J9.4 DEVELOPMENT OF A NOWCAST MODELING SYSTEM TO SUPPORT ARMY AVIATION FORECASTS

Robert Dumais*, Stephen Kirby, Brian Reen, David Knapp, Jeffrey Johnson, and Jeff Passner
U.S. Army Research Laboratory

1. Introduction

To support the U.S. Army's aviation missions, rapid-update cycling nowcast numerical weather predictions are required for operations in dynamic modeling domains (time and space) with rich to limited observation data available for model initialization. The Advanced Research Weather Research and Forecasting (WRF-ARW) model (Skamarock et al., 2008) has been adapted for the Army to provide gridded forecast output for use in Army mission execution, artillery and aviation.

The WRF-ARW's Four-Dimensional Data Assimilation (FDDA) method (Deng et al., 2009) has been implemented to integrate and apply observations from various conventional and unconventional battlefield sources into the model's initialization processes. This tailored version of the WRF-ARW, which takes advantage of any and all observation data sources, is called the Weather Running Estimate-Nowcast (WRE-N) modeling system. The WRE-N is designed to run up to hourly, producing 3-6 hour forecasts per cycle at horizontal grid point resolutions of several km to 500m.

The results are the creation of 4D "actionable" weather nowcast grids for use in mission execution planning. The WRE-N can run in support of both the Army Distributed Common Ground System (DCGS-A) and the next-generation Artillery Meteorological Measurement Set- Profiler (MMS-P) system, as well as for specific aviation tools such as the Automated Impacts Routing (AIR) tool (Johnson, 2011) which can support the Tactical Airspace Information System (TAIS).

* *Corresponding author address*: Robert Dumais, U.S. Army Research Laboratory, White Sands Missile Range, NM, 88002-5501; email: robert.e.dumais.civ@mail.mil.

To develop the WRE-N the U.S. Army Research Laboratory (ARL) has been performing research involving the WRF-ARW and its FDDA component based upon observation or "station" nudging. The focus has been upon the testing of the FDDA technique in various limited-area nested WRF-ARW configurations, for resolving scales of 1-3 km grid spacing (and occasionally even finer).

The idea of the WRE-N is to leverage the WRF-ARW model for generating tactical nowcast "rapid update cycle" grids of local battlefield weather conditions at storm/cloud scale resolutions. ARL has been experimenting with various configurations of the WRF-ARW, involving different model vertical resolution, time-stepping, moist microphysics, planetary boundary layer (PBL) physics, turbulence parameterization, and observation nudging data assimilation options/weights. Some of these results are discussed in Raby et al., 2011.

2. A typical WRF-ARW model configuration for the WRE-N

A 9-km, 3-km and 1-km triple-nest grid scheme is commonly used for the WRE-N, employing 175x175 grid points on the outer nest (1566 km x 1566 km), 241x241 grid points on the middle nest (720 km x 720 km), and 127x127 grid points on the inner nest (126 km x 126 km) respectively. In the vertical, a total of 57 log-linearly spaced terrain-following vertical levels are used, with a model top of either 50 mb or 10 mb depending upon application. To provide the initial atmospheric, surface, and lateral boundary conditions for the outer nest, the National Center of Environmental Prediction's (NCEP) North American Model (NAM) model (http://www.emc.ncep.noaa.gov/NAM/.php) or Global Forecast System (GFS) model (http://www.emc.ncep.noaa.gov/GFS/doc.php) gridded forecast fields are used for most research activities. The NAM and GFS models are nominally at about 12 km and ½ degree horizontal grid spacing respectively, so they maintain a reasonable scaling ratio with the 9 km outer nest. The size of the outer nest (1566 km x 1566 km) is sufficiently small so as to remain computationally viable on small cluster or even high-end multiprocessor workstations/laptops, yet large enough so that model solutions near the domain center remain fairly buffered from the influence of NAM or GFS lateral boundary condition effects (within the context of short-range rapid update cycle WRF-ARW forecasting).

The use of high data assimilation cycling frequencies, restricted continuous self-cycling periods (~ 12-24 h), and shorter model forecasts per cycle (3-6 h) all work additionally towards reducing the impact of model errors introduced through the outer nest lateral boundaries. The specifications of the WRF-ARW namelist options are given below in Table 1.

Namelist parameter	Option selected
Shortwave radiation	Dudhia scheme
Longwave radiation	RRTM
Explicit moist microphysics	Thompson
Cumulus parameterization	Kain-Fritsch-9 km only;explicit 3 &1 km
PBL scheme	Mellor-Yamada-Janjic
Surface layer	Mellor-Yamada-Janjic
Land surface scheme	NOAH
Time step (sec) to grid-spacing (km) ratio	3:1
Horizontal subgrid diffusion	2nd order on coordinate surfaces
Subgrid turbulence closure	Horizontal Smagorinsky 1st order
Number of vertical terrain-following levels	57
Vertical velocity damping	Yes
Feedback (two-way interactive)	Yes
Nesting	Yes
Terrain slope/shadow	Yes
FDDA	Yes
Nudging strength	4.0 x 10-4 s-1

Table 1. Namelist options for WRF-ARW used for WRE-N

3. Data Assimilation for WRE-N

The continuous atmospheric data assimilation technique of observation nudging (Deng et al., 2009) is a great deal less expensive computationally than more advanced 4D-variational methods such as used in the WRF Data Assimilation (DA) package (Huang et al., 2009), or ensemble Kalman filtering (Zupanski et al., 2008). The use of nudging is conceptually simplistic, but based upon the same underlying principles of Kalman filter theory as other optimal data assimilation methods used (Liu et al., 2005). The goal of all these methods is to estimate the Kalman Gain, which really requires a good estimate of background and observation errors. In nudging, this Kalman Gain is approximated by a somewhat ad-hoc nudging weighting function. The temporal relaxation feature of nudging allows for essentially continuous assimilation ability.

Other popular forms of intermittent atmospheric data assimilation for meso and synoptic scales such as 3DVAR (Barker et al., 2003), requiring temporal interpolation of observations to a specific analysis time, are more likely to cause initial shock in the model and to be less effective for asynoptic and high frequency observation networks. Determining balance conditions to use for such schemes also becomes quite difficult at storm scales and finer. The use of adjoint operations allows application (across multi-dimensions) of the chain-rule for partial differentiation, permitting more efficient calculation of the gradient of a cost-function. State-of-the-art mathematical minimization techniques are used for combining the cost function, gradient and analysis information and for generating an efficient “optimal” analysis. Some approaches have also been developed for 3DVAR such as First Guess at Analysis Time (Lee et al., 2005) to try and reduce the time-weighting issue related to pooling observations around a specific analysis time.

Overall, the technique of observation nudging has been shown to be a viable and effective method of assimilating asynoptic meteorological observations into high resolution atmospheric models for improving short-range forecasting (Liu et al., 2005). ARL uses this method in the WRE-N as the means for assimilating tactical asynoptic meteorological observations which are not regularly ingested into the Air Force Weather Agency (AFWA) operational WRF-ARW/ 3DVAR system (Surmeier and Wegiel, 2004). Surface, upper-air radiosonde/dropsonde, profiler, and airborne direct observations of wind, temperature, moisture and pressure are the current focus in WRE-N. Frequently updated “running estimates” of local battlefield weather conditions (i.e.; 4D weather cubes) can be used as actionable weather for decision aid algorithms, which in turn are used by commanders for execution planning purposes.

4. Observation Nudging FDDA

Station or observation nudging is a means to relax a model solution toward the observations rather than toward analyses, and is implemented by adding non-physical nudging terms to the model predictive equations. The method is implemented through an extra tendency term in the nudged variable's equations:

$$\frac{\partial \Theta}{\partial t} = F(\Theta) + G_{\Theta} W_{\Theta} (\tilde{\Theta}_0 - \Theta) \quad (1)$$

where $F(\Theta)$ represents the normal tendency terms due to physics/advection, G_{Θ} is a timescale controlling the nudging strength, and W_{Θ} is an additional weight in time or space (x, y,P) to limit the nudging as described more below. In addition, $\tilde{\Theta}_0$ is the observed value, and Θ is the model value spatially interpolated to the location of the observation.

These terms force the model solution at each grid point toward the observations, in proportion to the difference (innovation) between the data and the model solution. Each observation is ingested into the model at its observed time and location, with various user-defined space and time weights. Several recent papers have examined the impact of assigning appropriate horizontal and vertical radii of influence for observations based upon factors such as model nest resolution, boundary layer stability, terrain, synoptic forcing, and land surface heterogeneities (Gaudet et al., 2009; Reen et al., 2010; Xu et al., 2007; Pattantyus and Dumais, 2012).

Insight gained from such studies seems to indicate that for different grid resolutions, climatic/geographical locations, and meteorological and boundary layer conditions that slightly different rules of thumb may be required for optimal assignment of weights and radii of influence applied to the observation nudging. For now, a preselected "best" set of radii of influence values for the various nest resolutions is applied in the WRE-N application. Some quality control measures have been taken to monitor for bad or unrepresentative observations, based upon the OBSGRID auxiliary program available to WRF-ARW users (http://www.mmm.ucar.edu/wrf/users/docs/user_guide_V3/users_guide_chap7.htm).

5. FDDA Cycling Methodology

In a general sense, the concept of rapid update cycling involves a repeating process of model "self correction" through the assimilation of weather observations. On finer scales such as the meso-beta and meso-gamma, the continuous FDDA method has been shown a useful methodology for cycling, especially when a dense asynoptic observation network exists (Liu et al., 2005). For the WRE-N application a cycling rate of 1 h frequency is the target goal, although update frequency rates of 0.5 h, 3 h and 6 h are also being explored. In the context of a 1 h update cycle, a 3 h FDDA "preforecast" period would be followed by a 3 h prognostic forecast or "nowcast" period. Another second option for the 1 h update cycle is to use a 1 h FDDA "preforecast" followed by a 1 h forecast. This option would be used if WRE-N must be executed on more computationally-challenged compute platforms

In the DCGS-A or MMS-P applications of WRE-N, it is anticipated that 6-h production cycles of the NCEP GFS or the AFWA WRF-ARW mesoscale model (15 km/5 km) will be available as a source of initial and time-dependent lateral boundary conditions. Given the spatial and temporal resolutions of these operational models, along with those desired for the WRE-N, it is felt that "cold starting" the WRE-N using a new NCEP or AFWA model cycle for a refreshed initial condition (i.e.; GFS or WRF-ARW) should be done once every 12-24 h.

Between cold starts, the time-dependent lateral boundary tendencies for the outer WRE-N nest are provided from the same NCEP or AFWA model cycle used for the most recent "cold start". In addition, each successive hourly WRE-N cycle begins from an initial condition provided from the "t_0-2 h" WRE-N grids from the previous hourly cycle (recall that WRE-N steps back 3 h each cycle to perform FDDA). Figure 1 below provides a diagram that illustrates the hourly-cycling process in WRE-N. The WRF run option called "restart" is used for the cycling. Figure 2 shows an example of a typical WRE-N forecast output.

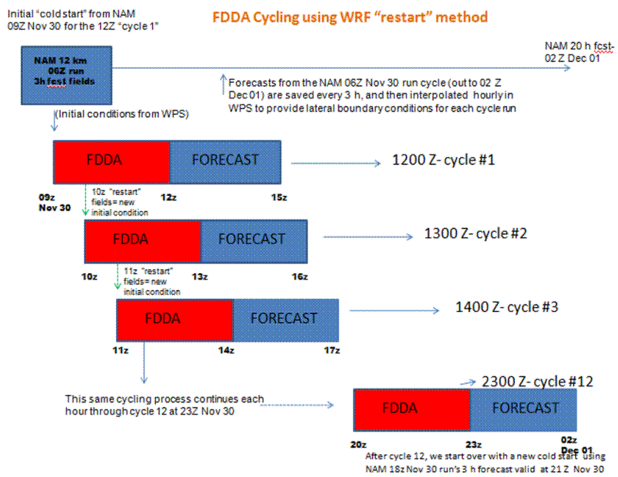

Figure 1. WRE-N with 1h cycling

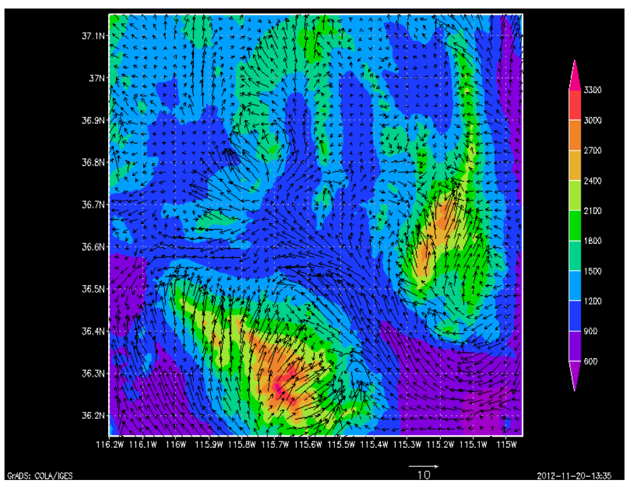

Figure 2. Example of a fine-nest 1h WRE-N surface wind field prediction near Creech AFB, Nevada valid at 2012 Nov 1 19 UTC.

5. Summary

ARL is performing research and development testing of an application called the WRE-N, based upon the WRF-ARW model using FDDA observation nudging. This tool is being tailored for rapid update cycle nowcasting in support of both the Army DCGS-A and Artillery MMS-P systems, as well as aviation routing tools. The spatial scales being targeted are generally storm-scales and below (< 3 km grid spacing), with update frequencies of up to 1 h. The system will also leverage high resolution global and mesoscale models produced from operational centers such as NCEP and AFWA. Key battlefield observations currently being targeted in WRE-N are those direct weather observations that can be obtained at the surface and aloft (such as from balloons and unmanned aircraft).

An example of an aviation tool that will leverage the 4D WRE-N grids is the AIR, with an example output shown in Figure 3. Atmospheric impacts on platforms along with alternative routing options which consider environmental factors along a planned path of movement are of significant importance during combat operations. Such options move towards improving survivability and movement efficiency of air and ground platforms and systems. Environmental factors which may adversely affect systems during combat operations along a projected path include adverse weather, threat activity, conflicting friendly operations, and other obstacles. ARL has developed the AIR for calculating optimized routes in 3D space, avoiding adverse atmospheric conditions and other obstacles during mission execution. The WRE-N grids are critical to supporting the AIR.

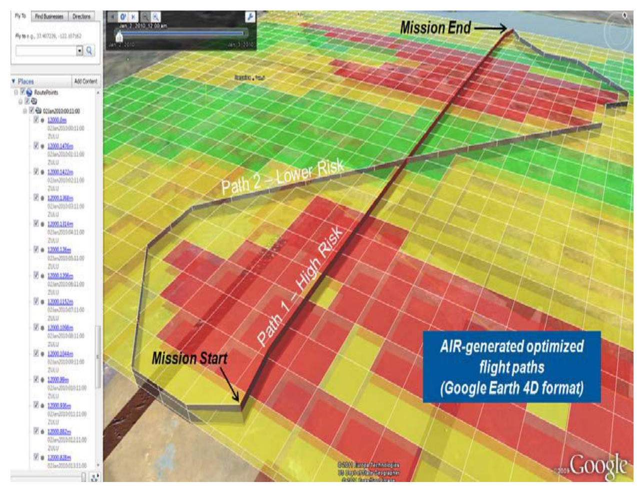

Figure 3. AIR output of two paths in Google Earth KML format: high risk and lower risk. The impacts used when the paths were calculated are shown as additional overlays.

Current efforts at ARL are investigating many aspects of the WRF-ARW and the FDDA at scales around 1 km grid spacing to support tools such as AIR. Examples include looking at the impacts of different PBL schemes and microphysics, impacts of radii of influence and coefficient strengths for nudging, impacts of explicit diffusion and damping terms selectable from the WRF-ARW namelist, sensitivity of lateral boundaries of nests to noise, etc. Work is also ongoing to improve an apparent weakness uncovered in the current WRF-ARW

FDDA scheme associated with water vapor mixing ratio observation nudging.

Interest also exists in the near future to explore a hybrid data assimilation approach for WRE-N that would combine variational, analysis nudging and observation nudging approaches. This would allow WRE-N an opportunity to more effectively assimilate indirect observables (such as possible through radar and lidar remote sensing, for example) which are currently outside the capability of a pure nudging approach (unless convertible into direct observables such as temperature, humidity or horizontal winds). An example of a variational approach that could be tested in this context is the 3D version of the Space-Time Mesoscale Analysis System (STMAS) under development at the National Oceanic and Atmospheric Administration's Global Systems Division of the Earth System Research Laboratory (Xie et al., 2011).

6. References

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