P11.1 ENHANCEMENTS OF THE NCAR AUTO-NOWCAST SYSTEM USING NRL, ASAP, MM5 AND TAMDAR DATA

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1. INTRODUCTION

Convection is one of the leading causes of air traffic delays in the US. Extrapolation and trending of radar data can be used to provide deterministic forecasts of position and intensity of existing storms. This information is useful for vectoring aircraft around existing storms, but does not prepare air traffic managers for the possibility that new storms will initiate in their airspace. The NCAR Auto-Nowcaster (ANC) is designed to provide combined 1-hour forecasts of both storm extrapolation and trending (deterministic) and the likelihood (probabilistic) for new storm initiation every 10 min. The ANC's unique capability of forecasting convection initiation is achieved by using a fuzzy logic engine which combines a set of predictor fields into a single storm initiation interest field. The predictor fields are used to characterize the large-scale environment (stability and large-scale forcing), boundary layer structure, boundary characteristics, cloud type and vertical development (as indicated by IR cooling rates). The probabilistic forecast of storm initiation is obtained by applying a threshold to the total storm initiation interest field.

ANC is a constantly evolving complex software system which can be enhanced when new datasets/algorithms become available. During the past several years, various new achievements in both observational and model developments have appeared. This paper will investigate the impacts of the following new datasets to the performance of ANC, 1) Naval Research Laboratory (NRL) cloud classifier for cumulus cloud identification, 2) Advanced Satellite Aviation Weather Products (ASAP) for cumulus cloud growth, 3) high-resolution MM5 model data for large scale environmental instability variables, and 4) Tropospheric Airborne Meteorological Data Report (TAMDAR) data for more frequent soundings. Possible enhancements of ANC by using each dataset are evaluated. Future usage of each dataset in ANC will also be discussed.

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2. NRL CLOUD CLASSIFIER

Satellite cloud analysis plays a key role in storm initiation forecast in ANC. Roberts and Rutledge (2003) were the pioneers who performed groundbreaking work in this area. The idea of forecasting storm initiation based on satellite data is rather straight-forward, since basically almost every storm starts with rapidly vertical development of cumulus clouds; the difficulty comes from how to develop a reliable algorithm to identify and monitor vertical growth of cumulus clouds. The NRL cloud classifier (Bankert 1994) is a neural network based cloud type identification algorithm which has a cloud classification accuracy of ~ 80%. Compared with the previous cloud type algorithm used in ANC, this method produces much more detailed cloud types, therefore it is possible that storm initiation forecasts could be improved by the NRL algorithm.

A total of six cases have been selected from summer 2004 over Illinois/Indiana region during the Federal Aviation Agency (FAA) summer demonstration project to test the NRL cloud classifier's impact on ANC storm initiation forecast. One example is given in Fig. 1. Apparently the false alarm rate (FAR) is greatly reduced by using NRL cloud type data, especially at the southwest and northeast end of the surface boundary. This result is not surprising at all since the NRL algorithm tends to give more detailed and more accurate cloud types, while the previous cloud typing algorithm used in ANC tends to over-estimate the cumulus cloud coverage. As a penalty of reduced FAR, the probability of detection (POD) might suffer slightly in certain areas (see Fig. 1).

3. ASAP CONVECTION INITIATION PRODUCTS

As discussed in section 2, two parameters from

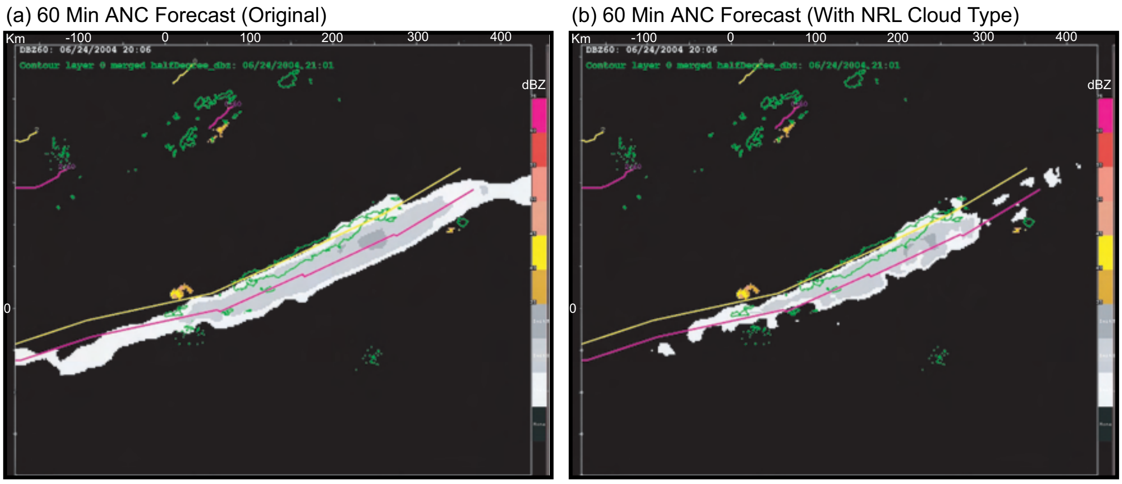

Fig. 1. Comparison of the 60 min ANC forecasts issued at 2006 UTC on 24 June 2004. a) original ANC, and b) ANC with NRL cloud type data. The green contour is the 30 dBZ radar reflectivity line at verification time (2101 UTC). The filled color contour represents the 60 min extrapolated radar reflectivity; the gray shading represents the 60 min initiation forecasts. The current boundary position is denoted by the yellow line, the 60 min extrapolated boundary position is shown as the magenta line.

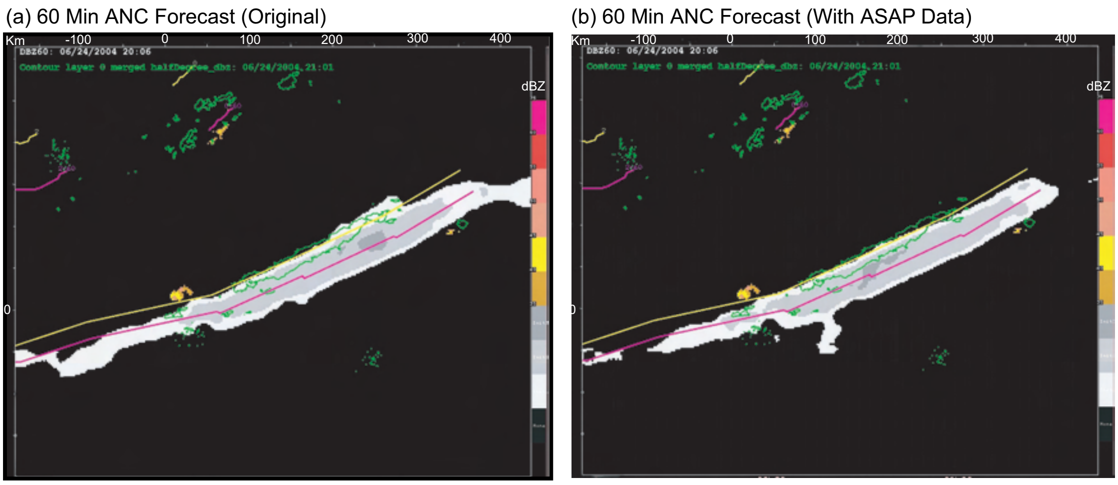

Fig. 2. Same as Fig. 1 except for comparisons between a) original 60 min ANC forecasts, and b) 60 min ANC forecasts using ASAP data.

satellite data analysis are essential to storm initiation forecasts in ANC; one is cumulus cloud identification, the other is cumulus cloud growth. The latter obviously depends on the former to be accurate. Based on Roberts and Rutledge (2003), Mecikalski and Bedka (2005) proposed a set of parameters which could be used to identify rapidly vertical growth of immature cumulus clouds by analyzing ASAP data. Each parameter is assigned an interest value of one if it meets certain criterion. The interest value from all parameters are summed up and named convection initiation (CI) interest. A high CI interest indicates a high potential of storm initiation.

The most proper way to use ASAP CI interest field in ANC is still under investigation. As the first attempt of using ASAP data, the 10.7 μm brightness temperature rate of change (ROC) field in the previous ANC is replaced by the corresponding ASAP field. This technique requires no change in the ANC forecasting logic, yet can provide some benefits of the ASAP data. The reason to use the ASAP 10.7 μm ROC field is because the ASAP algorithm employed a more sophisticated technique to compute this field as compared to the previous algorithm used in ANC. The same six cases used in section 2 for testing NRL cloud classifier are rerun to investigate the impacts of ASAP data. One example of a side-by-side comparison of ANC 60 min forecasts with/without ASAP data is shown in Fig. 2. Similar to the impacts of NRL data on ANC, the ASAP data also greatly reduced FAR at southwest and northeast end of the surface boundary but slightly lowered POD at the north edge of the convection.

4. MM5 DERIVED INSTABILITY PARAMETERS

A total of five instability parameters derived from RUC20 model data is being used in the current ANC. These five fields have a combined weight of ~0.68, which accounts for ~36% of the total weight of all membership functions for storm initiation. Apparently the accurate estimates of these instability parameters are essential to ANC. Since RUC20 model is the only model which has ever been used in the ANC to derive large scale environmental variables and it has a relatively coarse spatial resolution of 20 km, it would be interesting to find out how the performance of ANC will be affected if the RUC20 model were replaced by a high-resolution model with different model physics, such as 3.3 km resolution MM5 (fifth-generation Pennsylvania State University-NCAR Mesoscale Model). Another advantage of MM5 model is its ability of assimilating radar reflectivity data through a nudging technique (Liu et al.2002). Each of the five parameters used for representing large scale instability and forcing is discussed as follows.

(a) CAPE (Convective Available Potential Energy)

The atmosphere is divided into 25 mb layers in the vertical and all instability calculations are performed on those layers. The maximum CAPE value between 900 mb and 700 mb is chosen as the predictor field for CAPE.

(b) CIN (Convective Inhibition)

The average CIN value between 975 mb and 700 mb is used.

(c) Averaged Relative Humidity

The mean relative humidity between 875 mb and 725 mb is used as an indicator for the overall moisture content in the convective boundary layer.

MM5 Domain Configuration

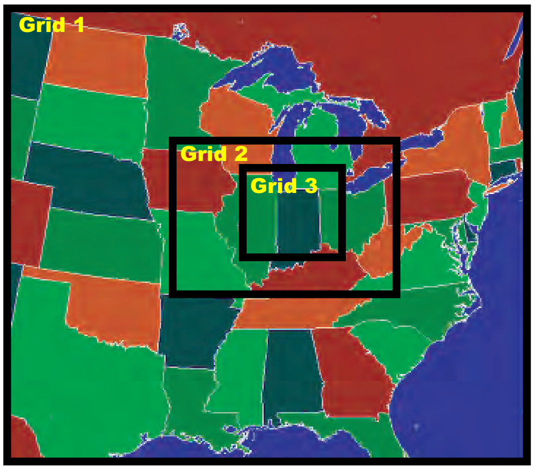

Fig. 3. Domain configuration for the MM5 model. Three nested domains are used in this study, which are represented by grid 1 (30 km resolution), grid 2 (10 km resolution) and grid 3 (3.3km resolution), respectively.

(d) Frontal Likelihood Field

This is an interest field which is designed to pinpoint the location of surface frontal zone. Surface convergence, vorticity and equivalent potential temperature gradient are used as input to produce the frontal likelihood field. The reader is referred to Mueller and Megenhardt (2003) for details of this technique.

(e) Number of Unstable Layers in the Vertical

This field is a count of how many unstable layers in the vertical according to the model data. Details of this technique can be found at Trier et al. (2002).

The MM5 model used in this study assimilates observations from various sources continuously and provides real-time local analyses and short-term forecasts in a cycling fashion. A three-grid configuration, with grid resolution of 3.3, 10 and 30 km is used (see Fig. 3). The model is cold started once a week, at 12 Z on Sundays. At each 3-hr cycle, a final analysis and a 9-hr forecast is produced.

A grid nudging scheme is used to assimilate the mosaic radar reflectivity data generated for CONUS (Xu et al. 2004). The radar reflectivity is first con-

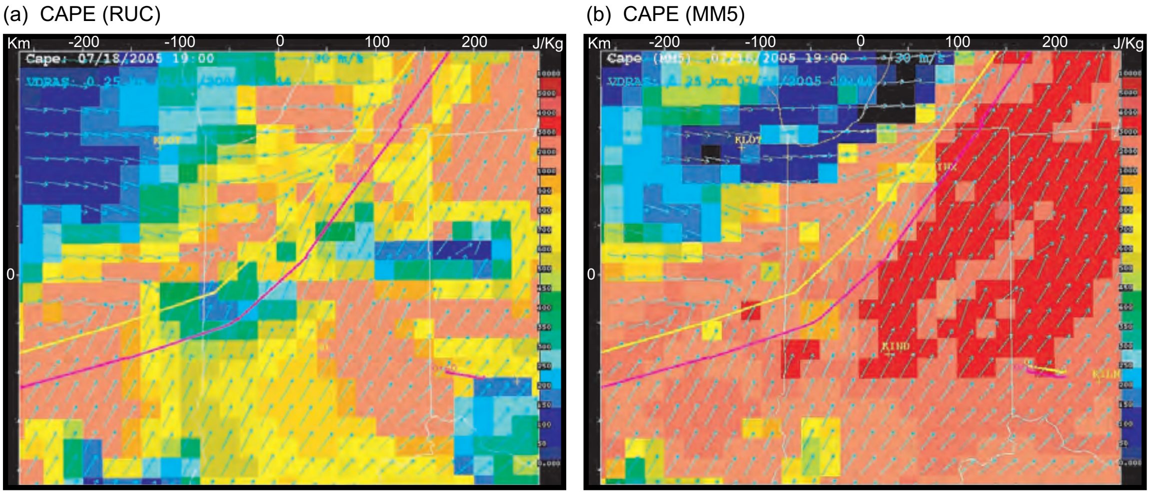

Fig. 4. Comparison of CAPE fields at 1900 UTC on 18 July 2005 derived from a) RUC20 model, and b) MM5 model. VDRAS surface winds are shown as arrows. The current boundary (a cold front) position is represented by the yellow line. The magenta line denotes the 60 min extrapolated boundary position.

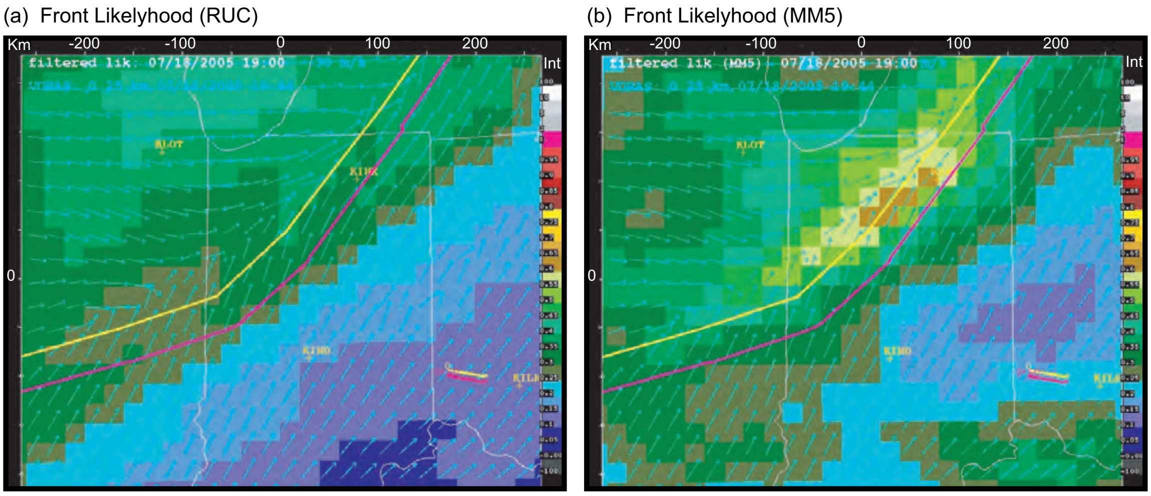

Fig. 5. Same as Fig. 4 except for the frontal likelihood interest fields.

verted to 3D precipitation field and interpolated to the model grid. Then the precipitation field, together with the corresponding latent heat, is nudged onto the two inner domains (grid 3 and grid 2 in Fig. 3). The data insertion are performed at an interval of 30 min on grid 2 (10 km resolution) and 15 min on grid 3 (3.3 km resolution). Humidity field is also adjusted according to the radar reflectivity data.

A total of six cases from the FAA summer demonstration project conducted over Illinois/Indiana in summer 2005 have been selected to investigate the impacts of MM5 model data on ANC performance. Examples of the side-by-side comparisons between the instability fields derived from RUC20 and MM5 model are shown in Figs. 4 and 5, respectively. A cold front, which is represented by the yellow line in the figures, can be easily identified as a convergence line in the low-level VDRAS (Variational Doppler Radar Analysis System) wind fields. MM5 model clearly suggests larger CAPE along and in the warm sector of the cold front for this particular case. The frontal likelihood interest field, which indicates the position of the surface frontal zone, is also better defined

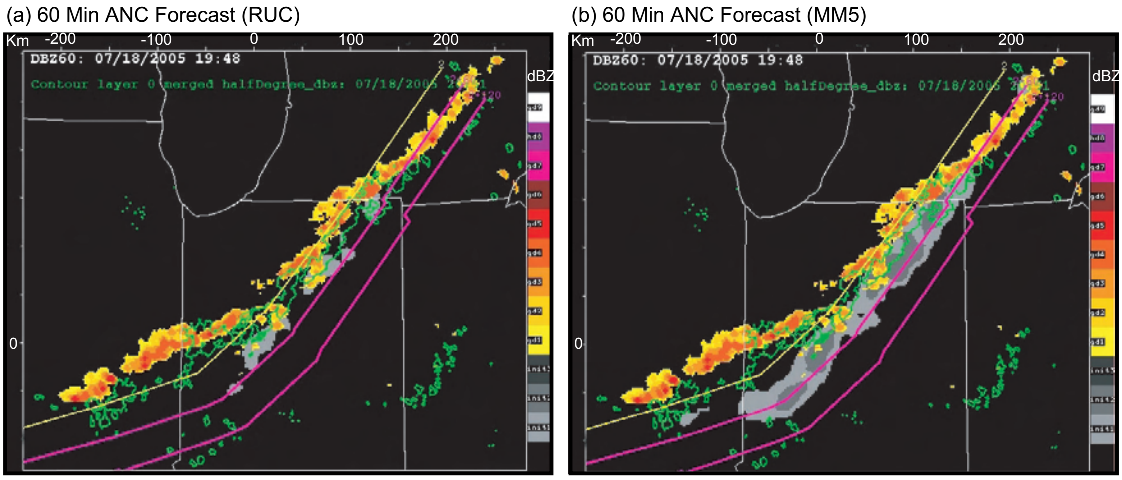

Fig. 6. Comparison of the 60 min ANC forecasts issued at 1948 UTC on 18 July 2005 using a) RUC20 model, and b) MM5 model. The green contour is the 35 dBZ radar reflectivity line at verification time (2051 UTC). The filled color contour represents the 60 min extrapolated radar reflectivity; the gray shading represents the 60 min initiation forecasts. The current boundary position is denoted by the yellow line; the 60 min and 120 min extrapolated boundary positions are shown as magenta lines.

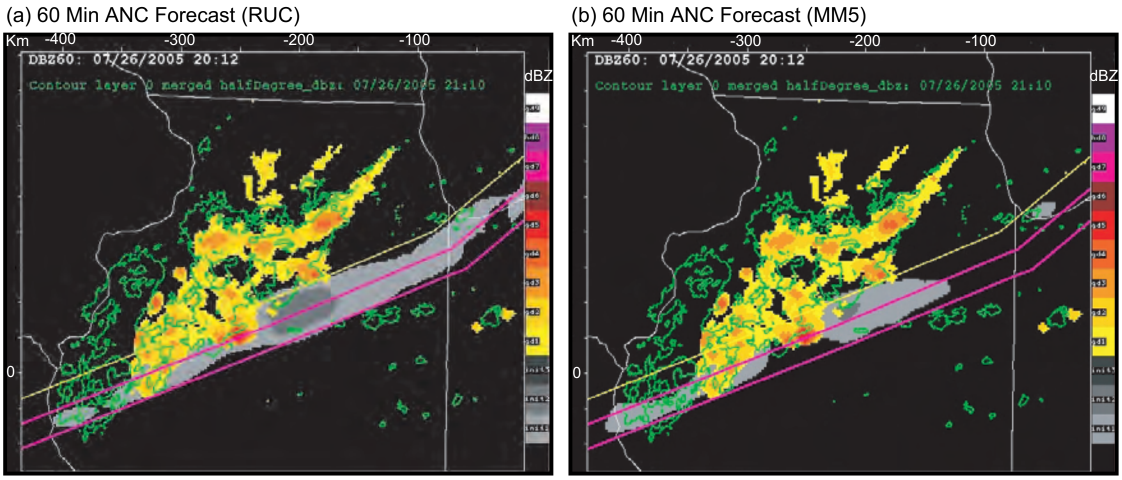

Fig. 7. Same as Fig. 6 except for 2012 UTC on 26 July 2005.

using MM5 model data. Notice the high frontal likelihood interest values are co-located nicely with the frontal zone derived from VDRAS winds and the current front position entered by a forecaster (the yellow line) in Fig. 5b.

The 60 min ANC forecasts (initiation plus extrapolation) using both RUC20 and MM5 model data for the six cases occurred during summer 2005 are carefully analyzed. Generally speaking, both models give pretty similar results most of the time. Occasionally, MM5 model performed slightly better than RUC20. Figures 6 and 7 are two examples of comparisons between ANC 60 min forecasts created using RUC20 and MM5 model data. Figure 6 is the same case as shown in Figs. 4 and 5. As a result of stronger CAPE and better-defined frontal likelihood interest field derived from MM5 model, ANC using MM5 data greatly increased the storm initiation forecasts along the cold front. Notice the initiation zone near the southern end of the boundary shown in Fig. 6b. This initiation forecast, which did not exist in Fig. 6a when RUC20 was used, probably is an indication that ANC was trying to forecast the cluster of smaller cells which occurred 60 min later near the southern end of the cold front.

Figure 6 shows one example in which ANC produced more initiation forecasts as a result of using MM5 model data. On the other hand, using MM5 model data could also reduce the initiation forecast by ANC. One such example is shown in Fig. 7. It is another cold front passing through ANC domain. ANC with MM5 data correctly reduced the false alarm along part of the cold front, and amazingly kept the correct initiation forecasts near both south and north end of the boundary.

5. TAMDAR DATA

Operational sounding data comes only twice daily. This greatly hampered our ability of accurate storm initiation forecasts since storms developed within a much short time period. Thanks to TAMDAR data, which is taken from sensors attached to some regional commercial jets, much more frequent sounding data can be obtained when the jets are taking off or landing. The TAMDAR data has been grabbed in real time by ANC at NCAR, reformatted for proper display and gone through preliminary quality control process. A few cases from summer 2005 have also been selected to rerun the CAPE/CIN algorithm and VDRAS to verify any benefits TAMDAR data might have on ANC performance. The case study results will be reported at the conference.

6. SUMMARY

Enhancements of NCAR ANC system using NRL, ASAP and MM5 data are presented. Potential benefits of using TAMDAR data are also discussed. It is found that both NRL and ASAP data reduce FAR for ANC storm initiation forecasts. Improvements in ANC performance by using MM5 model derived instability parameters are also noticed. Both NRL and ASAP data have been put into the real time ANC system deployed over Illinois/Indiana region during summer 2005 based on this study. More analysis will be needed before MM5 model and TAMDAR data can be used in the real time ANC system.

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