Retrieving Moisture Profiles from Precipitable Water Measurements Using a Variational Data Assimilation Approach

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Introduction

Atmospheric moisture distribution is directly related to the formation of clouds and precipitation and affects the atmospheric radiation and climate. Currently, several remote sensing systems can measure precipitable water (PW) with fairly high accuracy. As part of the development of an Integrated Data Assimilation and Sounding System in support of the Atmospheric Radiation Measurement Program, retrieving the 3-D water vapor fields from PW measurements is an important problem. A new four dimensional variational (4DVAR) data assimilation system based on the Penn State/National Center for Atmospheric Research (NCAR) mesoscale model (MM5) has been developed by Zou et al. (1995) with the adjoint technique. In this study, we used this 4DVAR system to retrieve the moisture profiles.

Because we do not have a set of real observed PW measurements now, the special soundings collected during the Severe Environmental Storm and Mesoscale Experiment (SESAME) in 1979 were used to simulate a set of PW measurements, which were then assimilated into the 4DVAR system. The accuracy of the derived water vapor fields was assessed by direct comparison with the detailed specific humidity soundings. The impact of PW assimilation on precipitation forecast was examined by conducting a series of model forecast experiments started from the different initial conditions with or without data assimilation.

4DVAR System

The 4DVAR system includes the forward model and its adjoint, and a minimization algorithm. The detailed descriptions of the forward model (MM5) and its adjoint are given by Grell et al. (1994) and Zou et al. (1995). The minimization procedure used the limited-memory quasi-Newton method (Liu and Nocedal 1989). A brief description of the working procedure of the 4DVAR system is as follows:

1. The forward model (MM5) integration started from a guess of the initial condition in the assimilation time window (t_0, t_R) gives the basic states, which are used to calculate the coefficients for its adjoint.

2. The backward integration of the adjoint model with the forcing terms added will give the gradients of the cost function with respect to the initial conditions. The forcing terms are usually calculated from the observed data available within the time window (t_0, t_R) and the model variables.

3. The gradients are used to determine the descent direction, and the initial conditions are corrected based on this descent direction.

4. With the new initial conditions, steps 1 to 3. are repeated This process continues iteratively and finally produces the optimal initial conditions, which make the model trajectory a best fit to the observations within the time window (t_0, t_R).

Here the cost function J is defined as

$$J(x_0) = \beta(qs(t_R) - qs_{obs}(t_R))^2 + \gamma(PW(t_R) - PW_{obs}(t_R))^2 \quad (1)$$

Where x_0 represents a vector of the model condition at $t = t_0$ and qs, PW, and qs_{obs}, PW_{obs} are the model and observed surface humidity and precipitable water at $t = t_R$. β and γ are the weighting coefficients.

Observed Data

The 3-hour soundings and the surface observations collected during the SESAME I case from 1200 UTC 10 to 1200 UTC 11 April 1979 were objectively analyzed to a 40-km grid using the Cressman scheme (Figure 1). The observed precipitable water is computed from the vertical integration of the specific humidity:

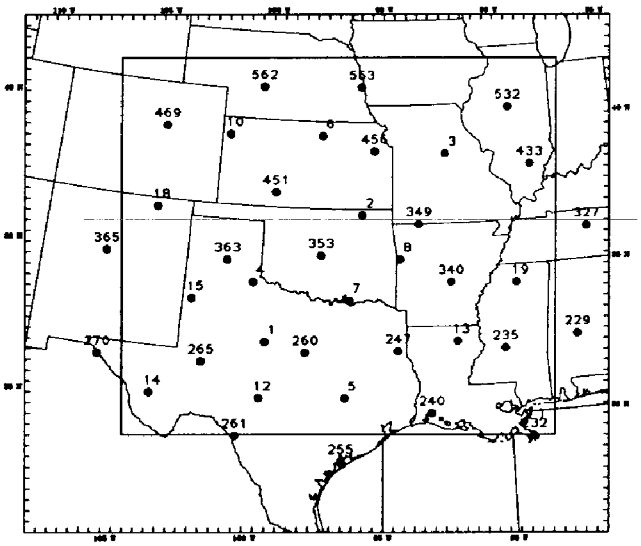


Figure 1. The model domain with the rawinsonde stations plotted. The numbers above the stations are the station ID. Inner box shows the region used for precipitation verification.

$$PW_{obs} = \frac{\tilde{p}}{g} \sum_{k=1}^{K} q_{obs}(k)\,\Delta\sigma \qquad (2)$$

where $q_{obs}(k)$ is the objective analysis of the specific humidity, $\tilde{p} = p_s - p_t$ (where p_s is the surface pressure and p_t is the pressure at the model top [100 mb]), K=10 is the total number of the model layers, $\Delta\sigma$ is the thickness of the layers (0.1), and g is the acceleration due to gravity. The specific humidity at the lowest model level $q_{obs}(k)$ was used as the observed surface moisture qs_{obs}. The model PW is calculated in the same manner.

Experiment Design

The data assimilation time window is 1 hour from 1700 UTC (t_0) to 1800 UTC (t_R) 10 April. The initial guess at $t = t_0$ was interpolated from the analyses of 1200 UTC 10 and 0000 UTC 11 April. Four experiments were conducted to assess the impact of the data assimilation (Table 1).

Results

To evaluate the quality of the retrieved specific humidity via the variational data assimilation approach, we calculated the rms, bias, and non-bias errors at 1800 UTC 10 April verified against the soundings observations at 36 stations and the

Table 1. Experiment design.

	1-H 4DVAR		6-H Forecast
Exp. Name	**Init. Guess at 1700 Z**	**Obs. Data at 1800 Z**	**Init. Cond. at 1800 Z**
ANAL	N/A	N/A	Analysis
INTP	N/A	N/A	Interp.
PW	Interp.	PW	From 4DVAR
QSPW	Interp.	PW, qs	From 4DVAR

threat scores for 3-hour accumulated rainfall forecast during the period of 1800 UTC 10 through 0000 UTC 11 April.

Errors

Figure 2 shows that the analyzed specific humidity is very accurate compared with the station observations. The vertically integrated rms error is only 0.15 g/kg. The interpolated q_{INPT} shows errors as large as 2 g/kg at level 8 and 9 and has integrated error of 1.2 g/kg. The assimilation of PW reduced the integrated error to 0.89 g/kg, and the addition of the surface moisture further deceases the error to 0.78 g/kg, which derived mainly from the improvements in the surface moisture field.

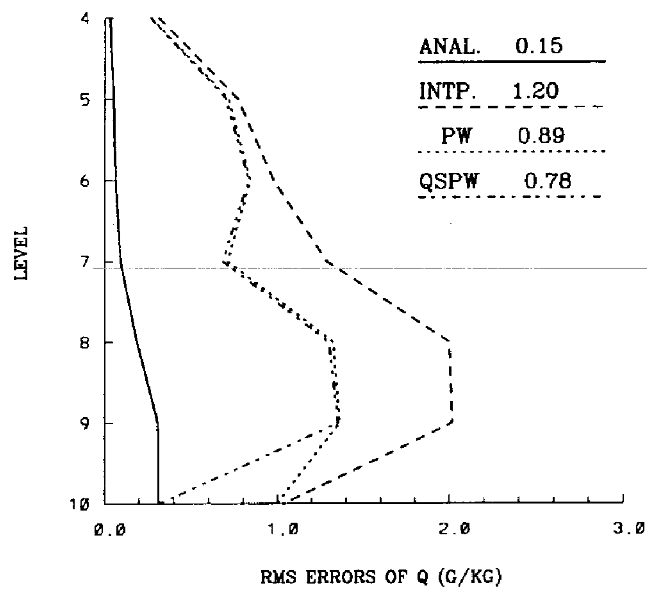


Figure 2. The rms errors of specific humidity field at 1800 UTC 10 April for Exp. ANAL, INTP, PW, and QSPW. The numbers above each of line patterns are the vertically integrated rms error.

Figure 3 shows the distribution of the errors for Exp. INTP, PW, and QSPW. Large bias (PW) errors of 1.42, 1.70, and 1.37 g/kg are found at station 353, 260, and 13 for Exp. INTP, respectively (Figure 3a). The rms errors are 2.04, 3.03, and 1.79 g/kg at these 3 stations (Figure 3b). As expected, the assimilation of PW or PW and qs effectively removed the bias errors. As a result the bias (PW) errors for Exp. PW and QSPW are close to zero (not shown), and the rms errors and non-bias errors are almost identical.

Figure 3c and 3d showed that assimilation of PW or PW and qs reduced the errors to 1.36, 1.53, 1.18 and 1.14, 1.41, 1.11g/kg at the 3 stations, respectively (Figure 3c and 3d). We also noticed two other interesting stations, 1 and 19. The rms errors for Exp. INTP are rather large (Figure 3b). Figure 4 shows the vertical moisture profiles at these two stations. Station 1 has very small bias error (0.18 g/kg). Therefore, the assimilation of PW alone would not be effective. However, the assimilation of PW and surface moisture reduced the errors dramatically from 3.73 to 1.33 g/kg (Figure 4a). Station 19 has a small bias (PW) error (0.50 g/kg) as well as the small surface moisture error (Figure 4b). According to the cost function in section 2, the forcing terms at this station were small, so the assimilation of PW and the surface moisture would not lead to improvement on this complicated vertical moisture structure.

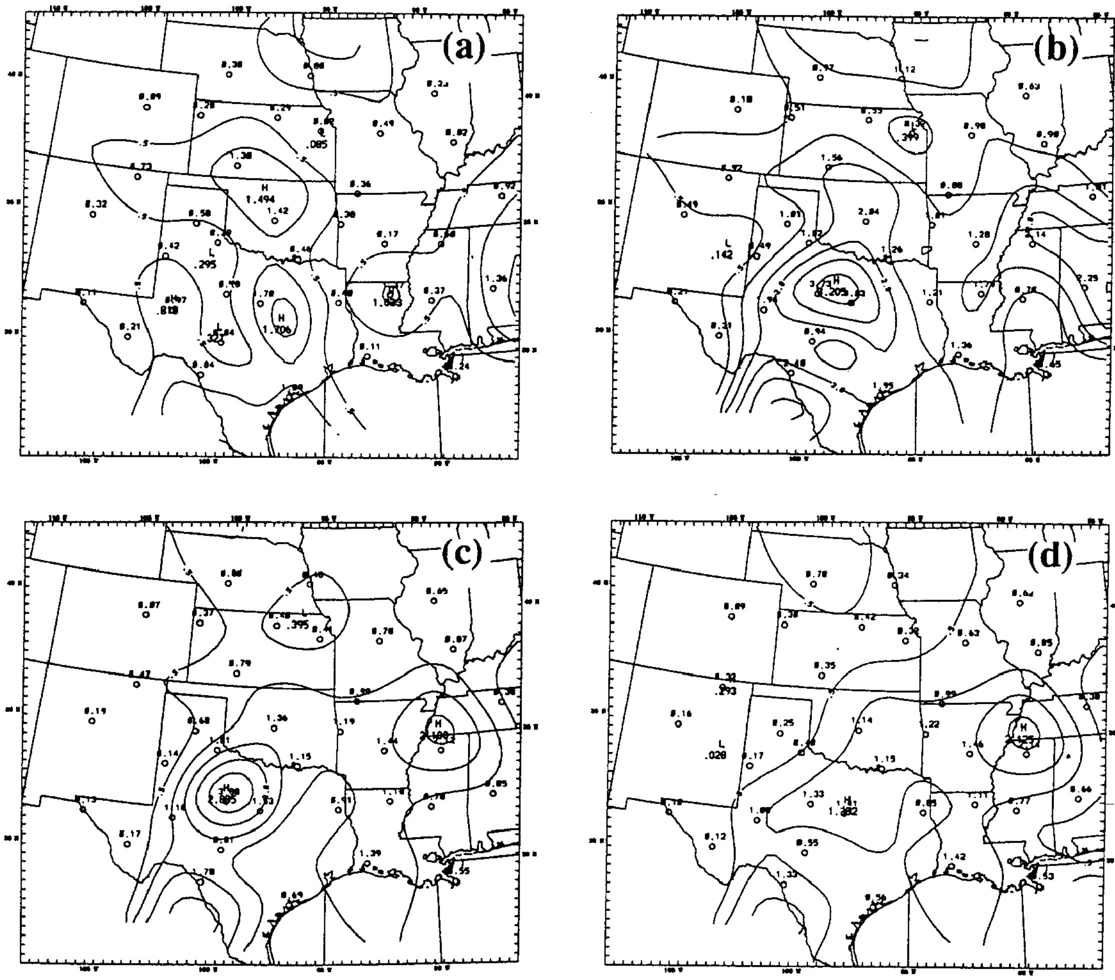
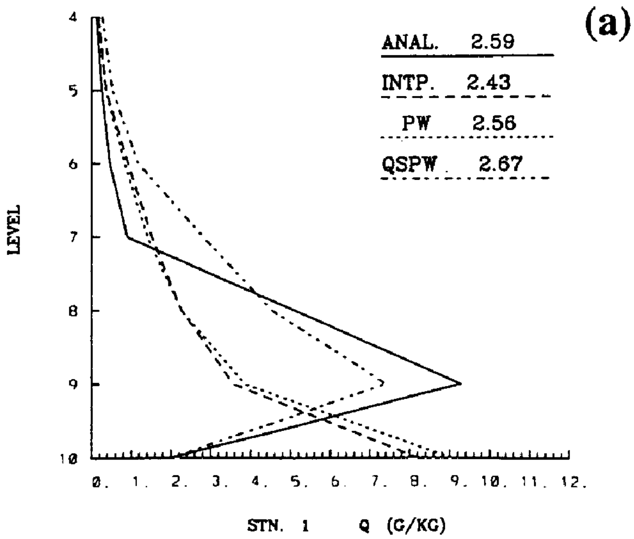


Figure 3. The distribution of the (a) bias errors and (b) rms errors of the specific humidity for Exp. INTP, and the distribution of non-bias errors of the specific humidity for (c) Exp. PW and (d) Exp. QSPW at 1800 UTC 10 April. The contour interval is 0.5 g/kg.



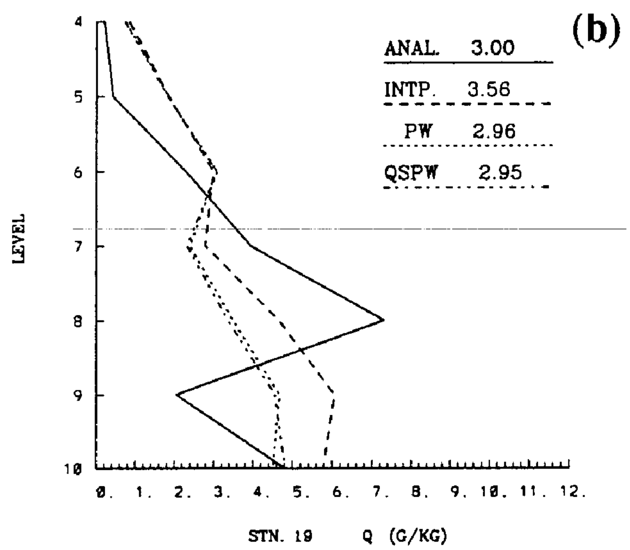


Figure 4. The vertical moisture profiles at (a) station 1 and (b) station 19 for Exp. ANAL, INTP, PW, and QSPW. The numbers above each of the line patterns are the mean values of the specific humidity (g/kg).

Verification of Precipitation Forecast

Figure 5 shows that the Exp. INTP has a very low precipitation forecast skill as verified against the forecast of Exp. ANAL, which has the detailed moisture analysis. The threat scores are close to zero. The assimilation of PW data improved the precipitation forecast considerably. Further improvements were found with the addition of surface moisture data in the assimilation cycle. Assimilation of the

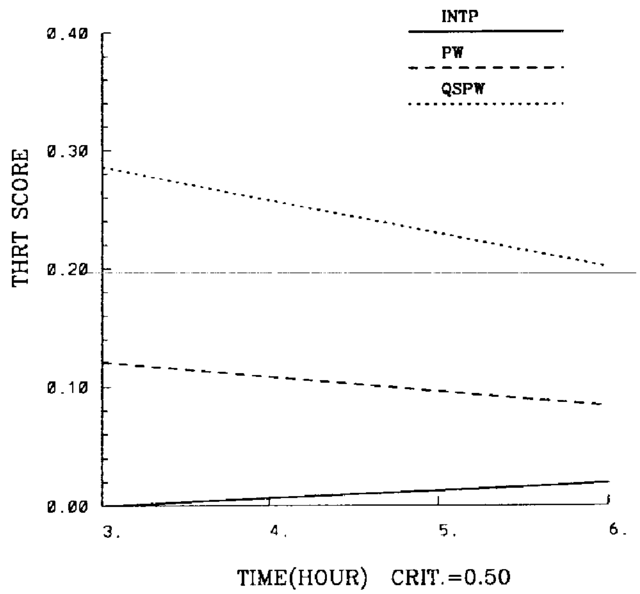


Figure 5. Threat scores of 3-h precipitation forecast at a threshold of 5 mm from 1800 UTC 10 to 0000 UTC 11 April for Exp. INTP, PW and QSPW verified against the forecast from Exp. ANAL.

moisture alone was certainly not enough to get a good precipitation forecast skills (TS is only 0.2~0.3; Figure 5). The best results were obtained when the PW and surface moisture data were assimilated in combination with the wind and temperature data (TS reached 0.5~0.6; Kuo et al. 1995).

Summary and Conclusions

In this study, the newly developed variational data assimilation system based on the Penn State/NCAR mesoscale model MM5 and its adjoint were used to conduct a series of experiments in retrieving the moisture profiles from the observed PW data. The PW observations at one time level, 1800 UTC 10 April 1979, were obtained from the vertical integration of the observed analysis of the specific humidity during the SESAME I period.

We found that the assimilation of precipitable water measurements can recover the vertical structure of water vapor. The use of surface moisture data can further improve the accuracy of moisture retrieval, particularly in the lower troposphere. The improved moisture analysis as a result of PW (and surface moisture data) assimilation can lead to improved characterization of the moisture field over the CART domain and, in general, improved short-range precipitation forecast.

References

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