# Initial Results Using WRF 3DVAR In MM5 Applications

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## 1. Introduction

The importance of accurate initial conditions to the success of an assimilation/forecast numerical weather prediction (NWP) system is well known, and in recent years much effort has been spent in the development of variational data assimilation systems to replace previously used schemes e.g. optimum interpolation (OI). This paper describes results of ongoing tests of the three-dimensional variational (3DVAR) data assimilation system designed and built in the Mesoscale and Microscale Meteorology (MMM) Division of the National Center for Atmospheric Research (NCAR) for use with the Pennsylvania State University/NCAR Mesoscale Model (MM5) (Barker et al. 2002). Guo et al. and Chen et al. (both this volume) describe results from additional applications of the MM5 system.

Initial motivations for developing a 3DVAR system for MM5 included a) Implementation in the Taiwanese Civil Aviation Authority (CAA)'s real-time MM5-based AOAWS forecasting system, b) Replacement to the OI system used operationally in world-wide domains run at the US Air Force Weather Agency (AFWA) and c) Release as a research community data assimilation system. In addition to these plans, the MM5 3DVAR system has more recently been adopted as the starting point for a data assimilation capability for the Weather Research and Forecast (WRF) model. Thus the nascent WRF 3DVAR has retained from the start an ability to run seamlessly within the MM5 modeling environment.

Although the WRF 3DVAR code has been written from scratch, the particular 3DVAR implementation discussed here is similar in basic design to that implemented operationally at the UK Meteorological Office in 1999 (Lorenc et al. 2000). In summary, the main features of the WRF 3DVAR system include:

- Incremental formulation of the model-space cost function.
- Quasi-Newton minimization algorithm developed at Argonne National Laboratory.
- Analysis increments on an unstaggered "Arakawa-A" grid. In the MM5 environment, the input background wind field is interpolated from the Arakawa-B grid of MM5 on input. Following minimization, the A-grid analysis wind increments are interpolated to a B-grid before output as an MM5 input format file.
- Analysis performed on the non-hydrostatic sigma-height levels of MM5.
- Jb preconditioning via a "control variable transform" $U$ defined as $\boldsymbol{B}=UU^{T}$.
- Preconditioned control variables include streamfunction, velocity potential, unbalanced pressure and a choice between specific or relative humidity.
- Linearized mass-wind balance (including both geostrophic and cyclostrophic terms) used to define a balanced pressure.
- Climatological background error covariances estimated via the NMC-method of averaged forecast differences. Values are tuned by comparison with estimates derived from observation minus background differences (innovation vector) statistics.
- Representation of the horizontal component of background error via isotropic recursive filters. The vertical component is applied through projection onto climatologically averaged eigenvectors of vertical error estimated via the NMC-method. Horizontal/vertical errors are non-separable in that horizontal scales vary with vertical eigenvector.
- Parallelization of 3DVAR code achieved using the software architecture of the WRF model project.

The code has been tested on a number of machines including DEC, IBM-SP, Fujitsu VPP5000, NEC-SX5, SGI, PC/LINUX and Alpha/LINUX platforms. Standard tests performed after each code change include adjoint/inverse correctness, single observation tests, study of selected case-studies, cross-platform checks and impact of differing numbers of processors. As well as outputting the analysis and (optionally) the analysis increment files in MM5 input format, multiple diagnostics are computed including O-B, O-B and A-B statistics, cost function minimization information and observation usage statistics.

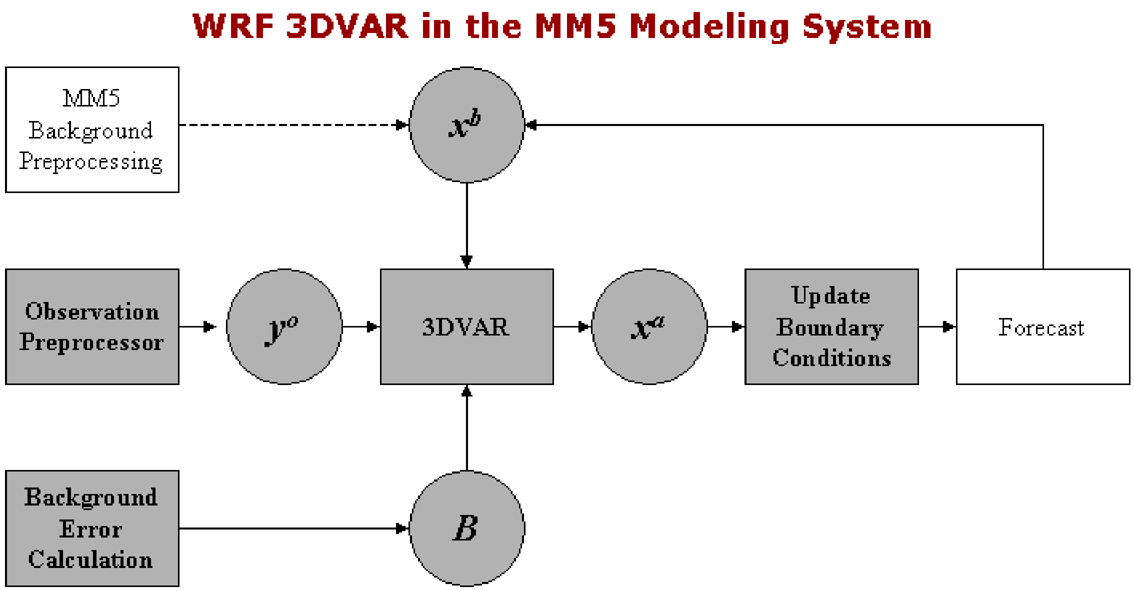


**FIG. 1. Components of the 3DVAR system (highlighted) and their interaction with pre-existing components of the MM5 modeling system. Note the background preprocessing is only required if 3DVAR is run in "cold-start" mode (dashed arrow). In "cycling" mode, a short-period forecast is used as the background field.**

The basic layout of 3DVAR in the MM5 environment is illustrated in Fig. (1) for both cold-starting mode, where the background forecast originates from another model and/or grid, and cycling mode where the background forecast is a short-range forecast from a previous 3DVAR analysis. The three input (background, observation and background error) and output (analysis) files are shown as circles. Highlighted rectangles indicate code especially written for use with 3DVAR and MM5. Clear rectangles represent preexisting code.

## 2. Parallelization

A major recent effort has been to develop a distributed memory capability for 3DVAR. The WRF software framework insulates the scientist from parallelism by encapsulating and hiding details that are of no direct concern to the model. It is organized functionally as a three-level hierarchy, with the low-level model layer protected from architecture-specific details such as message–passing libraries, thread packages, and I/O libraries. All management of domain decomposition, processor topologies, and other aspects of parallelism are handled by the framework. For use with the framework, 3DVAR model subroutines are written to be callable over an arbitrary rectangular subset of the three-dimensional model domain. The framework ingests the 3DVAR domain size from a namelist file and calculates tile, patch, and memory dimensions for each 2-D decomposition. These indices, along with descriptors necessary for exchanging halo communication and initiating parallel transpose operations, are stored into a Fortran90 derived type structure. In this way parallel configuration data can be neatly passed to 3DVAR subroutines, keeping argument lists compact.

The 3DVAR system contains a number of algorithms that pose new challenges to the WRF software architecture for running on distributed memory systems. Firstly, the specification of background error covariances via recursive filters and also the use of Fast Fourier transforms (FFTs) in 3DVAR's "control variable transform" requires a domain decomposition along thin strips extending across the entire domain (both North-South and then East-West). Secondly, the minimization algorithm requires the parallelization of large vector dot-products. Finally, the inhomogeneous nature of the observation network ideally requires an irregular, horizontal domain decomposition (although a regular decomposition is currently used).

The MPP speed-up achieved running 3DVAR with differing numbers of processors on NCAR's IBM-SP "blackforest" machine is shown in Fig. (2). The particular case studied is a 3DVAR run valid at 6Z on the 6th October 2001 in AFWA's 45km South-West Asian "T4" 140x150x41 domain. Minimization in this case is achieved in 98 iterations.

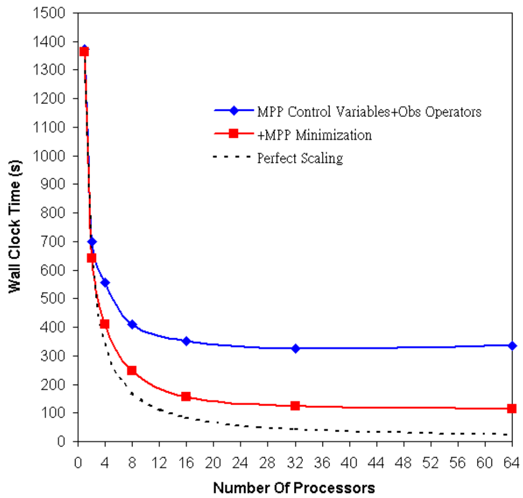


**FIG. 2. Wall-clock time for test 3DVAR run in AFWA's 140x150x41 45km T4 domain - 6th October 2001 case-study. Times shown are for runs on NCAR's IBM-SP Winterhawk II.**

Three curves are shown in Fig. (2): a) Speed-up following initial parallelization of control variables and observation operators, b) Speed-up following additional MPP work on minimization and c) Theoretical perfect scaling. For this case, wall-clock time for single processor 3DVAR is 1373s. This is reduced to 334s using 64 processors without and ~115s with MPP minimization. Although far from perfectly scalable (I/O is still serial), a run-time of 115s is well within the operational time-window of current applications. Differences in runs between different number of processors are expected due to the accumulation of rounding error differences in quantities summed over processors (e.g. components of the cost function). However, these differences are found to be negligible in cases studied to date.

## 3. Observation/Background Error Studies

Observation errors used in 3DVAR are prescribed in tables received from AFWA. In contrast, background errors are application-specific and approximated via the "NMC-method" which entails using averaged forecast differences as a climatological proxy for background errors. The validity of these errors has been tested by comparison with background and observation errors derived via accumulated radiosonde observation minus background (O-B) differences (Hollingsworth and Lönnberg, 1986). Two three-month periods of radiosonde minus CAA background data from the AOAWS system have been collected – a summer season (June-August 2001) and a winter season (December 2001-February 2002). Observation and background error estimates from the O-B data have been used to tune the errors used in 3DVAR.

As an illustration, observation and background error variance estimates from both winter and summer radiosonde wind O-B datasets are shown in Fig. (3). A number of features can be seen. Firstly, wind observation errors on average increase with decreasing pressure (i.e. altitude). Differences in observation errors are also seen between winter and summer seasons. Both these effects are partially explained by the dependence of wind error on wind speed. As for the background error variances, a similar dependence on pressure is seen as for the observation errors. An important result, which verifies earlier tests using background errors derived via the NMC-method, is the fact that background errors are generally smaller than their observation counterparts. Given the background in the CAA AOAWS system is a global analysis of the Taiwanese Civil Weather Bureau (CWB), this fact is not surprising - an analysis should be more accurate than the observations and forecast from which it is computed. The relatively small size of the background errors will therefore result in relatively small analysis increments as 3DVAR (in this application at least) puts more faith in the synoptic-scale features of the background rather than those of the observation network. In cold-start mode (as at CAA), where the background is a global analysis, mesoscale 3DVAR is not expected to have a significant impact on synoptic-scales but is ideally suited to introduce new and/or high resolution observational features into the analysis.

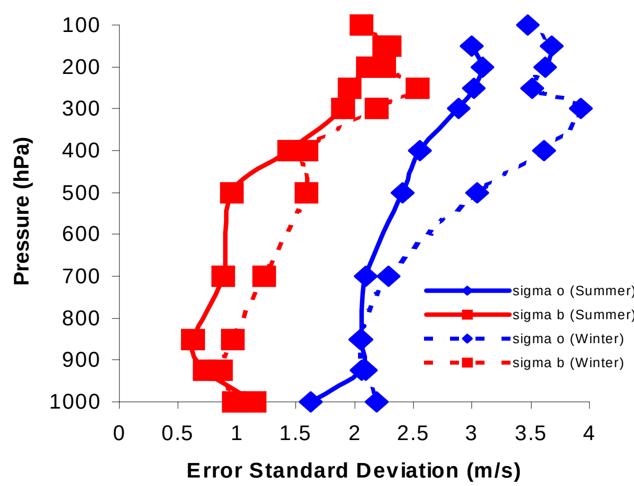


**FIG. 3. Observation and background error variances as calculated from accumulated O-B data. Values for both summer (solid) and winter (dashed) radiosonde data are shown.**

## 4. Verification Of First Real-Time Application Of 3DVAR in East Asia

The ultimate goal of 3DVAR implementation at the Taiwanese CAA is to produce analyses that improve MM5 forecasts in the AOAWS system relative to those run from the previously used LITTLE_R analysis scheme. The 3DVAR system already has the capability to assimilate numerous non-conventional observation types e.g. SATEMs, SSM/I, GPS TPW (and will contain more in the near future e.g. radar, radiances). However, in order to provide a fair comparison and benchmark for future 3DVAR upgrades, in these results 3DVAR assimilates only those conventional observations available to LITTLE_R.

Initial forecast verification scores for the u wind-component are shown in Fig. (4) for the 135km and 15km East-Asian MM5 domains 1 and 3. Verification is against radiosonde observations. The period chosen is 1 week from 00Z on the 28th March to 18Z on the 3rd April using forecasts initialized at 00Z, 06Z, 12Z and 18Z. The 3DVAR system is set up to "cold-start" from CWB global analyses at main synoptic hours (00Z and 12Z) and to "3-hour cycle" at other times i.e. the first guess at 03Z, 06Z, 09Z, 15Z, 18Z and 21Z is a previously run 3-hour MM5 forecast.

Although the analysis (T+00) fit to observations is closer for LITTLE_R than for 3DVAR, the T+06 fit to observations is significantly better using 3DVAR analyses. As discussed above, in a situation where observation errors are larger than background errors a close fit to observations is not expected. However, the improved short-range (T+06) forecast with 3DVAR does indicate that the 3DVAR wind analysis is producing better short-range forecasts. The 3DVAR forecasts continue to show some improvement relative to LITTLE_R forecasts out to ~36 hours for domains 1 and ~15 hours for domain 3.

Verification of temperature and moisture fields (not shown) similarly indicates slightly better forecasts using 3DVAR analyses. Verification has been performed for numerous periods over a 6 month pre-operational period. Again, similar results are found. Larger improvements are expected from ongoing work to introduce additional observation types and to improve on the currently climatological, isotropic and homogeneous background errors.

An encouraging note is that the 3DVAR system used here runs in ~1-2 minutes wall-clock time using 10 processors of the Fujitsu VPP-5000 of CAA compared to 10-15 minutes wall-clock for LITTLE_R. This speed-up is attributable not just to the MPP nature of 3DVAR but also to data compression and preconditioning algorithms. Thus even on 1 processor the computational cost of 3DVAR is only ~30% that of LITTLE_R. This efficiency could be used to perform higher resolution analyses for the same computational cost as LITTLE_R thus providing another method for improving forecasts. However, this would only be worthwhile given observations with high enough resolution to provide additional grid-scale detail.

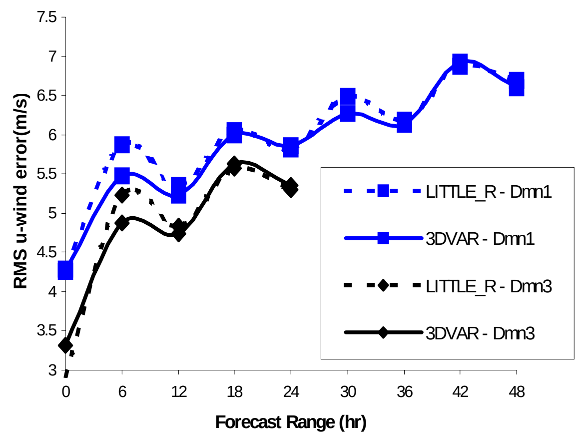


**FIG. 4. Verification of the u-component of wind for MM5 forecasts as a function of forecast range. Scores for AOAWS domains 1 and 3 (135km and 15km resolution) are shown.**

## 5. Summary and conclusions

This paper reports results of tests of the nascent WRF 3DVAR system applied in MM5 modeling system applications. Release of the WRF 3DVAR system to the research community is planned for summer 2002.

## 6. References


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