Tuning of WRF 3D-Var data assimilation system over Middle-East and Arabian Peninsula

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ABSTRACT

A series of experiments based on the recently implemented WRF Numerical Weather Prediction (NWP) system, and especially its component dealing with data assimilation had been carried out over Middle-East and Arabian Peninsula areas. The ultimate goal of this work is to put into operations a complete NWP configuration running in both assimilation and prediction modes, taking advantage of the best numerical and scientific techniques offered by WRF system, and achieving better forecast performance when compared to the native WRF forecasts based on the Global Forecasting System (GFS) initial states. The conducted experiments investigate the impact of using different background errors, tuning observation errors, multiple outer loops, First Guess at Appropriate Time (FGAT) and ingesting some high resolution non conventional data like Radar reflectivities. It was found that, when the positive impacts of these different ingredients are associated together, forecasts initiated from WRF 3D-Var initial states, in a warm cycling mode, outperform those based on GFS Grid point Statistical Interpolation (GSI) final analyses.

Key words: 3D-Var, data assimilation, background error statistics, case studies.

1. Introduction

To produce a good forecast, a good description of the initial conditions is necessary. A large part of forecasting deficiencies is connected with the imperfect assimilation of available data in the numerical weather prediction process. Many international NWP Centers are focusing their efforts on developing assimilation systems with a routinely increasing sophistication. Generally, these systems (ECMWF 4D-Var, NCEP GDAS, Met office 4D-Var, Météo-France ARPEGE) are dealing with global geographic domains, and this constitutes an impassible constraint for assessing the impact of high resolution backgrounds and observational networks.

Thus, Applying data assimilation for high resolution Limited Area Models (LAM) (HIRLAM, MM5, AROME, WRF ...etc) is becoming more interesting. But, to be meaningful, limited area data assimilation over a given domain should perform better than global systems. This is a real challenge, because of the difficulties inherent to many factors: Background errors , which highly govern the quality of any assimilation system, should be generated and tuned for high resolution; dense observational data coverage should be available with relevant errors assigned; quality control adapted; sensitivity studies for each observation type carried out; ...etc.

The present study is testing some of these factors inside the United Arab Emirates NWP system based on WRF package (UAE/WRF). The latter application is briefly described in the next session, followed in section 3 by an overview about the Middle-East and Arabian Peninsula areas climate specificities. Section 4 will describe our experimental design and list our data assimilation experiments. In section 5, the simulations results are presented and interpreted. And finally, the summary and conclusions are given in section 6.

2. Description of UAE/WRF application

UAE/WRF model is running operationally, since August 2006, over three two-way multi-nested domains with increasing horizontal resolutions of 40 km (d01), 13.3 km (d02) and 4.4 km (d03), centered on United Arab Emirates (24.5° N, 54.5° N) (Fig. 1). 38 hybrid sigma-pressure levels are considered on the vertical up to 50 hPa.

The current operational initial and lateral boundary conditions for d01 are taken from the global NCEP GFS/GSI (0.5×0.5) analysis and forecasts, at six hours frequency, up to 5 days.

Ferrier microphysics scheme is chosen for all model domains, whereas Kain-Fritsch cumulus parameterization scheme is employed only for d01 and d02.

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For planetary boundary layer and surface physics, Yonsei University PBL and Noah LSM surface schemes are respectively used.

Rapid Radiative Transfer Model (RRTM) long wave, and MM5 (Dudhia, 1993) shortwave radiation scheme are used. The model is run twice a day and produces forecasts up to 5 days with hourly post-processing (http://www.afmet.ae/main.html).



Fig. 1 UAE/WRF two-way nested operational model domains.

Verification procedure is automatically and routinely comparing model forecasts against the available conventional Global Telecommunication System (GTS) upper air and surface data. Basically, the forecast scores are satisfactory at the exception of a main frequently noted repetitive feature of delaying large scale active weather patterns by about 2 to 4 hours. This behavior could eventually be resolved when data assimilation will be adopted operationally.

3. Brief overview of the Middle-East and Arabian Peninsula areas climate

The geographical domain subject of the operational UAE/WRF model is characterized by an arid to semi-arid climate, very hot especially during summer with frequent fog occurrences along the western UAE coasts due to high amounts of humidity and persistence of high pressures during almost all the year. The winter active systems are very similar to those observed over midlatitudes temperate regions, but not very frequent. Summer is governed by the invasion of Indian monsoon winds advecting high upper-air humidity and, then, causing local thunderstorms especially severe over the mountainous eastern part of Arabian Peninsula.

Since its operational exploitation, the operational configuration of UAE/WRF based on GFS/GSI initial and LBC conditions, seemed to behave in a coherent way with the mentioned climatic characteristics.

4. Description of the case study and details of the experimental design

4.1 Overview of the meteorological situation over UAE during the test period

The experiments conducted in this study concern a spring situation, characterized by a severe weather system having scanned the entire northern Arabian Peninsula, with intense convective precipitations, particularly over United Arab Emirates on 02 April 2007. More than 25 mm rainfall was reported over Sharjah (25.33° N, 55.51° E), Dubai (25.25°N, 55.33°E) and Ras-Al-Khamah (25.61° N, 55.93° E), during less than four hours (from 1200 to 1600 UTC). Infra Red satellite images (Fig. 2) show clearly the convective cells embedded in a large and active low to medium clouds pattern, advected in a north-westerly to westerly flow. Before reaching the Arabian Gulf Sea, this system, which was formed over eastern Mediterranean Sea, gave heavy precipitations over northern Saudi Arabia, southern Iraq and Kuwait. When entering the Gulf Sea, this system gained a big amount of humidity from the surface due to high Convective Available Potential Energy over Qatar and UAE regions during the first half of the day.



Fig. 2 Satellite image showing an active system covering Gulf area during 02 April 2007 at 1400 UTC.

The operational UAE/WRF model, using NCEP GFS/GSI initial state, was able to simulate most of these system features at synoptic scale, 12 hours before, but partially failed in placing correctly the convective cells formed along the western UAE coasts as showed by Al-Dhafra Radar (24.32° N, 54.89° E) in Fig. 3. At the time indicated on the

Radar image (1350 UTC), WRF placed these cells 300 km westward.



Fig. 3 Al-Dhafra Weather Radar PPI image at 1350 UTC on 02 April 2007.

4.2. Brief description of the observational data distribution over Middle-East and Arabian Peninsula regions

The set of observational data used in this study consisted in all GTS conventional data (TEMP, PILOT, SYNOP, SHIP, BUOY, AIREP, AMDAR, METAR, GEOAMV (SATOB), SATEM) enriched by some non conventional data like GPS Refractivity, and Radar Reflectivity and Radial Velocity.

The Radar network is assured by 6 Doppler WSR-88D platforms covering UAE. The corresponding data is collected each 15 minutes in BUFR format, at 500 meters horizontal resolution and 11 increasing antenna elevations. A preprocessing procedure consisting in decoding, reformatting and thinning these data was developed. The assigned observational errors are inspired from a study carried out by Dong-Kyou Lee, Johan Lee and Hyun-Ha Lee at Seoul National University, Korea. Their study recommended 1.4 m s⁻¹ and 10 dBZ respectively for radial velocity and reflectivity. In our study only the impact of horizontal reflectivities was assessed.

Atmospheric Motion Vectors (AMV) generated from METEOSAT 8 geostationary satellite images (Fig. 4), have been used to carry out observation usage experiments with the WRF 3D-Var assimilation. Only reports with more than 85 % percentage confidence were considered.

Several impact studies with the different international analysis and forecasting systems have in the past shown a very clear negative impact of using SATOB data. However, a lot of progress in the production of these data has been made by satellite data providers. We will show in this individual study their clear positive impact. The GPS refractivity data are taken from currently onboard CHAMP and SAC-C satellites, which provide several profiles inside our study region.



Fig. 4 Geostationary Atmospheric Motion Vectors data originating from METEOSAT 8

The observational data are pre-processed by the WRF 3DVAR_OBSPROC package and organized in 7 packets corresponding to 7 time-slots around the different analyses times. This will enable the use of FGAT technique (First Guess at Appropriate Time).

4.3. Background errors

Background Errors Statistics (BES) determine how the variational analysis procedure converts the differences between observed and forecast variables into corrections of the meteorological fields. In this study, these background errors are computed using the so-called NMC method (Parrish and Derber, 1992) over a period of 4 weeks.

Single observation experiments were performed, in domain d03, to compare the shape of the structure functions interpolated from NCEP BES (CV3), to the locally computed CV5. The horizontal and vertical effect on the temperature increments of a single 700 hPa temperature observation at 25.5° N 55.5°E are examined. The vertical impact on the temperature increments is illustrated by a vertical cross-section in the west-east direction in Fig. 5. For CV5, the temperature increments are isotropic on the horizontal with a relatively coherent length scale (~ 200 km). The inserted temperature observation was assumed to have a very small error with a standard deviation of 0.2 K. This explains the strong impact of this single observation. The change in sign of the vertical correlations above the Tropopause is also clearly illustrated: with a cooling of the Tropopause,

the corresponding level and temperature will be respectively lower and warmer. CV3 raw structures show very sparse horizontal effect (not shown), but relatively narrow influence on the vertical. Inside domains d02 and d03, with respective resolutions of 13.3 and 4.4 km, these CV3 BES may lead to inconsistent increments. They were tuned in term of length scales in order to mimic the shape of CV5 (Fig. 5).



Fig. 5 Vertical cross section of temperature increments generated by a single temperature observation introduced at model level 12 (~3 km) using a) tuned CV3 BES and b) raw CV5 BES.

4.4 Experimental design

The situation described in 4.1 constitutes a good case study to assess the performance of WRF 3D-Var. An assimilation cycle of 6 hours window was designed for the period between 30 March 2007 at 1800 UTC and 03 April 2007 at 0000 UTC followed by 120 hours free forecast based on the WRF 3D-Var analysis of 03 April 2007. Another short range 24 hours forecast is initiated from the WRF 3D-Var

analysis of 02 April 2007 at 0000 UTC. The beginning initial condition at 1800 UTC 30 March 2007 and all the boundary conditions are created for domain d01 by WRF Pre-processing System (WPS) from NCEP GFS/GSI Final Analyses.

Each domain among d01, d02 and d03 is performing its own 3D-Var analyses. It was possible not to opt for the application of data assimilation inside d02 and d03, and just interpolate their initial states from d01. But, we considered that this configuration will never perform better than the operational cold start, at least because of the following reasons:

- GFS/GSI final analyses are performed at almost the same horizontal resolution (~35 km) as domain d01.
- The ingestion of High resolution Radar data will have a very small to neutral impact at 40 km horizontal resolution.

The 120 hours forecast is verified each 12 hours against the actual upper air data, and each 6 hours against surface data. This forecast has the role of quantifying the quality of each assimilation experiment described hereafter. The verification procedure used a set of observations a priori quality controlled, and took benefit of the existing observation operators inside WRF 3D-Var code to calculate the forecasts Root Mean Square Errors (RMSE). Whereas the 24 hours forecast will assess the added value of 3D-Var at high resolution (domain d03), with respect to the occurrence and the placement of the above-described convective cells.

The six experiments conducted are configured as follows:

NCEPGSI: The reference, corresponding to the operational configuration. The above mentioned 24 and 120 hours forecasts are initiated from GFS/GSI analyses in cold start mode. No assimilation is done.

TUNEDCV3: Cycling is done, but all 3D-Var analyses are using the tuned global NCEP background errors statistics (BES) option CV3. Domain d01 is using these BES without any scaling factor for length scales, because it has almost the same resolution as NCEP/GFS, whereas d02 and d03 are reducing the length scales by a factor of 0.5 and 0.25 respectively. Vertical length scales are increased 50 %, and variances are decreased 80 %. These tunings are valid for stream function, unbalanced potential velocity, unbalanced part of temperature and pseudo-relative humidity control variables. The unbalanced part of the surface pressure was attributed the factors 0.5, 1.0 and 1.0 respectively for variance, horizontal and vertical length scales.

RAWCV5: Warm cycling performing 3D-Var analyses using local BES generated for each domain by the NMC method based on one month forecast dataset. The above-described, single observation experiments (Fig. 5.b) suggested that the length scales are realistic and then no tuning is needed for the structure functions. Error variances could however be tuned if necessary to satisfy the Desroziers and Ivanov (2001) criterion, as it will be explained in the next experiment.

ERFCV5: Error factors are applied to each term of the cost function and to each observation type in the spirit of adjusting the real cost function to what it should be if one wants the Desroziers and Ivanov, 2001, criterion to be satisfied. This criterion is suggesting that the expectation of the minimized cost function is given by a half of the effective number of observations. It is an interesting a posteriori diagnostic tool assessing the quality of an assimilation system. The factors computed for observation and background terms, for domain d02, are shown in Table 1.

OBS TYPE	u	v	Т	р	q	
SYNOP	2.05	1.89	1.14	1.45	0.69	
METAR	1.90	1.79	1.31	0.97	0.68	
SHIPS	1.00	1.00	1.00	1.00	1.00	
GEOAMV	2.26	1.74	-	-	-	
SOUND	1.82	1.72	1.43	-	0.88	
SONDSFC	2.79	1.69	1.35	1.06	1.12	
AIREP	1.31	1.20	0.91	-	-	
PILOT	1.60	1.59	-	-	-	
Jb Factor			1.79			
	SATEM		GPSREF	R	RADAR	
Thickness	1.63		-		-	
Refractivity	-	-			-	
Reflectivity	-		-		0.95	

Table 1. Observation tuning factors computed	in
FGAT mode on 13 3D-Var analyses.	

It has to be noted here, that the process of determining these factors is an iterative offline procedure consisting in determining the ratio of the real cost function, calculated during the previous minimization, to its expectation. The latter is given theoretically by the traces of the matrices **HK** (for the observation term) and **KH** (for the background term), where **H** is the linearized observation operator and **K** the Kalman gain matrix. Experimentally, a randomization method is used to estimate these traces. Deeper details could be found in Desroziers and Ivanov, 2001 and Chapnik et al., 2005.

ITS3CV5: It consisted in redoing the previous ERFCV5 and imposing 3 outer loops instead of only 1. During each loop, different BES scaling factors are applied. This experiment will take advantage of the

benefits offered by the outer loops technique (Veerse and Thépaut, 1998): Non-linearities in the observation operators will be considered, and observations will be quality controlled multiple times. The BES scaling applied, in addition, in a decreasing way during the successive outer loops, will contribute to a final analysis in which large scales and small scales will be correctly fitted. Table 2.a and 2.b. give the BES tuning factors for the three outer loops.

(a)	Outer loop	Outer loop	Outer loop
	1	2	3
Stream function	1.75	1.00	0.5
Velocity	1.75	1.00	0.5
potential			
Unbalanced	1.75	1.00	0.5
temperature			
Specific	1.00	1.00	0.5
humidity			
Unbalanced	1.75	1.00	0.5
pressure			
(b)	Outer loop	Outer loop	Outer loop
(b)	Outer loop 1	Outer loop 2	Outer loop 3
(b) Stream function	Outer loop 1 1.00	Outer loop 2 0.50	Outer loop 3 0.25
(b) Stream function Velocity	Outer loop 1 1.00 1.00	Outer loop 2 0.50 0.50	Outer loop 3 0.25 0.25
(b) Stream function Velocity potential	Outer loop 1 1.00 1.00	Outer loop 2 0.50 0.50	Outer loop 3 0.25 0.25
(b) Stream function Velocity potential Unbalanced	Outer loop 1 1.00 1.00 1.00	Outer loop 2 0.50 0.50 0.50	Outer loop 3 0.25 0.25 0.25
(b) Stream function Velocity potential Unbalanced temperature	Outer loop 1 1.00 1.00 1.00	Outer loop 2 0.50 0.50 0.50	Outer loop 3 0.25 0.25 0.25
(b) Stream function Velocity potential Unbalanced temperature Specific	Outer loop 1 1.00 1.00 1.00 1.00	Outer loop 2 0.50 0.50 0.50 0.50	Outer loop 3 0.25 0.25 0.25 0.25
(b) Stream function Velocity potential Unbalanced temperature Specific humidity	Outer loop 1 1.00 1.00 1.00 1.00	Outer loop 2 0.50 0.50 0.50 0.50	Outer loop 3 0.25 0.25 0.25 0.25
(b) Stream function Velocity potential Unbalanced temperature Specific humidity Unbalanced	Outer loop 1 1.00 1.00 1.00 1.00 1.00	Outer loop 2 0.50 0.50 0.50 0.50 0.50	Outer loop 3 0.25 0.25 0.25 0.25 0.25 0.25

Table 2. Three sets of progressive a) variance and b)length scales, tuning factors for the experimentsbased on 3 outer loops.

It has to be noted that in order to achieve this experiment, WRF 3D-Var source code was modified to allow the use of different background scaling factors during each outer loop.

NOGMV: Same as ITS3CV5 but high density Geostationary Atmospheric Motion Vectors (GEOAMV) were not assimilated.

RADCV5: Same as ITS3CV5 but Radar reflectivities are ingested.

5. Numerical results

Figure 6 gives the 120 hours forecast RMSE of temperature, wind speed, and specific humidity for all the experiments against Sounding and SYNOP actual data.



Fig. 6 120 hours range forecast errors against sounding for **a**) temperatur, **b**) specific humidity, and **c**) zonal wind for NCEPGSI (red), TUNEDCV3 (black), RAWCV5 (magenta), ERFCV5 (blue) and ITS3CV5 (green).



Fig. 7 120 hours range forecast errors against SYNOP for a) temperature, b) meridional wind for NCEPGSI NCEPGSI (red), TUNEDCV3 (black), RAWCV5 (magenta), ERFCV5 (blue) and ITS3CV5 (green).

The first obvious result to notice in almost all the experiments is the bad performance at the beginning of the forecast period (first 24 to 48 hours). The aim of any data assimilation system, especially at high resolution, is to reduce the period of spin-up, and then behave correctly since the very beginning. In our point of view, this problem is due mainly to the absence of initialization during the 3D-Var process, as a weak constraint (Gauthier and Thépaut, 2001), or posterior to 3D-Var process (Lynch and Huang, 1992). We believe that initialization will reduce the dynamic imbalance between model variables, while maintaining a closer fit to the observations.

NCEPGSI is practically unbeatable when compared to all the other experiments, except ITS3CV5. This could be explained by at least by the two following arguments:

 GFS GSI (Wu et al.) is a mature data assimilation system based on 3D-Var technique at a global resolution of about 35 km considered competitive when compared to the nowadays regional models resolutions (10 to 30 km). - GFS GSI data assimilation system is taking benefit of more diversified set of non conventional observation data, like SSMI, Quick SCAT, NOAA HIRS and AMSU radiances, among other types. These non conventional satellite data are known to have a clear positive impact on forecast systems (Bouttier and Kelly, 2001). The experiments conducted in this study use only GPFS REF and RADAR data as non conventional observations.

TUNEDCV3 experiment gave the worst forecast scores. The bad performance of CV3 even with coherent tuning factors could be explained by the two following reasons:

- CV3 BES were derived using NMC method applied to NCEP GFS forecasts. GFS is a global model using different physics and dynamics packages than WRF. It is then very likely that CV3 BES, are not suitable for WRF 3D-Var.
- CV3 BES were computed using 48 and 24 hours forecast ranges valid at the same time. These ranges are perhaps chosen to be larger enough to avoid accounting for the initial state errors. But,

they are eventually not adequate to reflect the background errors at 6 hours forecast range, which is the 3D-Var assimilation window used in our experiments.

RAWCV5 is generally better than TUNEDCV3, but still bad when compared to NCEPGSI. We guess that this failure of RAWCV5 is due to the following causes:

- CV5 BES were determined using NMC method for each domain on a period of one month. But, the used forecasts were produced in cold start WRF runs. We suppose that better CV5 could be generated when using differences of forecasts initiated by warm WRF starts (during cycling). On the other hand, it could be adequate to use the differences between short range forecasts for high resolution models when deriving NMC statistics, for example, 6 /12 hours for d03 and d02 (4.4 and 13 km resolution respectively), and 12/24 hours for d01 (40 km resolution).
- The high Geostationary Atmospheric Motion Vectors originating from METEOSAT 8 are very dense. Thinning of this data was based only on their percentage of confidence (85 % as a rejection threshold). Even though, their number remained predominant. This could have been harmed the quality of the analyses. Furthermore, table 1 shows very high observation tuning factors for GEOAMVs, which means that 3D-Var process was unable to approach its ideal performance, with respect to Desroziers and Ivanov criterion, without rejecting a big amount of these data.

ERFCV5 is slightly better than RAWCV5, but remains also far from beating NCEPGSI. The slight improvement is certainly due to a better deal with the set of observations. Its failure could be explained by the fact that almost all the observations tuning factors used were contributing to data discarding since they are greater than 1 (except for humidity observations). The analyses increments (not shown), in their majority, were smaller than RAWCV5 indicating a more important fit to the first guess field. To resolve this problem, a solution is to apply, in the same time than observation tuning factors, scaling factors for the background term. This was the objective of ITS3CV5 experiment.

ITS3CV5 in which error factors were applied for both observation and background term in the cost function, gave the best results. It was able to perform the same or better than NCEPGSI despite the poor set of observational data used in this study. When verified against soundings, for example, ITS3CV5 Temperature RMSE was 5 to 10 % better with respect to the corresponding NCEPGSI. This experiment was successful due to an optimum compromise between the errors attributed to the different sources of information (observations and background). But it is worth to note that the scaling factors for the background term should be carefully chosen. In fact, the values employed in our study were inspired from previous similar studies (Y.-R. Guo, NCAR and Dong-Kyou Lee, Korea). They are, of course, conducted with UAE/WRF on a different geographical domain, but with almost the same horizontal resolutions.

In the first outer loop, background errors variance is increased by a factor of 1.75 to allow more observations to be ingested, then this factor become progressively smaller in the subsequent outer loops to fit more and more the previously updated first guess.



Fig. 8 *RMSE of temperature and specific humidity* against respectively a) soundings and b)SYNOP. for NOGMV (black) and ITS3CV5 (red).

Figure 8 shows the impact of GEOAMV observations. One can notice the degradation in the

forecast quality when excluding these data in the experiment **NOGMV**. But, more and deeper studies still needed to assess their impact and inform about the way of their optimum use.

RADARCV5 (not shown) gave the same performance as ITSCV3. In addition, the active weather system of 02 April 2007 was better simulated in domain d03, when Reflectivities were added. But we were constrained to redo ITS3CV5, NCEPGSI and RADARCV5 experiments, modifying the micro-physics scheme, during all the involved forecasts, from option 5 (Ferrier, new ETA, scheme) to option 2 (Lin et al. scheme). The latter is able to separate the water variable to six hydrometeors classes: water vapor, cloud water, rain, cloud ice, snow and graupel. Rain water component is needed in the Radar reflectivity observation operator.

The technique of error tuning factors described above suggested a factor of 0.95 (Table 1) indicating that the original assigned reflectivity error is coherent. Figure 9 shows the ratio between the final values of the cost function to the effective number of observations used for domain d03. Desroziers and Ivanov criterion seems to be satisfied which suggest consistent 3D-Var analyses for this domain with Radar reflectivities ingested.



Fig. 9 Ratios of the final value of the cost function to the effective number of observations used in RADARCV5 during the first outer loop.

When comparing the Radar Reflectivity parameter simulated at 1400 UTC by forecasts initiated at 0000 UTC on 02 April 2007, in experiments NCEPGSI, ITS3CV5 and RADARCV5, the following results were revealed:

- NCEPGSI (Fig. 10. a) delayed the occurrence of the convective cells showed by the actual composite Radar image along the western UAE coasts. This is a usual feature remarked in the operational UAE/WRF model since its put into operations in August 2006.

- ITS3CV5 (Fig 10. b) predicted correctly the time of occurrence of the convective cells, but it slightly misplaced their pattern and underestimated the intensity of their activity.
- RADARCV5 (Fig. 10. c) succeeded in simulating the convective cells in a satisfactory way despite a slight misplacement to the east.



Fig. 10 Radar reflectivity at 1400 UTC 02 April 2007 as simulated by experiments a) NCEPGSI, b) ITS3CV5 and c) RADARCV5. Panel d) is illustrating the actual corresponding Radar image.

6. Summary and conclusions.

This paper studied the performance of WRF 3D-Var and the WRF model when applied over a region situated in the frontiers between the mid-latitudes temperate climate and the sub-tropical semi arid one. WRF model, in cold start mode, with a suitable choice of physics schemes, gave satisfactory forecasts for almost all the known weather phenomena over this region. But it still fails in predicting correctly the place and time of convective cells. Generally, WRF delays the active winter weather systems by more than 3 hours.

A series of experiments were carried out in order to implement and tune a data assimilation system based on WRF 3D-Var for UAE/WRF operational suite, with its three nested geographical domains. The most important results from this study are summarized as follows:

1) Background error covariances are a vital input to variational assimilation. Their tuning is a necessary task whether calculated locally using the NMC method or interpolated from another data assimilation system. In our case study, the locally prepared CV5 BES showed consistent analysis features and lead to better forecasts.

2) Forecasts initiated either by warm starts (cycling) or cold starts (NCEP GFS analyses) showed very bad scores during the first 36 hours. This is eventually due to the lack of an initialization process using for example a digital filter to minimize the dynamical imbalance between fields generated by the analysis process.

3) Forecasts initiated from WRF 3D-Var didn't outperform easily those initiated from NCEP GFS/GSI. Particularly the GFS/GSI showed better forecast scores on the surface due eventually to the presence of surface data assimilation in this system and its usage of more surface data, especially non conventional types (SSMI, Quick SCAT, ATOVS ...etc).

4) Observation errors tuning factors, and background structure functions scaling are necessary to achieve consistent WRF 3D-Var analyses. These tuning should be performed for every nest to take into account its own geographical and resolution characteristics.

5) The technique using multiple outer loops with different tuning factors for both observation and background terms constitutes a very promising multiscale 3D-Var approach. It was able to perform similarly or better than GSI in this study. It succeeded particularly, in assimilating the ingested Radar data.

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