Feasibility study of data assimilation using a mobile water vapor

S. Yoshida(a), T. Sakai(a), T. Nagai(a), S. Yokota(a), H. Seko(a), and Y. Shoji(a)

(a) Meteorological Research Institute
Nagamine 1-1, Tsukuba, Ibaraki, 305-0052, Japan
syoshida@mri-jma.go.jp

Abstract: Vertical profiles of water vapor mixing ratio \( (q_v) \) obtained with a Raman lidar (RL) are assimilated into the Japan Meteorological Agency non-hydrostatic model using three-dimensional local ensemble transform Kalman filter as a feasibility study. Comparison of forecast and analysis of humidity field with precipitable water vapor (PWV) observed by Global Navigation Satellite System (GNSS) on surface indicates that data assimilation of vertical profiles of \( q_v \) reduces errors in forecast and analysis of humidity field. However, data assimilation of vertical profiles of \( q_v \) degrades estimation of humidity field in the late of the data assimilation experiment. The assimilation of \( q_v \) produces heavy precipitation three hours prior to the actual precipitation, causing cold outflow prevailing on surface in the model domain. The cold outflow accompanied by the early precipitation decreases PWV around thunderstorms, resulting in increasing errors in forecast and analysis of humidity field.

Keywords: Raman lidar, water vapor, data assimilation

1. Introduction

Water vapor in atmosphere exerts strong influence on initiations and development of thunderstorms. Small change on water vapor horizontal distribution sometimes causes strong impact on weather phenomena [e.g. 1]. Knowledge of water vapor distribution in atmosphere is very important for precipitation prediction with a use of data assimilation. In a couple of decades, data assimilation of water vapor obtained with space-borne imager [e.g. 2], Global Navigation Satellite System (GNSS) [e.g. 3], and water vapor lidar on airplane [4] and ground [5,6] are assimilated to numerical models and improvement of analysis and forecast of humidity field was presented.

A water vapor Raman lidar (RL), which emits laser pulses into air and receives Raman backscattered light form air molecules, provides vertical profile of water mixing ratio \( (q_v) \) by emitting lidar pulses vertically. One important and major advantage of water vapor lidar observation is providing vertical profiles of \( q_v \) that are not observed by GNSS. Therefore, development of the data assimilation of \( q_v \) obtained with lidars has been paid attention by a lot of researchers. This study examine the assimilation of vertical profiles of \( q_v \) obtained with a mobile RL into Japan Meteorological Agency non-hydrostatic model (JMA-NHM) [7] using three-dimensional local ensemble transform Kalman filter (LETKF). The quality of the data assimilation experiment is assessed by comparison of model-derived precipitable water vapor (PWV) with independent GNSS-observed PWV on ground. The impact of the data assimilation of the vertical profile on forecast and analysis is evaluated.

2. Data and Method

In the feasibility study, we focused on a heavy rainfall occurred on Kanto plane in Japan on 17 August 2016. At 1800 UTC on 17 August 2016, humid southerly winds prevailed near south part of the Kanto plane because a stationary front, accompanying an extratropical cyclone at Sea of Okhotsk, was located northern part of Kanto plane. The stationary front caused a group of cumulonimbus clouds around low level convergence between 0900 and 2100 UTC. Local heavy rainfall, exceeding 100 mm/2h, was recognized near the low level convergence around 1800 UTC.

We conducted RL observation to obtain vertical profile of \( q_v \) in Tsukuba, Japan, from 2 August 2016 to 6 December 2016. The RL was consisted of a Nd:YAG laser, and a beam expander, a telescope, and photomultiplier tubes (PMTs), and a transient recorder. The laser emitted light pulses at 355 nm with
pulse energy of 200 mJ and 10 Hz. The emitted beams were expanded to a diameter of about 5 cm by the beam expander. The light backscattered by atmospheric molecules and particles were received by the telescope and divided into three wavelengths, that are, 355 nm for elastic backscatter light, 386.7 nm for Raman nitrogen, and 407.5 nm for Raman water vapor with PMTs. Each light signals through the PMTs were digitized in the transient recorder. Figure 1 shows a time-height plot of $q_v$ obtained with RL on 17 August 2016. It appears that $q_v$ at low level (generally less than 1 km) increased by 2 g/kg between 0900 UTC and 1200 UTC.

To check the observational bias of RL, we performed comparison of $q_v$ observed by RL and that estimated in high-resolution local analysis (LA) data, which provides meteorological parameters based on calculation of JMA-NHM. The comparison was performed using data observed between 2 August 2016 and 30 September 2016. Figure 2a shows a scatter plot of $q_v$ obtained with the RL versus $q_v$ estimated in LA. Figure 2a shows that most $q_v$ obtained by RL agrees with $q_v$ estimated in LA. To discuss the relationship in details, Figures 2b and 2c, respectively, show vertical profiles of bias (RL $q_v$ minus LA $q_v$) and root mean square (RMS) between RL $q_v$ and LA $q_v$. As seen in Figure 2b, the biases are positive below altitudes of 2.5 km, indicating that RL $q_v$ has wet bias in the low level compared to LA.

In this study, we employed nested LETKF as data assimilation system. In the outer LETKF, the interval of horizontal grid was 15 km. The mesoscale analysis and global forecast were employed every 6 hours as boundary conditions. The JMANHM was employed to perform an ensemble forecast. In the outer LETKF, no data are assimilated. In the inner LETKF, we performed three assimilation experiments to explore the impact of RL data assimilation. The first assimilation experiment is termed as “TEST1”, in which RL-observed $q_v$ is directory assimilated. The second assimilation experiment is termed as “TEST2”, in which RL-observed $q_v$ is assimilated after the bias value shown in Figure 2b is subtracted from RL-observed $q_v$. The observation errors employed in TEST2 are set to RMS values shown in Figure 1c divided by square root of 2. The last assimilation experiment is termed as “CNTL”, in which no data is assimilated. In TEST1 and TEST2 experiments, RL data are assimilated in a 3-h assimilation window and no other data are assimilated.
3. Results

To explore the impact of assimilation of RL data, Figure 3 shows ensemble means of PWV in TEST1 at 1200 UTC. Figure 3 indicates that the RL data assimilation contributes to increasing PWV. The assimilation of RL has influence on the areas within about 200 km of the RL observation site as seen in Figure 3c. We perform comparison of GNSS-observed PWV with ensemble means of PWV in forecast and analysis to discuss the bias and root mean square (RMS). We performed two quality controls (QC) before the comparison to eliminate GNSS-observed PWV that might have large error. Firstly, we eliminate GNSS PWV when altitude differences between model surface and PWV site elevation are larger than 40 m in this comparison. Secondly, we eliminate GNSS PWV when precipitation more than 5 mm/h is recognized within 25 km of GNSS observation site.

The bias and RMS between forecast and GNSS observation, respectively, are -0.82 kg/m$^2$ and 2.75 kg/m$^2$. While, the bias and RMS between analysis and GNSS observation, respectively, are -0.27 kg/m$^2$ and 2.45 kg/m$^2$. Here, the bias indicates ensemble means of PWV minus GNSS-observed PWV. Since RMS and absolute value of bias in analysis is smaller than those in forecast, the assimilation of RL data contributes to improvement of humidity field at 1200 UTC. It should be noted that similar results are obtained in TEST2 experiment. Overall, the assimilation of RL seems to improve estimation of humidity field at 1200 UTC.

To examine the impact of the data assimilation, Figure 4 shows the bias and RMS between ensemble means of PWV and GNSS-observed PWV every 20 minutes. We applied the same QC scheme employed in Figure 3 before the comparison. As shown in Figure 4a, the absolute values of bias in TEST1 and TEST2 assimilation experiments are closer to zero compared to those in CNTL almost all the time. Moreover, Figure 4b shows that RMS in TEST1 and TEST2 is lower than the CNTL before 21 UTC. These results suggest that data assimilations of RL data contribute to improvement of humid field estimation up to the 21 UTC. However, after 21 UTC, the data assimilations degrades forecast and analysis of humidity field.

![Figure 3. Comparison of ensemble means of PWV between TEST1 and GNSS observation. (a) PWV forecast and (b) analysis. (c) Difference of ensemble means of PWV (analysis - forecast).](image)

![Figure 4. Time series of bias and RMS between ensemble means of PWV in TEST1 and GNSS-observed PWV.](image)
4. Discussion and summary

In the previous section we showed that RMS associated with TEST1 and TEST2 after 21 UTC becomes larger than those of CNTL. When we limit the area for calculating bias and RMS from all model domain, which corresponds to Figure 4, to an area indicated by white rectangle in Figure 3a, degradation of bias and RMS is recognized after 1800 UTC (not shown). These results indicate that data assimilation of RL degrades forecast and analysis of humidity field after 18 UTC. Figure 5 shows time series of the maximum rain rate every 5 minute for TEST1, TEST2, CNTL, and Radar-AMeDAS (RAM) around area where heavy rain fall occurred. Maximum rain rate observed by RAM has two peaks at 1630 UTC and 1805 UTC. On the contrary, peaks of rain rate in TEST1 and TEST2 are recognized only around 1500 UTC. It seems that rain rate peak in RAM at 1805UTC might correspond to the rain rate peak at 1505 UT in TEST1 and TEST2 data assimilation experiments because location of heavy precipitation of RAM at 1805 UTC are close to location of heavy precipitation of TEST1 at 1500 UTC. This suggests that data assimilation experiment of TEST1 and TEST2 produced heavy rainfall 3 hour prior to the actual heavy rainfall. The heavy precipitation produced in TEST1 and TEST2 might cause cold outflows on surface from thunderstorms. These cold and dry outflows prevailed around Tochigi prefecture and Gunma prefecture, where actual heavy precipitation occurred. Eventually, the sequence of procedures following heavy precipitation produced three hour earlier to the actual heavy rain in TEST1 and TEST2 lowers PWV in forecast and analysis compared to GNSS-observed PWV.

Figure 6. Observation and model results at 1520 UTC. (a) Observed rain rate, (b) ensemble mean of precipitation in TEST1, (c) difference of ensemble means of qv on ground between TEST1 and CNTL, and (d) difference of ensemble means of temperature on ground between TEST1 and CNTL.
Figure 6 shows rain rate, $q_v$, and temperature on surface comparison of 1520 UTC. At 1520 UTC, heavy precipitation is presented in TEST1 (Figure 6b), while no heavy rain was observed in actual (Figure 6a). Figures 6c and 6d, respectively, show difference of $q_v$ on surface between TEST1 and CNTL, and difference of temperature on surface between TEST1 and CNTL, showing noticeable decreases of $q_v$ and temperature on surface in TEST1 compared to CNTL. It appears that cold flows might have begun to propagate from thunderstorms accompanied by heavy precipitation around 1500 UTC in TEST1, resulting in decreasing $q_v$ and temperature on surface. In TEST2 experiment, similar results to TEST1 experiment are obtained (not shown).

One possible reason why heavy precipitation has started three hours prior to the actual precipitation is overestimation of $q_v$ and PWV in data assimilation process at 1200 UTC. At that time, overestimation of PWV in TEST1 and TEST2 compared to GNSS observations are recognized around area where PWV are high (exceeds 65 km/m$^2$) (not shown). Thunderstorms in TEST1 and TEST2 are triggered around the PWV overestimated area and developed northeastwards. Finally, they cause precipitation around south part of Tochigi prefecture, where heavy rainfall is presented in TEST1 and TEST2 around 1500 UTC. Therefore, it appears that overestimated PWV field “mis-triggered“ thunderstorms so that they cause heavy precipitations three hours prior to the actual precipitation.

In this presentation, we performed data assimilation of RL data and showed that data assimilation of vertical profiles of $q_v$ contributes to improvement of forecast and analysis of humidity field. However, forecast and analysis of humidity field were degraded after heavy precipitation three hours prior to actual are produced in the model. For further improvement of RL data assimilation, development of assimilation scheme and modeling is needed.

5. Acknowledgement

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6. References


