Application of the MM5 3DVAR System for a Heavy Rain Case over the Korean Peninsula

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1. Introduction

Recently, the Korea Meteorological Administration (KMA) deployed a high-density network of Automatic Weather Stations (AWS) over South Korea to collect real-time observations of surface meteorological parameters including temperature, wind speed and direction, relative humidity, pressure, and rainfall at high temporal resolution. How to use the AWS data effectively to improve forecasting of heavy rain events over the Korean Peninsula is a challenging task. Within the context of numerical weather prediction, it would be very difficult to make use of the surface observations from such an AWS network, to improve the three-dimensional analysis of the atmosphere, with the traditional static objective analysis technique.

Obtaining an accurate model initial state is recognized as one of the biggest challenges in accurrate model prediction of weather events. The variational data assimilation approach is one of the most promising techniques available to directly assimilate heterogeneous mesoscale observations, in order to improve the estimate of the model initial state. During the past three years, a research version of the MM5 3DVAR (3-Dimensional Variational Data Assimilation) system has been developed to assimilate a variety of conventional and remote sensing measurements such as upper-air sounding (TEMP); NWS surface observation (SYNOP, SHIPS, METAR); aircraft data (AIREP, MDCRS); satellite cloud track wind (SATOB); satellite retrieved thickness (SATEM); and Ground-based GPS precipitable water (GPSPW) (Barker et al, 2002). By adding new observation operators and their adjoints, we can implement an AWS component into the MM5 3DVAR system. This will also enable the direct assimilation of AWS data within the current KMA operational environment.

In this study, the observation operators, based on the similarity theory, are developed to directly assimilate the 10-m wind, 2-m temperature and moisture data from the AWS network. With this new surface data assimilation approach, more than 90% of AWS measurements are ingested in 3DVAR. We assimilate AWS data collected for the 14 July 2001 heavy rain case, and perform MM5 forecast experiments to assess the impact of the AWS data assimilation on mesoscale analysis and forecast. In order to compare the 3DVAR results with those from the KMA operational 3-Dimensional Optimal Interpolation (3DOI) system, we also perform MM5 forecasts initialized from the KMA 3DOI analysis at 0000 and 1200 UTC 14 July 2001.

2. AWS observations and heavy rain case

There are approximately 470 AWS stations over South Korea (Fig. 1). The surface meteorological parameters observed by AWS are 1-min and 3-min averaged wind, temperature, pressure, relative humidity, and hourly rainfall. The temperature, wind, and rainfall are the primary measurements, with pressure and humidity being less reported. An example of the different parameters available at 0000 UTC 14 July 2001 is shown in Table 1.

Table 1 AWS data used in MM5 3DVAR with old and new surface assimilation approach

Approach	Old	New	Available
Temperature	260	472	472
Wind-U	221	394	394
Wind-V	21	394	394
Pressure	32	70	70
Humidity	35	71	81
Number of sites	472		

Figure 1 shows the 12-h accumulated precipitation from 1200 UTC 14 to 0000 UTC 15 July 2001, based on the AWS hourly rain observations. The rainband lies along the border between North and South Korea, and the maximum amount of rainfall is 340.5 mm.

3. Surface observation operator

Two different approaches were used in the assimilation of AWS data: the old approach and a new approach. As we demonstrate, they differ in data handling and assimilation.

(1) Old approach for surface data assimilation

In the old approach, the measurements go through an initial data screening. If the elevation of an observed site is lower than the height of the model's lowest level by more than 100 m, this station is discarded. If the elevation of an AWS station is above the height of the model's lowest level, then the measurements from this station are used in the same way as the upper air data. If the elevation of an AWS station is below the model's lowest level, but not more than 100 m, the measurements are used to retrieve (or estimate) observed atmospheric state at the model's lowest level.

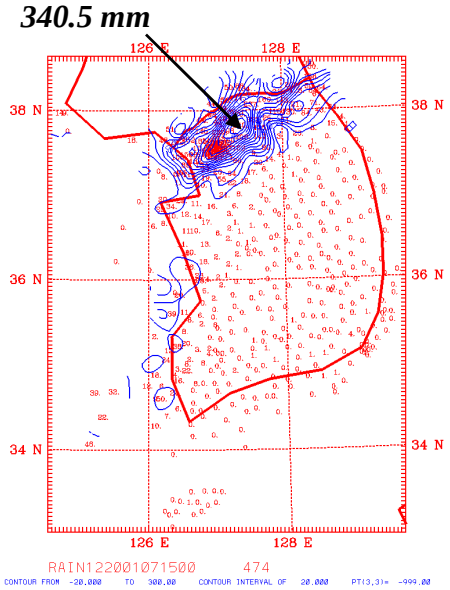


Figure 1: KMA AWS network and 12-h accumulated precipitation from 1200 UTC 14 to 0000 UTC 15 July 2001.

The advantage of this approach is that no tangent linear and adjoint codes are needed for the surface data assimilation except the interpolation. However, this method also has seriously deficiencies:

a) In order to retrieve the atmospheric state at the model's lowest level, the information from a background field must be used, due to the single-level nature of the AWS data. Thus, the data assimilated in 3DVAR in the old approach is a mixture of actual observations and a background field. This eliminates one of the main advantages of variational data assimilation – direct assimilation of measurements.

b) To reduce errors associated with the "retrieval" of the atmospheric state at the model's lowest level, measurements from AWS stations that are located more than 100 m below the model's lowest level have to be rejected. When we apply the MM5 3DVAR to the KMA 10-km model (domain 2), we find the maximum height difference between station elevation and the model's lowest level is 787 m. As shown in Table 1, nearly 50% of the AWS data is discarded using this approach.

c) Treating the measurements from AWS sites whose elevations are above the model's lowest level as the "upper air data" can also cause inconsistency (lower wind, and higher or lower temperature, compared with actual upper-air measurements).

(2) New approach for surface data assimilation

In order to ingest most of the AWS data into the MM5 3DVAR system, we develop a new approach for the surface data assimilation. In the new approach:

a) All the observed sites are assumed to be located at the model surface, regardless of the actual difference in elevation between the AWS measurement and the model surface.

b) Based on the surface similarity theory implemented in the MRF PBL scheme (Hong and Pan, 1996), the forward observation operators for 2-m temperature and moisture, and 10-m wind are developed from the model's analysis variables, as well as their corresponding tangent linear and adjoint codes.

c) The observations from AWS, except for the surface pressure, are directly assimilated without any modifications. In this study, the observed surface pressure is still reduced to the model's lowest level, before assimilation.

With the new approach, the observation operators for 10-m wind and 2-m T and Q are used during the minimization process. All AWS data are ingested in 3DVAR (see Table 1), and the minimization converges well. Figure 2 shows the temperature increments at the model's lowest ? level from 3DVAR experiments with the new approach of AWS assimilation (Fig. 2a), and the difference between increments from the new and old approach used in 3DVAR (Fig. 2b). The positive differences in the increments are located over northeast Korea, with a maximum of 1.13^{o}C; and the negative differences in southwest Korea with a minimum of –1.43^{o}C. These differences may help improve the heavy rain forecast.

4. Experiment design

To assess the impact of assimilating AWS data into the MM5 3DVAR system on the heavy rainfall forecast, six MM5 experiments (Table 2) are carried out. The experimental model domain is the same as the KMA operational mesoscale model domain 2 (see Fig. 2), which has 160x178 grid-points with 33 vertical levels. The grid size is 10-km.

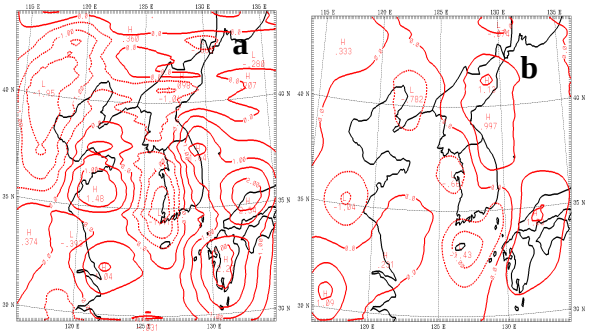


Figure 2: (a) Temperature increments at ? = 0.995 from 3DVAR with new surface data assimilation approach; (b) The difference of the temperature increments from the new and the old approaches (new - old) at ? =0.995.

Table 2, Summary of MM5 forecast experiments for the 14 July 2001 case

Exp.	Initialization	Assimilation approach
3DOI	From KMA 30-km 3DOI analysis	3DOI
3DOI12Z	From KMA 30-km 3DOI analysis at 1200 UTC 14	3DOI
3DVAR24-1	3DVAR at 0000 UTC 14	Old
3DVAR24-2	3DVAR at 0000 UTC 14	New
3DVAR03-1	3DVAR 3-h cycling at 0000, 0300 0600, 0900, 1200 UTC 14	Old
3DVAR03-2	3DVAR 3-h cycling at 0000, 0300, 0600, 0900, 1200 UTC 14	New

In 3DVAR experiments, the background at 0000 UTC 14 July is obtained from the KMA 3DOI analysis, and the background error statistics are derived from the archived KMA operational forecast data, using the "NMC"-method. The observations available for 3DVAR are conventional upper-air and surface data, plus KMA AWS measurements.

In the 3DOI and 3DOI12Z experiments, the 10-km analysis is obtained by interpolation from the KMA 30-km 3DOI analysis. The 3-hourly lateral boundary and low boundary are provided by the KMA 30-km (domain 1) forecast, similar to the KMA one-way-nesting operational runs. All experiments are integrated from 0000 UTC 14 to 0000 UTC 15 July 2001.

5. Results

The main purpose of assimilating the high resolution AWS data is to help improve the heavy rain forecast. In this regard, the preliminary results from the 3DVAR experiments, using the new approach to assimilate the AWS surface observations, are quite encouraging.

(1) New and old approach for surface data assimilation

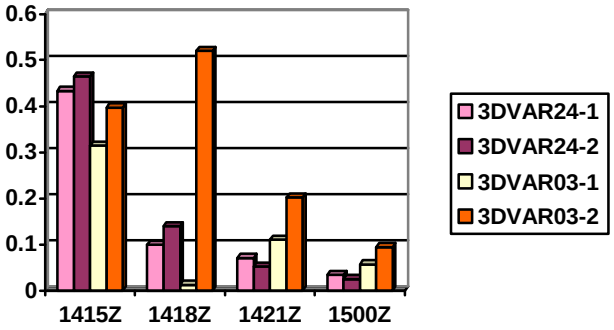


Figure 3: Equitable threat scores with a threshold of 10 mm 3-h accumulated rainfall for 3DVAR experiments: 3DVAR24-1, 3DVAR24-2, 3DVAR03-1, and 3DVAR-3-2.

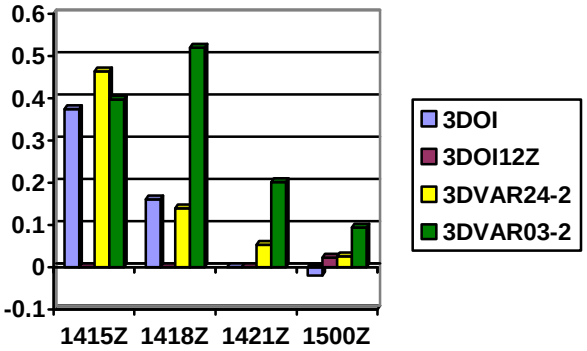
Figure 3 shows the equitable threat scores with a threshold of 10 mm 3-hour accumulated rainfall, for four 3DVAR experiments. With the new surface data assimilation approach (Exp. 3DVAR24-2 and 3DVAR03-2), we produce higher scores than with the old approach (Exp. 3DVAR24-1 and 3DVAR03-1). This is especially true when the procedure of the 3-hourly 3DVAR update cycle is carried out, in which the 3-hour forecast from the previous cycle serves as the background for the next cycle and the AWS data is updated every 3 hours.

(2) Comparison with the KMA 3DOI initialization

The equitable threat scores with a threshold of 10 mm 3-h accumulated rainfall for KMA 3DOI and MM5

3DVAR initialization experiments are shown in Fig. 4. Except for the forecast at 1800 UTC 14 from Exp. 3DVAR24-2, the 3DVAR initialization is much more accurate than the 3DOI (KMA operational analysis), especially when the procedure of 3-hourly 3DVAR update cycle is applied. It is surprising that a cold-start forecast initialized by KMA 3DOI at 1200 UTC 14 shows almost no skill in predicting this heavy rain event, while the 3DVAR03-2 with AWS data assimilated by four 3-h cycles produces a heavy rain forecast with significantly higher skill during the 12-h period from 1200 UTC 14 to 0000 UTC 15 July 2001.

The equitable threat score at 0000 UTC 15 from 3DOI gives a negative value of -0.021, which means the skill of 3DOI is less accurate than the forecast by chance at that time (Schaefer 1990).



Figures 4: Equitable threat scores with threshold of 10 mm 3-h accumulated rainfall for Experiments 3DOI, 3DOI12Z, 3DVAR24-2, and 3DVAR03-2.

(3) Hydrometeor fields passed through between the cycles

In 3-h 3DVAR cycling experiments, the forecast from the previous cycle serves as the background for the next cycle. To overcome the spin-up problem with this short-range forecast, instead of using the hydrometeor fields initialized by zero at the beginning of each cycle, it might be helpful to initialize them with the forecast of hydrometeor fields from the previous cycle. So we carry out one more experiment with the hydrometeor fields forecast passed through between the update cycles (3DVAR03-2Q).

Fig. 5 shows the comparison of this experiment with 3DVAR03-2 and 3DOI. Although 3DVAR03-2Q is still better than 3DOI, there is no improvement over 3DVAR03-2. Instead, it degrades the heavy rain forecast skill when the forecast hydrometeor is passed

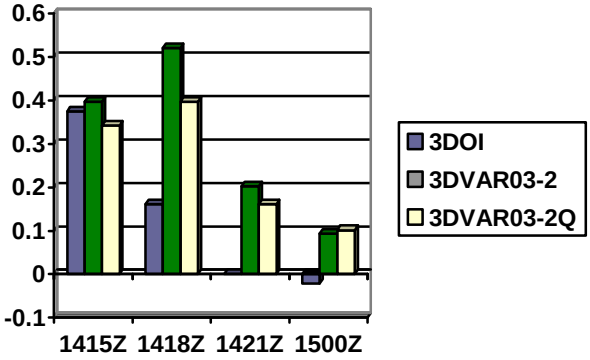


Figure 5: Equitable threat scores with threshold of 10 mm 3-h accumulated rainfall for 3-h 3DVAR cycling experiments without and with the hydrometeor fields passed through between the cycles.

through the cycles. This may be caused by the poor quality of these 3-h hydrometeor fields. Further examination is required to fully understand this deficient performance.

6. Summary and conclusions

In this study, we develop a new observation operator and its corresponding adjoint to assimilate KMA AWS surface observations, based on the similarity theory, using the MM5 3DVAR system. We also perform forecast sensitivity experiments to assess the effects of AWS data and assimilation approaches, on the short-range prediction of a heavy rain event over Korea.

Our preliminary results show that 3DVAR assimilation of high-resolution KMA AWS data can substantially improve the model skill in short-range prediction of heavy precipitation for the 14 July 2001 case over the Korean peninsula.

The new surface data assimilation approach with a 3-h update cycle can effectively extract useful information from the high temporal and spatial resolution AWS observations.

We found that using the forecast hydrometeor fields passed through between the cycles in the 3-h 3DVAR cycling run, performance of 3DVAR data assimilation was not improved. Further investigation is required to fully understand this effect.

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