievals. Variational methods provide a statistically *optimal* method of combining observations with a background, which accounts for the assumed error characteristics of both. For this reason they are often referred to as *Optimal Estimation* retrievals.

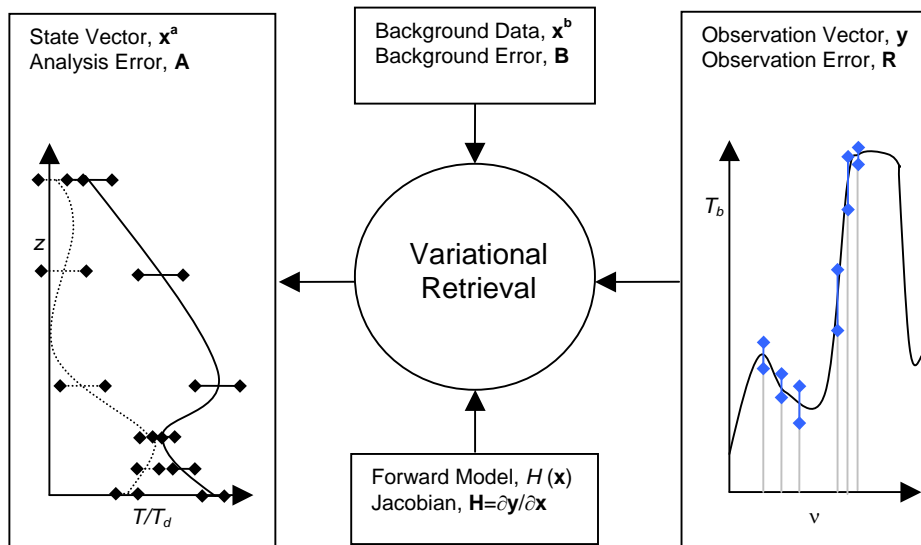


Figure 1 Schematic of inverse problem of retrieving profiles from observations.

The 1D-VAR retrievals presented here are similar to the *Integrated Profiling Technique* [Löhnert *et al.*, 2004], but takes its background from an NWP model instead of radiosondes and uses different control variables to concentrate on retrieving profiles of atmospheric temperature and humidity.

The 1D-VAR retrieval is performed by adjusting the atmospheric state vector, \mathbf{x} , from the background state, \mathbf{x}^b , to minimize a cost function of the form Rodgers [2000]:

$$J(\mathbf{x}) = [\mathbf{x} - \mathbf{x}^b]^T \mathbf{B}^{-1} [\mathbf{x} - \mathbf{x}^b] + [\mathbf{y} - H(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{y} - H(\mathbf{x})] \quad (1)$$

where \mathbf{B} and \mathbf{R} are the error covariance matrices of the background, \mathbf{x}^b , and observation vector, \mathbf{y} , respectively, $H(\mathbf{x})$ is the forward model operator and T and $^{-1}$ are the matrix transpose and inverse, respectively, using the standard notation of Ide *et al.* [1997].

a) Background Data and State Vector

The mesoscale version of the Met Office Unified Model is used to provide background data for the retrievals in the form of profiles of temperature, humidity and liquid water. The model grid points are interpolated to the position of the observations. This model is initiated every six hours, including data from radiosonde stations. A short-range forecast (T+3 to T+9 hr) is used for the background, as would be available to operational assimilation schemes. This is independent of any radiosondes launched at observation time, which may be used to validate the retrievals.

The state vector, \mathbf{x} , used in the retrievals is defined as the temperature and total water on the lowest 28 model levels. These extend up to 14 km, but are concentrated near the surface, where most of the radiometer's information is.

In this study the humidity components of the state vector are defined as the natural logarithm of total water, $\ln q_t$. (q is the specific humidity.) This control variable is a modified version of that suggested by DeBlonde and English [2003], with a smooth transfer function between water vapor for $q_t/q_{sat} < 90\%$ and liquid water for $q_t/q_{sat} > 110\%$ (where q_{sat} is q at saturation.) The condensed part of the total water is further partitioned between liquid and ice fractions as a linear function of temperature, producing pure ice at -40°C . The choice of total water has the advantages of reducing the dimension of the state vector, enforcing an implicit super-saturation constraint and correlation between humidity and liquid water. The logarithm creates error characteristics that are more closely Gaussian and prevents unphysical retrieval of negative humidity.

The background error covariance, \mathbf{B} , describes the expected variance at each level between the forecast and true state vector and the correlations between them. In this work, \mathbf{B} was taken from that used to assimilate data from satellite instruments operationally at the Met Office. The diagonal components of \mathbf{B} are shown for reference in Fig. 4.

b) Observations

This study uses observations from the Radiometrics TP/WVP-3000 microwave radiometer. This has 12 channels: seven in the oxygen band 51-59 GHz, which provide information primarily on the temperature profile and five between 22-30 GHz near a water vapor line, which provide humidity and cloud information. This radiometer includes sensors to measure pressure, temperature and humidity at ~ 1 m above the surface. The pressure is taken as a reference from which geopotential height is calculated at other pressure levels via the hydrostatic equation. The instrument's integral rain sensor is used to reject periods which may be contaminated by scattering from precipitation, as this is not included in the forward model and emission from raindrops on the radome, which may bias the calibration. This instrument incorporates an optional zenith-viewing infrared radiometer (9.6-11.5 μm) to provide information on the cloud base temperature.

In this study the observation vector, \mathbf{y} , is defined as a vector of the zenith brightness temperatures (T_b) measured by the radiometer's 12 channels, with additional elements for the surface temperature (T_{AMB}) and humidity (converted to $\ln q_{AMB}$) and the infrared brightness temperature (T_{ir}):

$$\mathbf{y} = [T_{b1}, T_{b2}, \dots, T_{b12}, T_{AMB}, \ln q_{AMB}, T_{ir}] \quad (2)$$

The observation error covariance, \mathbf{R} , has contributions from the radiometric noise (\mathbf{E}), forward model (\mathbf{F}) and representativeness (\mathbf{M}) errors ($\mathbf{R} = \mathbf{E} + \mathbf{F} + \mathbf{M}$). These terms were evaluated by Hewison [2006].

c) Forward Model and its Jacobian

A forward model, $H(\mathbf{x})$, is needed to transform from state space to observation space. For the microwave radiometer, each channel's T_b is calculated at an equivalent monochromatic frequency [Cimini *et al.*, 2006] using the radiative transfer equation to integrate down-welling emissions from each atmospheric layer between model levels using a standard absorption model [Rosenkranz, 1998], which was found to have small biases in these channels [Hewison *et al.*, 2006]. The forward model for the surface temperature and humidity sensors is trivial – a 1:1 translation to the lowest level of the state vector, \mathbf{x} . A simple forward model defines T_{ir} as the temperature of the lowest level with any cloud. A more sophisticated radiative transfer model is used here to calculate T_{ir} which accounts for extinction by atmospheric water vapor and liquid water cloud, assigning extinction coefficients of $0.02 \text{ Np/km} \cdot (\text{kg/kg})^{-1}$ and $33.3 \text{ Np/km} \cdot (\text{kg/m}^3)^{-1}$ respectively. This model

gives more Gaussian error characteristics, due to having less abrupt transitions at cloud boundaries. Examples of the forward model and its Jacobian are shown in Figure 2 and Figure 3.

The *Jacobian* is the matrix of the sensitivity of the observation vector, \mathbf{y} , to perturbations of each element of the state vector, \mathbf{x} , $\mathbf{H} = H'(\mathbf{x}) = \nabla_{\mathbf{x}} \mathbf{y}$. It is needed to minimize the cost function (see section e)). In this study, \mathbf{H} is calculated by *brute force* – each level of the state vector, \mathbf{x} , is perturbed by 1 K in temperature or 0.001 in $\ln q_i$. The magnitude of these perturbations was selected to ensure linearity of \mathbf{H} , while preventing numerical errors due to truncation.

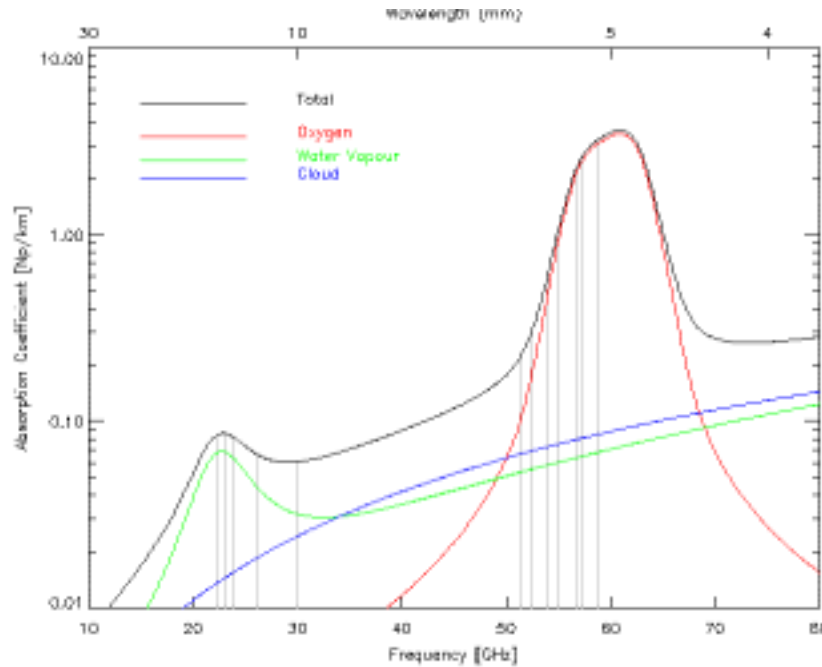


Figure 2 Atmospheric absorption spectrum for typical surface conditions: $T=288.15$ K, $p=1013.25$ hPa, $RH=100\%$, $L=0.2$ g m⁻³ following Rosenkranz [1998]. Lines show total absorption coefficient and contribution from oxygen, water vapour and cloud, coloured according to the legend. Grey vertical bars show centre frequencies of the Radiometrics TP/WVP-3000 microwave radiometer.

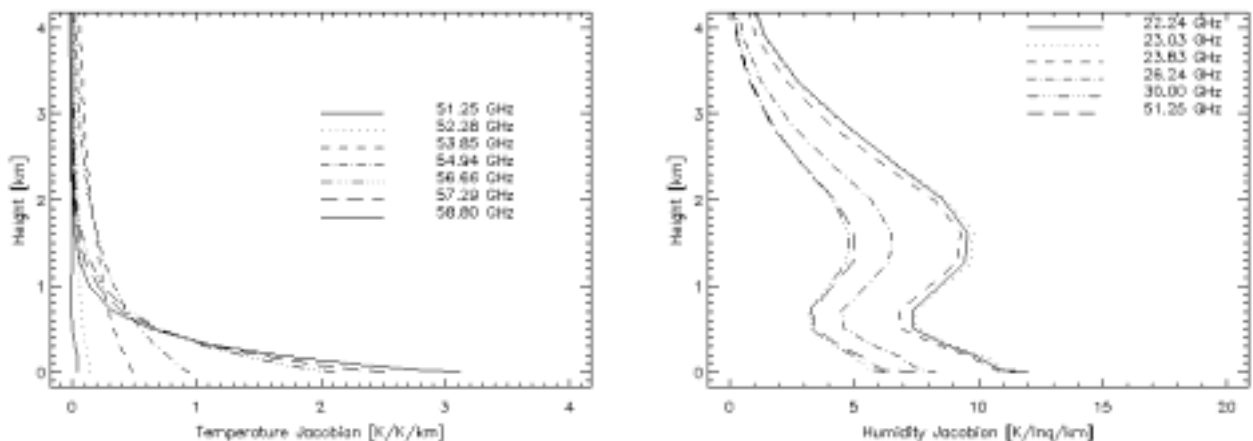


Figure 3 Jacobian's temperature component of 51-59 GHz channels (left) and humidity component for 22-51 GHz channels of Radiometrics TP/WVP-3000 (right), scaled by model layer thickness, Δz : $H/\Delta z = (\partial y/\partial x)/\Delta z$. Calculated for clear US standard atmosphere.

d) Error Analysis

An estimate of the uncertainty on the retrieved profile can be derived by assuming the errors are normally distributed about the solution and that the problem is only moderately non-linear. In this case, the error covariance matrix of the analysis, **A**, is given Rodgers [2000] by:

$$\mathbf{A} = (\mathbf{H}_i^T \mathbf{R}^{-1} \mathbf{H}_i + \mathbf{B}^{-1})^{-1} \quad (3)$$

where **H_i** is evaluated at the solution (or final iteration).

Although the vertical resolution can be defined from **A**, this is a somewhat arbitrary definition and not particularly helpful. Instead, it is better to express the observations' information content with respect to the background as the *Degrees of Freedom for Signal, DFS*. This represents the number of layers in the profile which are retrieved independently. It can be calculated [Rabier *et al.*, 2002] as:

$$DFS = \text{Tr}(\mathbf{I} - \mathbf{A}\mathbf{B}^{-1}) \quad (4)$$

where **I** is the identity matrix and **Tr**() is the trace operator.

A has been evaluated for different combinations of instruments for a *clear* US standard atmosphere in Fig. 4, although it depends on the reference state through **H_i**. This shows error in the temperature profile retrieved from the radiometer is expected to approach 0.1 K near the surface, but increases with height, to exceed 1 K above 5 km and includes 2.8 degrees of freedom. For the humidity profile, **A** varies greatly with **x**. In this example the retrieval's **lnq** error increases from 0.05 (~5%RH) near the surface to 0.4 (~40%RH) by 3 km and includes 1.8 degrees of freedom, increasing by ~1.0 in cloudy conditions. This presents a substantial improvement on the background and the surface sensors alone, which only influence the lowest 500 m. However, above ~1 km it falls short of the radiosonde's accuracy, which is also shown in Fig. 4. However, the radiometer provides much more frequent observations than radiosondes can, reducing errors of representativeness applying their data to analysis at arbitrary times.

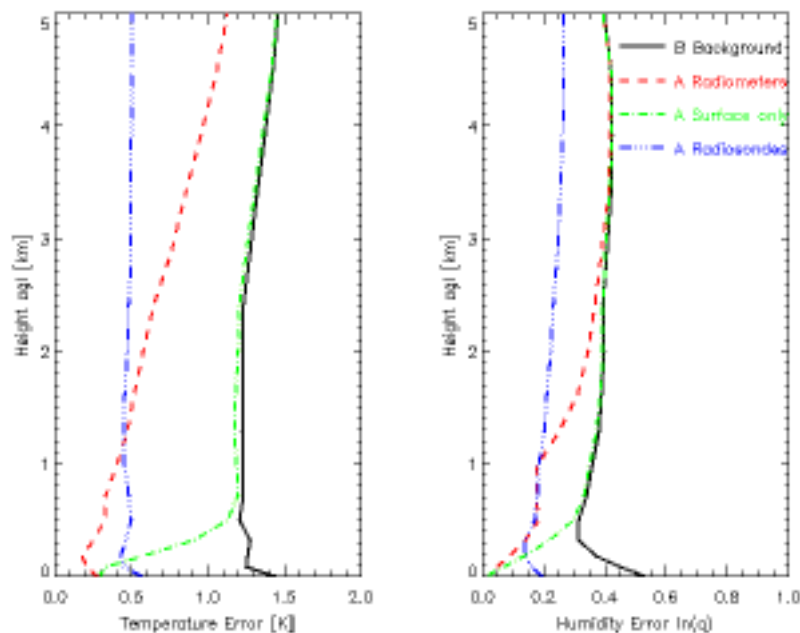


Fig. 4 Background error covariance from mesoscale model, $\sqrt{\text{diag}(\mathbf{B})}$, (black) and analysis error covariances, $\sqrt{\text{diag}(\mathbf{A})}$, with surface sensors only (green), radiometers and surface sensors (red), and radiosonde only (blue). Plotted as square root of the matrices' diagonal components for the lowest 5 km of temperature [K] and humidity (**lnq**) [dimensionless].

e) Minimization of Cost Function

Variational retrievals are performed by selecting the state vector that minimizes a cost function in the form of (1). For linear problems, where \mathbf{H} is independent of \mathbf{x} , this can be solved analytically. However, the retrieval of temperature profiles above ~ 1 km and humidity profiles is moderately non-linear, so the minimization must be conducted numerically. This has been achieved using the Levenberg-Marquardt method [Rodgers, 2000] (which was found to improve the convergence rate in cloudy conditions compared to the classic Gauss-Newton method) by applying the following analysis increments iteratively:

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \left((1 + \gamma) \mathbf{B}^{-1} + \mathbf{H}_i^T \mathbf{R}^{-1} \mathbf{H}_i \right)^{-1} \left[\mathbf{H}_i^T \mathbf{R}^{-1} (\mathbf{y} - H(\mathbf{x}_i)) - \mathbf{B}^{-1} (\mathbf{x}_i - \mathbf{x}^b) \right] \quad (5)$$

where \mathbf{x}_i and \mathbf{x}_{i+1} are the state vector before and after iteration i , and \mathbf{H}_i is the Jacobian matrix at iteration, i .

This minimisation typically requires several iterations and is computationally expensive as \mathbf{H}_i must be evaluated at each iteration. For many practical applications this necessitates the development of a fast forward model, often as a parameterization of a more accurate model with full physics, such as a line-by-line radiative transfer model.

f) Information Content Trade-offs

The concept of the Degrees of Freedom for Signal (DFS) from Equation (4) can be used to quantify how much the information available from the observations can improve the NWP background. DFS can be used to compare the benefits of different observing strategies.

For example, Hewison [2006] showed that observing 4 different elevation angles with a microwave radiometer and averaging these observations over 5 minute periods increased the DFS for temperature to ≈ 5 (from ≈ 3 for instantaneous zenith observations only). This would improve the accuracy of temperature profiles retrieved from the observations as well as their vertical resolution. Results of the DFS analysis for different combinations of radiometer elevation angles and averaging periods are given in Table 2.

Table 2 Degrees of Freedom for Signal in temperature (DFS_t) and humidity (DFS_q) available from Radiometrics TP/WVP-3000 in different configurations with/without averaging 55-59 GHz channels.

	Instrument Combination	Averaging Period	Clear		Cloudy	
			DFS_t	DFS_q	DFS_t	DFS_q
(a)	Radiosonde		8.6	7.1	8.6	7.1
(b)	Surface sensors only		1.0	1.0	1.0	1.0
(c)	(b) + Radiometrics TP/WVP-3000	Instantaneous Zenith obs. only	2.8	1.8	2.9	3.0
(d)	(b) + Radiometrics TP/WVP-3000	Averaging obs. over 300 s	3.2	2.0	3.3	3.0
(e)	(c) at 4 elevation angles +zenith IR	Averaging obs. over 300 s	4.4	2.7	4.4	5.0

In a similar way, DFS could be used to evaluate the relative benefits of different instruments to the retrieval of particular state vectors, such as temperature, humidity and/or cloud profiles. However, the results also depend on the assumed accuracy of the NWP background information (\mathbf{B}). This could be exploited in the evaluation of different network densities and their distribution by adjusting \mathbf{B} , following [Löhnert *et al.*, 2006].

3. POSSIBLE COMPONENTS OF INTEGRATED PROFILING STATION

The variational method allows different instruments to be combined and can provide a basis for the development of *Integrated Profiling Systems*, which have the potential to improve the profiles retrieved from the microwave radiometer alone. This has been demonstrated by a simple example in this paper. Although the inclusion of surface temperature and humidity sensors in the observation vector was trivial (they provide a direct observation of two elements of the state vector), the infrared radiance needed a more complex forward model to describe its sensitivity to the humidity profile as well as the cloud-base temperature. For each new observation type a forward model operator is required, together with estimates of the observation error covariance. In future the 1D-VAR retrievals will be further extended to include observations from other instruments, described below. These are expected to improve the vertical resolution of the retrievals.

a) Ceilometer

Ceilometers (or *laser cloud base recorders*) are simple backscatter LIDAR (Light Detection and Ranging) systems that form part of the operational network of observations, commonly deployed at airports to provide measurements of the cloud-base height. They work by transmitting laser pulses near vertical and measuring the backscattered signal in a range of discrete gates. Although they typically operate in the near infrared (e.g. 905 nm), they are capable of penetrating thin cloud and able to measure the height of up to 3 distinct cloud layers. Ceilometers are typically configured to report cloud bases up to 8 km every 30 s. In fact, they are capable of providing much more information in the form of full backscatter profiles, which can indicate the height of inversions that trap aerosol layers near the surface. However, this is not currently exploited operationally due to difficulties interpreting their signal, which is a complex function of aerosol content, type and humidity. The signal can also be adversely affected by the sun when it is high in the sky.

The height of the lowest cloud base could be used in the 1D-VAR retrieval in a similar way to the infrared brightness temperature. It could either be used as a cloud classification indicator and the retrieval's first guess modified to ensure that it is cloud free below the cloud base, but saturated at that level – or by constructing a simple forward model for the cloud-base height and including this in the observation vector. The latter approach is likely to cause convergence problems of the type encountered with the infrared radiometer due to its non-Gaussian error characteristics (i.e. on/off). The ceilometer backscatter signal is generally more sensitive to cloud than the thermal infrared radiance and it will detect cloud layers that are transparent at microwave frequencies. For these reasons, it is unlikely that the ceilometer alone will have a large impact on the retrievals when an infrared radiometer is also available, although it remains attractive in principle, as this combination would provide both the height and temperature of the cloud base, and thus fix a point in the profile.

It may also be possible in future to use time-series of ceilometer observations to estimate profiles of fractional cloud occurrence in situations with broken cloud. This could be used to complement the time-series of retrievals from microwave radiometer observations with high time resolution.

b) Cloud Radar

Cloud radars typically operate in the designated bands at 35 GHz and 94 GHz, where backscatter is dominated by liquid and ice drops, for which signal is proportional to their number density and the 6th moment of the drop size distribution [Westwater *et al.*, 2005]. This results in a much greater sensitivity to large cloud droplets, especially precipitation and insects, while clouds comprising of small droplets, such as small cumulus and fog may go undetected. It also makes the relationship between backscatter and liquid water content a nonlinear function of the drop size distribution.

[0] Cloud radars operate in window regions, where absorption is dominated by the water vapour continuum, which becomes significant at higher frequencies and must be accounted for in quantitative interpretation of the signal.

In their simplest form, observations from a cloud radar can be used to define cloud boundaries, which can then be combined with microwave radiometer data by methods similar to those suggested above for ceilometers. A more sophisticated approach is to define a relationship between the backscatter and the liquid water content (*LWC*) and use this as a forward model to include the backscatter profile in the observation vector. This approach was adopted in the *Integrated Profiling Technique* [Löhnert *et al.*, 2004] for pure liquid water cloud. Cloud radar and ceilometer data have been combined to classify cloud conditions over a profile as either clear, pure liquid water, pure ice or mixed phase cloud or drizzling cloud [Hogan and O'Connor, 2004]. These classifications may be used to improve the accuracy of the relationship between backscatter and *LWC*.

c) Integrated Water Vapour column from GPS

Data from high precision GPS (Global Positioning System) receivers at fixed positions can be used to estimate the Integrated Water Vapour (IWV) by measuring the phase delay of signals transmitted from multiple GPS satellites [Bevis *et al.*, 1992]. This information is also available from microwave radiometer observations at two or more channels in the 20-40 GHz band with comparable accuracy, so the integration of the two systems does not seem to offer much potential for improving the retrievals. However, GPS sensors may allow a reduction in the number of channels needed for a microwave radiometer to retrieve temperature profiles accurately above 1 km or provide a calibration reference for water vapour channels [Hewison, 2006].

d) Wind profiling radar signal

A wind profiler is a ground-based Doppler radar with 3 or more beams which measures signals backscattered from refractive index fluctuations associated with turbulence. The Doppler components of the beams from different directions are used operationally to estimate profiles of the wind vector, assuming the wind field to be homogeneous over their projected area. Typically wind profilers operate in the UHF band for profiling the boundary layer, while VHF systems can be used to profile most of the troposphere. In addition to measuring the wind vector, the signal to noise ratio from wind profiler radars is sensitive to the magnitude of the gradients in the refractive index. These provide indications of the height of temperature inversions (for VHF systems in the upper troposphere) and hydrolapses (for UHF systems in the lower troposphere), which can be used to monitor the height of the top of the boundary layer. This information could improve profiles retrieved from microwave radiometer data.

The first guess profiles could be modified from the backgrounds available from NWP models so the height of any temperature inversions or hydrolapses are consistent with the profile of signal to noise ratio observed by a co-located wind profiler. However, attempts to modify the first guess in a similar way did not improve the retrieval of an inversion that was present at the wrong height in the NWP model background. So it is unlikely that this technique alone would be more successful when applied to wind profiler data, without additional modifications to the assumed background error covariance. A slightly different approach is to use only the height of the wind profiler's peak signal strength by including an additional term in the cost function to constrain this to coincide the corresponding features in the state vector.

A more sophisticated approach would be to construct a reliable forward model to predict the wind profiler's signal to noise ratio from the NWP model fields, together with estimates of its error characteristics. This may be reliably modelled from the elements used in the state vector of the retrievals described here – i.e. temperature and humidity. However, a more accurate model may need additional terms in the state vector to account for turbulence. A thorough review of this topic was performed by Gaffard and Nash [2006].

4. ASSIMILATION INTO NWP MODELS

a) Providing Data to NWP Models

There are different methods by which observations from different instruments may be combined in future *Integrated Profiling Systems* and supplied for assimilation in NWP models:

1. Provide a live data feed of radiances and error estimates with forward model operators and their gradients as well as any constraints imposed by physics or derived from other instrumentation. Scientific documentation would need to be supplied in sufficient detail to allow the coding of an assimilation scheme. The forward model could be supplied either as an independent fast model or by modifying RTTOV [Saunders *et al.*, 1999].

In this option there is flexibility in the distribution of instruments in the network:

- a. Assimilation of data from different instruments at the same site simultaneously.
 - b. Assimilation of data from different instruments at different sites simultaneously.
2. Provide a live data feed of profiles (with error estimates) retrieved by a 'stand-alone' algorithm. This could be either:
 - a. A 1D-VAR retrieval combining observations from different instruments with an NWP background. These retrievals would then be assimilated into NWP as 3- or 4D-VAR.
 - b. Provide a live data feed of profiles (with error estimates) retrieved by a 'stand-alone' neural network or other regression technique.

Further development is needed to determine which of these options to pursue, taking into account the implications for further development of the technique and integration of observations from other instruments.

In addition, to address the question of which method of assimilation is preferable, different techniques will be compared including statistical regression, neural network and 1D-VAR. These are described in the next section. If only the radiometer data is available, several studies have shown that it is better to supply the data as radiances for assimilation into NWP. However, if we can also use the signal from the wind profiler, it may be better to supply a retrieved profile for assimilation, ultimately by 4D-VAR. This would allow the retrieval of small scale vertical structures, which otherwise could be lost by assimilation into an NWP model with coarser vertical resolution. This approach would also be useful for nowcasting applications.

To decide between these fundamental approaches, we need to know if we can quantify the humidity gradient from the wind profiler signal reliably. If this is possible, it will also be necessary to investigate the optimal background to use for the retrievals – climatology has the advantage of independence from NWP, while NWP should provide a more accurate background in most cases.

In addition to the above error budgets and experiments, further work is needed to establish whether it is possible to retrieve vertical humidity gradients from wind profiling radars. The ongoing review of factors affecting the signal to noise ratio of the wind profilers should be continued, and recommendations made for any hardware modifications needed to fully exploit these data. Algorithms for determination of boundary layer and/or tropopause height should also be assessed, as these may give more limited, but useful, information to improve the retrieval from microwave radiometers.

b) Exploiting Observations' High Time-Resolution

One of the greatest potential benefits of ground-based observations is their high temporal resolution. However, to fully exploit their high time-resolution requires a 4-Dimensional assimilation scheme, such as 4D-VAR. This has the potential to correct gross errors in the timing of (for example) fronts passing the observation location, and this has knock-on effects on much larger scales. As well as direct assimilation of observations in 4D-VAR, it is also possible to use it assimilate profiles retrieved by 1D-VAR [Marécal and Mahfouf, 2003]. 4D-VAR is computationally expensive. So, although it is now operational in global models at the Met Office and other centres, it is not expected to be implemented in operational convective scale NWP models for several years – and it is in these high-resolution models that ground-based observations are expected to have most impact. Meanwhile, other methods of exploiting the observations' high time resolution suggested in the following paragraphs could be investigated.

One of the basic assumptions about the potential benefit of observations from ground-based instruments is that their high temporal resolution can be used a proxy for horizontal resolution in the direction of atmospheric advection. In 3D-VAR, their data is assimilated at nominal observation times with relatively short windows every few hours. In practice, most operational 3D-VAR schemes use the First Guess at Appropriate Time (FGAT) method, comparing the observation with the background at the observation time.

The next step up in the evolution of assimilation methods is 2D-VAR using a single column NWP model, as demonstrated by Lopez *et al.* [2006]. They set up this unconventional system to investigate the problems of assimilating observations from a co-located microwave radiometer, cloud radar, GPS and rain gauge. This assimilation aims to find initial temperature and humidity profiles that give the best fit between *a priori* information from the model and the observations over a 12 h time window at a given geographical location. They assimilated radiometer and GPS observations at 30 minute time resolution, although the cloud radar data needed to be time averaged to achieve convergence. The obvious limitations of this method are that it only produces increments of temperature and humidity co-located with observations and has no feedback from the 3D dynamics (unlike 4D-VAR) and that it cannot modify the forcing – e.g. convergence in 2D.

A relatively simple scheme has been demonstrated that uses the variability seen by the observations to calculate the representativeness errors dynamically in real-time [Hewison, 2006]. Although this showed little reduction in the variance of the retrieved profiles compared to co-located radiosondes, the errors in this comparison were limited by those of the radiosondes and the background, which was assumed to be fixed. Similar limitations were found when averaging retrieved profiles over a short period prior to validating them against radiosonde. However, this method is expected to produce an average profile which is closer to the average of the NWP model's grid box.

It is also possible to use observations at high time-resolution to estimate the sub-gridscale variability within each model box and relate this to other quantities in the model. For example, the variance could be calculated as well as the mean of a series of profiles retrieved by 1D-VAR, or these could be used to estimate the cloud fractional occurrence within a model grid box. The variance could be empirically correlated to other model parameters as indicators of convective activity. However, while the background error covariance remains constant, it will be difficult for this method to improve the accuracy of 1D-VAR retrievals. Alternatively, cloud fraction could be added as a control variable in retrievals using a time-series of observations.

It is also possible to use profiles retrieved from a time-series of observations, taking the analysis of one 1D-VAR retrieval as the background for the next and take its analysis error covariance as the background error covariance for the next. This makes the reasonable assumption that the observation errors are independent between successive retrievals. However, it also assumes that the errors introduced at different stages in the successive retrievals are independent, which is more dangerous as it could result in the reinforcement of retrievals that converge on erroneous minima.

c) Observing System Synthesis Experiments

The choice of possible distribution of observing systems within national or international networks is difficult to evaluate quantitatively. Inevitably, there will be practical restrictions constraining the network's design – e.g. it may be prohibitively expensive to relocate existing systems or there may be other user requirements which effectively limit their redeployment or retirement. These factors must be taken into account when designing different options for network configurations. The impact of each configuration can be tested using Observing System Synthesis Experiments (OSSEs). In these trials forecasts are repeated based on analyses derived from different sets of synthetic observations. This requires the development of a forward model for the observations and its adjoint, as well as the full assimilation scheme. Although this represents a substantial investment, OSSE results are not always conclusive. However, they are the only practical method to compare the benefits of different network configurations on forecast accuracy.

d) Demonstrating Observations' Impact on NWP

1D-VAR retrievals have demonstrated that the microwave radiometer can improve the temperature and humidity profiles in the NWP background up to ~3 km. However, there is still a requirement to demonstrate that these observations will improve the accuracy of NWP forecasts. The latter is a more complex question involving a thorough understanding of the model physics and parameterizations, although generally it is expected that more accurate analyses lead to more accurate forecasts.

The best way to demonstrate the impact an observation has on NWP is to conduct parallel trials – with and without the assimilation of the observation. However, this requires a considerable investment in terms of developing the assimilation suite for that instrument. Before investing in this development, it is necessary to demonstrate that the observation will have an impact. This is the fundamental *chicken and egg* problem facing those making the decision to invest in the assimilation of data from new instruments.

A simpler way to demonstrate an impact on the analysis would be to set-up an offline 1D-VAR, based on NWP model background fields. Experiments will then be conducted to assess whether the observations can help:

- a) Add absent features to a background profile (e.g. temperature inversion, hydrolapses),
- b) Suppress erroneous features,
- c) Correct vertically displaced features.

This experiment should include an independent data source as truth – for example, radiosondes that have not been assimilated. This allows the demonstration of which model parameters are improved by the use of data from the radiometer. It should also provide case studies showing the impact of timing errors. The establishment of the *Integrated Profiling Station* would provide such a dataset. We could also exploit data from existing datasets, including the Convective Storms Initiation Project (CSIP). This has already been done for the radiometer alone and in combination with surface and infrared sensors. Follow-on work should extend this analysis to include observations from other systems.

5. CONCLUSIONS

A 1-D variational retrieval has been developed to allow observations from ground-based microwave and infrared radiometers and surface sensors to be combined with a background from an NWP model in an optimal way, which accounts for their error characteristics. This has been used to retrieve profiles of temperature, humidity and cloud using a novel total water control variable. This has been shown to be advantageous over methods taking their background from statistical climatology [Cimini *et al.*, 2006].

The 1D-VAR retrievals also have the advantage of providing an estimate of the error on the retrieved profile. Error analysis has shown the microwave radiometer improves the NWP background up to 4 km, retrieving temperature profiles with <1 K uncertainty and 2.8 *Degrees of Freedom for Signal (DFS)* and humidity with <40% uncertainty and 1.8 *DFS*. Most of the radiometer's information is concentrated in the boundary layer: in the lowest 1 km, the accuracy of the temperature and humidity profiles is <0.5 K and <20%, respectively. These results depend on the background error covariance. However, the vertical resolution of the retrieved profiles is poor and degrades with height. Furthermore, the retrievals were not able to move a misplaced feature in the background profile.

The variational method allows different instruments to be combined if their observations' forward model operator and error estimates are available. This provides a basis for the development of *Integrated Profiling Stations*. In the future the 1D-VAR retrievals will be extended to include observations from other instruments, such as the cloud base height from a ceilometer, cloud base/top from cloud radar and refractive index gradient from a wind profiler.

The variational framework allows observations from any instruments to be combined if:

1. They are sensitive to a parameter of the *state space* of the retrieved profile.
2. A forward model can be defined to transform from state to observation space.
3. This function can be differentiated to yield the adjoint.
4. Error bars can be defined for the observation.

This integration allows the strengths of different observing systems to be combined and its development requires liaison between data assimilation scientists and instrument engineers.

Assimilation of these observations could improve mesoscale Numerical Weather Prediction (NWP), especially boundary layer and cloud properties. There is an open question of whether this integration is best done by a stand-alone retrieval or within the framework of an NWP model by assimilating the observations directly. However, to fully exploit the high time resolution available from ground-based instruments will require a 4-Dimensional assimilation method, such as 4D-VAR.

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