Boundary layer thermodynamic profiling using ground-based microwave radiometry and 1DVAR for Nowcasting

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ABSTRACT

Ground-based microwave radiometer profilers in the 20-60 GHz range are operational at numerous worldwide sites. Recently, it has been demonstrated that a One-Dimensional Variational technique coupling radiometric observations with a numerical weather prediction model output outperforms traditional temperature and humidity profiling retrieval methods. This technique has been applied to observations from a microwave radiometer deployed at Whistler, British Columbia, operated by the Meteorological Service of Canada to support nowcasting and short term weather forecasting during the 2010 Vancouver Winter Olympic. Here we show the results obtained during the Olympics including comparison with radiosonde profiles to quantify the achieved accuracy.

1. INTRODUCTION

Ground-based microwave radiometer profilers (MWRP) in the 20-60 GHz range are operational at numerous worldwide sites. Continuous thermodynamic profiles including the boundary layer are traditionally retrieved from ground-based MWRP observations using neural network or regression methods. In the last few years it has been demonstrated that a One-Dimensional Variational (1DVAR) technique coupling radiometric observations with a numerical weather prediction model output outperforms other temperature and humidity profiling retrieval methods ([1-3]). This approach avoids error inherent in neural network or regression retrieval methods and benefits from recent surface, radiosonde, satellite, radar and other data residing in the local forecast. Recently, this technique has been applied to observations from the MWRP (Radiometrics MP-3031A) deployed at the base of the Whistler Creekside Gondola, Whistler, British Columbia, operated by the Meteorological Service of Canada (MSC) (Figure 1). The continuous thermodynamic soundings at Whistler were used to generate traditional forecast tools and indices by MSC to support 2010 Vancouver Winter Olympic nowcasting and short term weather forecasting. Also, atmospheric pressure, temperature, and humidity profiles were measured by balloon-borne radiosondes launched by MSC from a nearby station (Nesters). In this paper we show the results obtained during the Olympics including comparison with radiosonde profiles to quantify the achieved accuracy. Finally we discuss the 1DVAR potential for large scale MWRP networks that are currently being established.

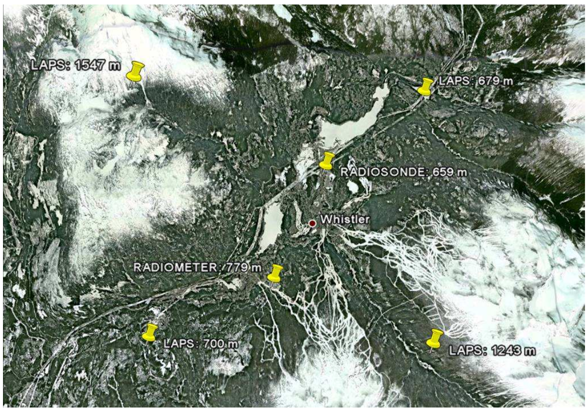

Figure 1. *Radiometer, radiosonde and LAPS analysis grid points altitudes at Whistler.*

2. RETRIEVAL TECHNIQUE

MWRP multichannel observations at a number of elevation angles have been used to accurately estimate profiles of temperature and moisture by virtue of the multiplicity of weighting functions probing depths that such a set can provide. Because of the fundamental physics of ground-based radiometric observations, the vertical resolution and accuracy of the derived profiles degrades with increasing altitude. Traditionally, temperature and humidity profiles are retrieved from ground-based MWRP observations using linear (e.g. regression), nonlinear (e.g. iterative), or neural network methods [4], partially overcoming the lack of sensitivity at the higher altitudes by incorporating statistical correlations between lower and higher levels. Use of proper background data and vertical statistics is vitally important to achieving the highest accuracy. Recent results [1-3] show that coupling the radiometer data with a forecast model through 1DVAR can greatly improve the retrieval accuracy over either linear or neural network methods alone. The 1DVAR method combines observed and forward-modeled local analysis brightness temperatures with covariance matrices to optimize retrieval accuracy. The analysis contributes primarily to retrieval accuracy in the upper troposphere, and the radiometer to the boundary layer and lower troposphere. Thus, the 1DVAR approach avoids error inherent in neural network or regression retrieval methods and benefits from current surface, radiosonde, satellite, radar and other data residing in the local forecast.

The details of the 1DVAR implementation used here are given in [3]. The solution is given by

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

where $\mathbf{x_i}$ and $\mathbf{x_b}$ are the current and background state vector, **B** and **R** are the error covariance matrices of the background and observation vector **y**, $F(\mathbf{x})$ indicates the forward model operator, **K** the Jacobian matrix of the observation vector with respect to the state vector, and finally γ is the Levenberg-Marquardt factor adjusted after each iteration.

The Numerical Weather Prediction (NWP) model used here is the NOAA Local Analysis and Prediction System (LAPS). The state vectors are profiles of temperature and total water (i.e. total of specific humidity and condensed water content), given on the same 81 vertical levels defined for the LAPS model, although we perform retrieval just for the levels between 0 and 10 km. The observation vector is given by brightness temperatures (Tb) at 22 channels at two elevation angles (zenith and 15°) and surface pressure, temperature and humidity readings. The air and sky temperature conditions experienced during the Winter Olympics in Whistler are illustrated in Figure 2.

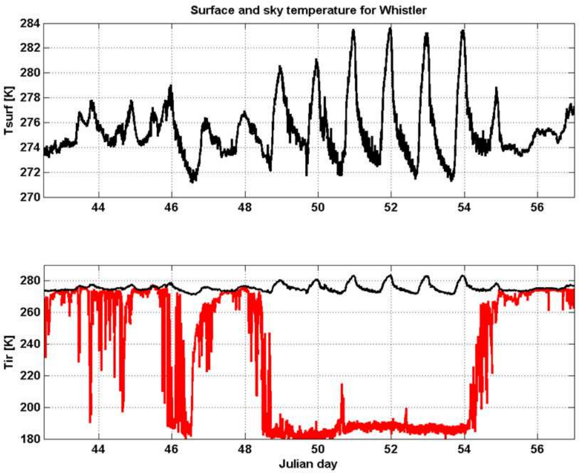

Figure 2. *Surface air temperature (Tsrf, black) and sky infrared temperature (Tir, red) time series.*

3. RESULTS

Preliminary results of the 1DVAR implementation for the period of the winter Olympics are presented. First of all, statistical comparison of observed and simulated data is required in order to determine instrument bias and NWP background error covariance (called **B** hereafter).

3.1 Tb comparison

Tb simulations were obtained by processing radiosounding observations (RAOB) and LAPS model output with a radiative transfer simulator. The first level of both RAOB and LAPS soundings was adjusted to match the altitude of the radiometer (776 m ASL). RAOB Tbs were computed twice: once assuming clear sky (no hydrometeor) and once assuming a cloud model. LAPS Tbs were forward modeled from temperature, water vapor, liquid and ice water profiles. The comparison between radiometric observations and simulations was performed quantitatively for all the 22 MWRP channels. An example for the MWRP channel at 22.5 GHz is shown in Figures 3 (time series) and 4 (scatter plots).

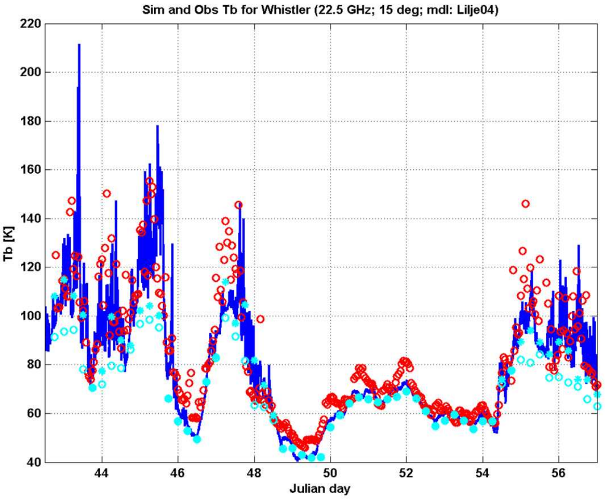

Figure 3. *Tb observations (blue), LAPS (red) and radiosondes (clear: cyan circles; cloudy: cyan stars) simulations at one of the MWRP channels.*

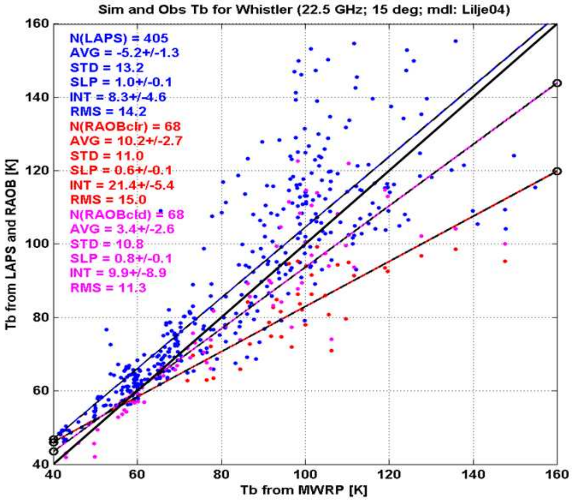

Figure 4. *LAPS (blue) and radiosonde (cloudy: red; clear: magenta) simulated Tb scatter plots for one of the MWRP channels (clear and cloudy data are shown).*

3.2 Background covariance error estimation

The temperature and specific humidity profile background error covariance matrices ($\mathbf{B_T}$ **and** $\mathbf{B_Q}$, respectively) were computed from simultaneous LAPS and RAOB profiles during the Vancouver Winter Olympics (12-28 Feb 2010). $\mathbf{B_T}$ and $\mathbf{B_Q}$ were computed both at LAPS and standard MWRP retrieval height levels. The square-root of $\mathbf{B_T}$ and $\mathbf{B_Q}$ diagonal terms up to 10 km height are shown in Figure 5. The resulting statistical information (Tb bias, $\mathbf{B_T}$, $\mathbf{B_Q}$) are then considered in our 1DVAR retrieval development. One example is shown in Figure 6, where temperature and humidity profiles from the radiosounding in Nesters and the radiometric retrievals obtained with neural network and 1DVAR approaches are plotted together.

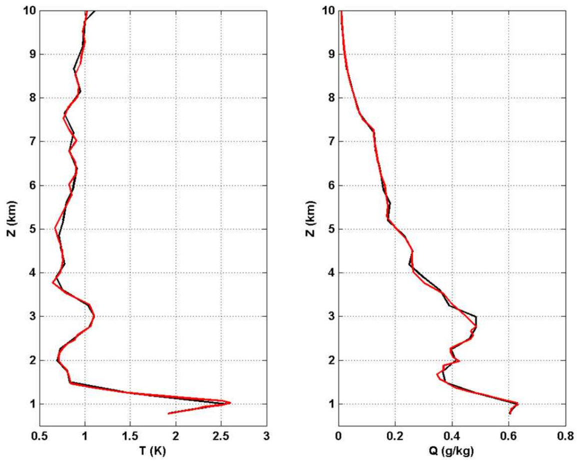

Figure 5: *Diagonal terms (square root) of B_T (left) and B_Q (right) at LAPS analysis (black) and radiometer (level 2) retrieval (red) height levels.*

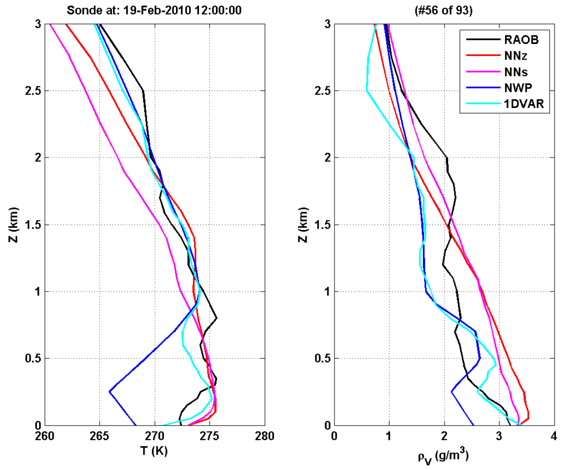

Figure 6: *Temperature (T) and humidity (ρ_V) profiles as measured by the radiosounding in Nesters and retrieved from radiometric observations using neural network and 1DVAR techniques.*

4. CONCLUSIONS AND FURTHER WORK

A 1DVAR technique for the retrieval of temperature and humidity profiles from ground-based radiometric observations has been developed and tested. Early results seem to confirm the expectations that 1DVAR technique outperforms other traditional methods. However, more work is needed to tune the technique for operational use. In particular, methods to increase the reliability and the efficiency (convergence speed) for humidity retrievals should be developed. Finally, it is noteworthy that capturing boundary layer and lower tropospheric thermodynamic effects is critical to improving local short term forecast accuracy, for example for aviation weather, air quality, outdoor events, fire weather, hazardous airborne material dispersion, and renewable (wind and solar) energy management.

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