Assessing the Improvement of Severe Weather Prediction Over Western Africa in WRF by 3DVAR Data Assimilation System using Conventional and Radiance observational Data

P. Moudi Igri, D. A. Vondou, Roméo S. Tanessong, and F. Kamga Mkankam

University of Yaounde I, Laboratory of Environmental Modeling and Atmospheric Physics PO.Box: 812 Yaounde, Cameroon, moudipascal@yahoo.fr

(Dated: 14 May 2012)

IGRI MOUDI Pascal

Abstract

We present the results of the impacts of 3D Variational Data Assimilation (3DVAR) system within the WRF-Var real time forecast system version 3.3. In this study, severe weather parameters are calculated from an experimental ensemble forecasts, and then compared to a control ensemble forecast in which no ensemble-based data assimilation is performed , initializing with the GFS data at 00 UTC on 15 August 2011. Prepbufr and radiance data were used to ingest observations in a time window of ±3hours with the WRF 3D-Var scheme. Relative humidity, zonal and meridional wind components, 2 metre temperature and rainfall were compared with ERA Interim and TRMM observational data. The results showed a good agreement between these variables and observations and demonstrated that WRF system aims to produce high precipitation over western Africa. For instance, WRF_DA experiment ameliorates simulations by displaying highest correlations and smallest scores errors.

1- Introduction

Widespread floods associated with heavy precipitation episodes are common occurrences in Western Africa regions and the southern Sahel during the boreal summer months ranging from June to September (Nicholson et al., 2000). Climate variability leads to economic and food security risks throughout the world, particularly in Africa, because of its major influences on agriculture and human health (Adejuwon et al., 2007). Rainfall events result in land slides, flash foods and damage to crops that have impacts on the society, economy and environment (Mohanthy et al., 2011). Furthermore, in the last decades, great attention has been paid to the study of the devastating effects of the recurring droughts and flash foods on Africans (Nicholson et al., 2000). Unfortunately, Western Africa is an area with few observations stations (monitoring sites), and very often the quality of data is poor (Djiotang and Mkankam, 2010). Therefore, real-time numerical simulation of severe weather events or satellites data are an indispensable tools for agricultural countries dependent, health planning and others important policy recommendations.

In recent years, many efforts have been focused in numerical weather prediction using Regional Climate Model (RCM). Mesoscale numerical weather prediction by using mesoscale models has played an important role in severe weather forecasting by high-performance computing (Dong-Kyou et al., 2010; Grell et al., 1994). The forecasts performance of the mesoscale models critically depends on the quality of the initial conditions (Mohanthy et al., 2011; Dong-Kyou et al., 2010). Therefore, assimilation approaches that ingest local observations are important to develop improved analyses (Daley, 1991).

Data Assimilation (DA) is known as the process of creating the best estimate of the initial state for numerical weather prediction (NWP) models through combining all sources of information, including the first guess from previous short-term forecasts and observations, along with the associated uncertainties in each source of information (Wheatley e t al., 2012, Talagrand, 2003, Barker et al. 2004). Until now, studies devoted to simulating extreme events using DA in Western Africa are poor. However, worldwide, Hatwar et al. (2005) found positive impact of ingesting special observations available from Arabian Sea Monsoon Experiment (ARMEX-II) on the Indian Meteorological Department limited area forecast system. Routray et al. (2010) demonstrated that DA improves the capability of WRF model to simulating heavy rainfall events over India monsoon region. Dong-Kyou et al. (2010) showed that Automatic Weather System (AWS) and Radar data assimilation improved the temporal and spatial distribution of diurnal rainfall over Southern Korea and AWS data assimilation increased the predicted rainfall amount by approximately 0.3mm/3hr . Similarly, Vinod et al. (2007) suggested that improvement of monsoon depression simulations were equivalent or better than that of increasing the model resolution from 30 km to 10 km grid spacing.

The main and prime objective of this study is to evaluate and investigate the performance of WRF-Var systems in WRF model over Western Africa. We attempt to demonstrate the ability of WRF-Var with assimilation of Prepbufr conventional and radiance observations in the analyses of the 2011 August 15-17 events. The WRF analyses outputs are compared to the TRMM and Era Interim data sets.

2. WRF Modeling System and Setup

2.1 WRF Modeling System

The Weather Research and Forecasting (WRF) Model is a next-generation of mesoscale numerical weather prediction system designed to serve both operational forecasting and atmospheric research needs. It features multiple dynamical cores, a 3-dimensional variational (3DVAR) data assimilation system, and a software architecture allowing for computational parallelism and system extensibility. WRF is suitable for a broad spectrum of applications across scales ranging from meters to thousands of kilometers.
The formulation of 3DVAR is developed on the basis of Bayesian probabilities and Gaussian error distribution (Lorenc, 1996; Lorenc et al., 2000). In general terms, VAR systems may be categorized as those data assimilation systems which provide an analysis via the minimization of a prescribed cost function (Ide et al., 1997). The adopted version of 3DVAR in WRF is robust and can assimilate heterogeneous observations from in situ weather stations, Doppler weather radar and the satellite data sets. Most assimilated variables are wind components, temperature, relative humidity and pressure.

2.2 Model setup

WRF configurations used in this study are summarized in table 1. The choice of each scheme is based on a test sensitivity (not shown here) devoted to find the Weather Research and Forecast model (WRF v3.3) configuration best suited for accurately simulating a real-time weather prediction in Western Africa.

Table1: Model setup and configurations

WRF Core	ARW
Resolution/Sigma Levels	20 km/41
Microphysics scheme	Thompson
Cumulus parameterization	Modifed Tiedtke scheme
Land Surface Model	Rapid Update Cycle
Planetary boundary Layer (PBL) parameterization	Mellor Janjic
Long Wave and Short wave radiations schemes	RRTMG

In this study, two experiments have been performed: the WRF_CNTL is done without assimilation and the WRF_DA is done with data assimilation using 06 hours cycling mode.

3. Data used

For the purpose of verification, we used the Tropical Rainfall Measuring Mission (TRMM) data as ground truth. In this work, version 6 of data 3B42 combined is used. This product version provides three hourly estimations of rainfall on a grid of 0.25°x0.25°. In addition, daily full resolution (075°x075°) ERA Interim data sets are used to validate relative humidity, winds and 2 metre temperature. NCEP ADP Global Upper Air and Surface (PREPBUFR formats) Weather Observations (used for data assimilation), composed of a global set of surface and upper air reports operationally collected by the National Centers for Environmental Prediction (NCEP) are used for data assimilation. These include land surface, marine surface, radiosonde, pibal and aircraft reports from the Global Telecommunications System (GTS), profiler and US radar derived winds, SSM/I oceanic winds and TCW retrievals, and satellite wind data from the National Environmental Satellite Data and Information Service (NESDIS). The reports can include pressure, geopotential height, temperature, dew point temperature, wind direction and speed. Report time intervals range from hourly to 12 hourly. Radiance products used in the NCEP Global Data Assimilation System include: Atmospheric Infra Red Sounder (airs) HSB processed brightness temperatures, Advanced Microwave Sounding Unit-A (1bamua), Advanced Microwave Sounding Unit-B (1bamub), High resolution Infra Red Sounder-3 (1bhrs3), High resolution Infra Red Sounder-4 (1bhrs4), and Microwave Humidity Sounder (1bmhs) NCEP processed brightness temperatures. Data are Supported by the National Center for Atmospheric Research, available online at http://dss.ucar.edu/datasets/ds735.0/.

4. Results

4.1- Rainfall distribution

Figures 1 and 2 display the 24 hours accumulated rainfall on 15 and 16 August 2012 respectively. The geographic distribution of rainfall in West Africa, like the other climatic parameters, is zonal and is given in relation to the position of the Inter Tropical Convergence Zone (ITCZ) which is around 20° N in August. The overall rainfall spread is reasonably well captured by WRF model. It reproduces satisfactory the spatial distribution compared to TRMM data, although it is slightly moved southward and capture the main features of the rainfall amount over all the given domain. Unfortunately
the model failed to capture some rainfall occurrences in Mauritania and over the Atlantic Ocean as shown by TRMM observations. Indeed, the WRF_DA experiment (fig 1(b) and fig 2(b)) distribution has the closest behavior of the observational data. So far, the spatial distribution is well highlighted, specially in the coastal regions such as Ivory cost, Liberia, Senegal and some regions in the Western part of Cameroon. The correspondence between predicted and observed

rainfall is more readily compared by computing spatial correlation and errors scores, such bias and mean absolute errors. Statistically, the model over predicts the precipitations by simulating high rainfall. Forecasts with data assimilation improve quantitatively the results in the range of 15%-25%. This is a major finding and is consistent with the results found by Fink A. et al (2011). They stated that data assimilation using AMSU-A and AMSUA-B channels close to the surface over Africa demonstrated an important improvement of analyzed fields and of precipitation forecasts over parts of the Tropics and specially over West Africa, as validated with African Monsoon Multidisciplinary Analysis (AMMA) observations. Rainfall intensity is an important characteristic of the climate of West Africa. Part of the precipitation falls in heavy storms with intensities of 50 mm/h or more. Peaks may even reach 250 mm/h over short periods. Significant rainfall was also reported over Central Africa Republic on 16 August as found by both model and observations, event if the model does not reproduce some occurrences over Mauritania. The major discrepancies between simulated and observed rainfall is the results of heterogeneous topography in the continent, errors derived from initial and boundary conditions with respect to the model resolution and sparse synoptic weather stations. Precipitations occurrences in Central and Western Africa are associated with organized mesoscale convective systems (MCSs) embedded in large scale synoptic systems, while majority of rainfall episodes are linked to isolated convective cells not exceeding a few hundred meters in extension. In addition, African Easterly and equatorial waves and mid latitudes thermal depression have been identified to modulate low pressure structure, Saharan heat low, thus convection in Central and Western Africa (Lenoue and Mkankam, 2008, Janicot, 1992}. This circulation can explain biases recorded between simulated and observed rainfall. In spite of the fact that the variation in correlation coefficient and error scores is rather small, it is still sufficient to justify significant variations while changing physics options. These high rainfall intensities often result in rain splash, surface crusting, and soil compaction which, in turn, lead to high runoff, sheet and gully erosion, and, finally to soil loss.

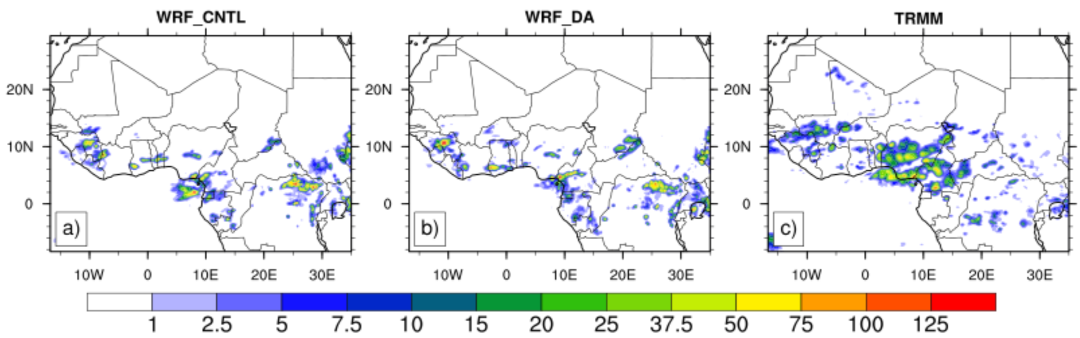

Fig. 1: 24 hours accumulated rainfall (mm/J) initialized at 00 UTC, valid on 15 August 2011, (a) for WRF_CNTL experiment, (b) for WRF_DA experiment with data assimilation and (c) for TRMM observational data

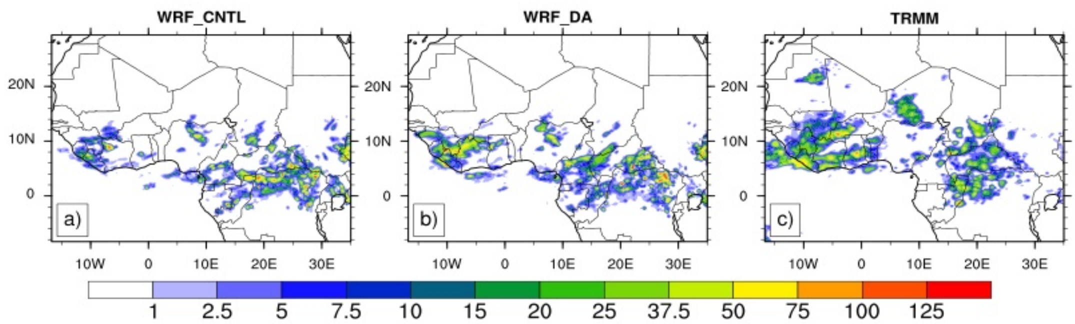

Fig. 2: Same as 1-a but valid on 16 August 2011.

4.2 Relative humidity, winds and 2 metre temperature distributions.

Figure 3 shows the spatial distribution of relative humidity as simulated by WRF control experiment (WRF_CNTL), WRF with data assimilation (WRF_DA) and reanalysis from ERA interim (ERA_INTERIM). The model captures the main features of the spatial distribution of relative humidity and shows strong correlation (0.99) between WRF and Era interim reanalysis data. In the coastal areas, air humidity is high, mostly due to the vicinity of Atlantic Ocean from where is originating moist air, but the model failed to capture low humidity around 18°N to 25°N. WRF model has captured (not shown) the sudden rise of relative humidity values during the model simulated hour as in the observation, from 45% to 95% in midday. Overall, WRF_DA experiment has ameliorated the simulations in view of figure 5 by showing low biases . We also remark from figure 5 that humidity biases correction due to data assimilation is only valid below 850 hPa. Additional atmospheric sounding need to be added in WRF-Var scheme for improving simulations in upper air. Overall, WRF both simulations (WRF_CNTL and WRF_DA) well simulated the humidity patterns, WRF_DA experiment showed an improvement of about 5%-7%. As stated earlier, most of rainfall episodes are due to convective cells. The Inter tropical convergence zone plays an important role in this process. Rainfall distribution is consistent with the fact that whether the prevailing blowing wind carry moist air (monsoon wind) or dry air (Harmattan). As shown in figure 3, the areas compassing the Soudano-Sahelian zones and some part of Northern Africa, ranging from 10°N to about 20°N in latitudes is known as the areas with low humidity, generally below 30%, thus with less rainfall. Lack of rainfall amount in these areas cause many threats to people, such as droughts and famine.

The distribution of the 2 metre temperature in West Africa is given in figure 4. Because of the highest marine influence, many clouds are present and the area is less sunny than the Sahel, thus the temperature in the southern part of West Africa is relatively low. The highest temperatures occur in the Sahel zone (Mali, Niger, Mauritania...). The lowest values are recorded along the south coast, where sea surface temperatures are high and direct onshore winds blow from a warm ocean. The highest values occur in the northern Mali and Burkina Faso.

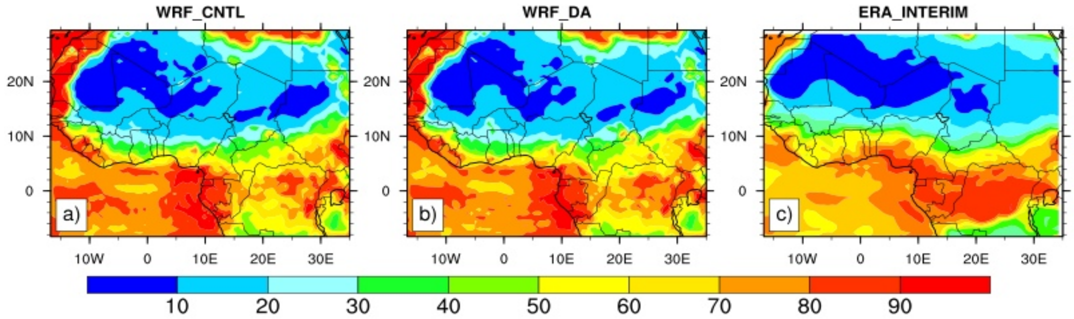

Fig. 3: Spatial distribution of relative humidity (in %) at 1000 hpa valid at 21 UTC on 15 August 2011

The high temperatures in the north (Sahara) reflect the very high night temperatures that occur there because of the low outgoing radiation and the relatively high day temperatures. We also noticed that simulations show systematic cold bias, approximately equal to -0.5°C. This temperature distribution is associated with the Harmattan winds whom the influence decreases in southerly direction. In the other hand, WRF_DA (fig 4 b) experiment has the closest behavior of the observational data. From an agricultural point of view, maximum and minimum temperatures are of great importance.

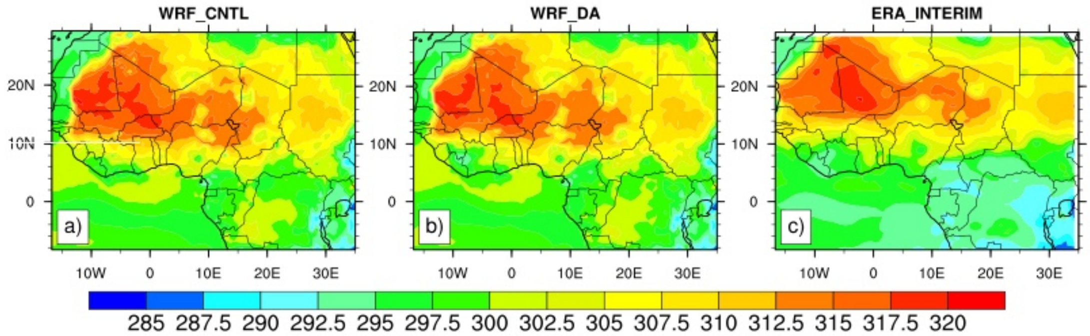

Fig. 4: Spatial distribution of 2 metre temperature (K) valid at 18 UTC on 16 August 2011

The spatial distribution of wind speed (not shown) is also studied. The monsoon flow is reasonably well simulated by WRF experiments compared to observations. For instance, the WRF_DA experiment is one more the closest to observational data illustrated by figure 6. WRF_Da experiment shows the smallest wind speed (m/s) biases. The zonal wind speed biases in figure 6(a) highlight negative biases at 925 hpa in the order of -0.1m/s, but generally biases are positive for all the remaining pressure levels. The highest bias is 0.57 m/s corresponding to WRF_CNTL experiment. Figure 6-b clearly demonstrates the ability of data assimilation in improving simulations. Overall, WRF simulations overestimated wind speed over the continent. Figure 7 depicts the atmospheric circulation of the study zone valid at 21 UTC of August 16 2011. The southwesterly monsoon flow is associated with the equatorial crossing of the southeast trade winds that arise on the equatorward flank of the subtropical high. Thus the monsoon flow is distinguished by a clear southerly component. The vertical cross-section of the meridional wind (not shown) suggests that the monsoon flow is confined to the lowest levels of the troposphere. The southerly component decreases rapidly above 900 hPa, generally disappearing by 850 hPa. In contrast

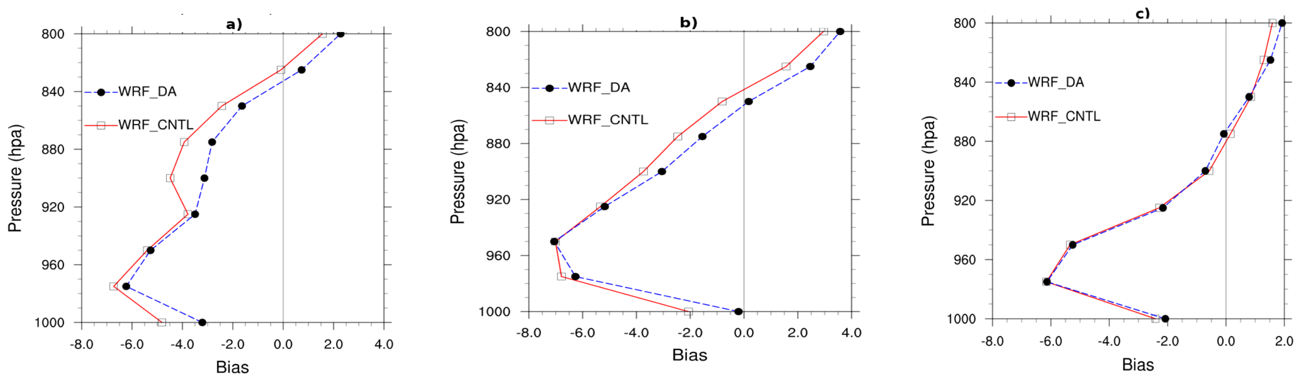

Fig. 5: Relative humidity biases between WRF experiments and ERA Interim observational data valid on 15 August 2011. (a) is valid at OO UTC , (b) is valid at 06 UTC and (c) is valid at 00 UTC on 16 August

the westerly component of the flow has a maximum at 850 hPa, where the southerly component approaches zero (Nicholson et al, 2007). In addition, WRF simulations (fig 7-a and fig 7-b) display stronger winds over the continent than Era Interim observations. Biases come from deficiencies on both formulation of the model and boundary conditions and is the consequence of errors in the non-rotational wind component (Kamga et al, 2010). The rainy period, also known as the West African Monsoon (WAM), which is a regime of mostly southwesterly winds blowing from June to September and carrying moist air from the Atlantic Ocean into the continent (Djiotang and Mkankam, 2010) is associated with a seasonal reversal of prevailing winds in the lower atmosphere, where moist air is blown in from the Atlantic Ocean and released over the Continent.

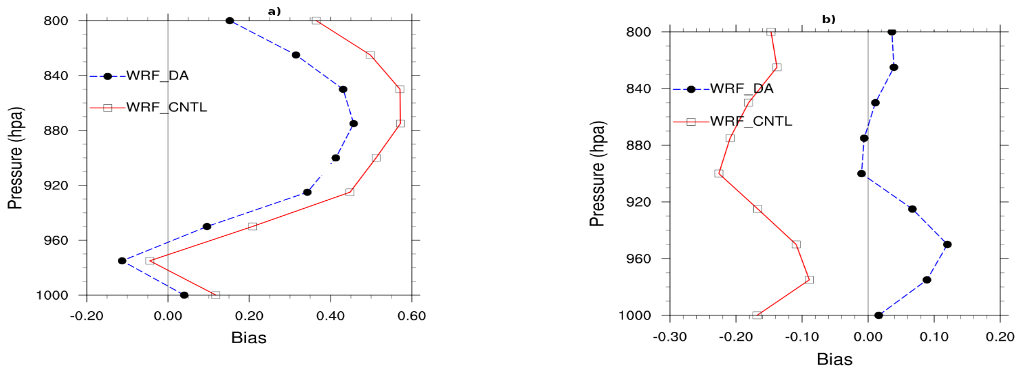

Fig. 6: Same as figure 5, but (a) is for u wind and (b) is for v wind components valid on 2011-08-16_00:00:00

Tomas and Webster (1997) suggest that such a westerly jet arises not as part of the monsoon, but as a result of an inertial instability mechanism that leads to off-equatorial convection. The most intense lies at roughly 20°N and corresponds to the surface position of the ITCZ in August. The other straddles the Guinea Coast of the Atlantic and corresponds to the frictional convergence of the sea breeze. These two merge along the West Coast at about 15°N (Nicholson et al, 2007). For instance, WRF_DA experiment outperforms WRF_CNTL with less scores errors and high correlation.

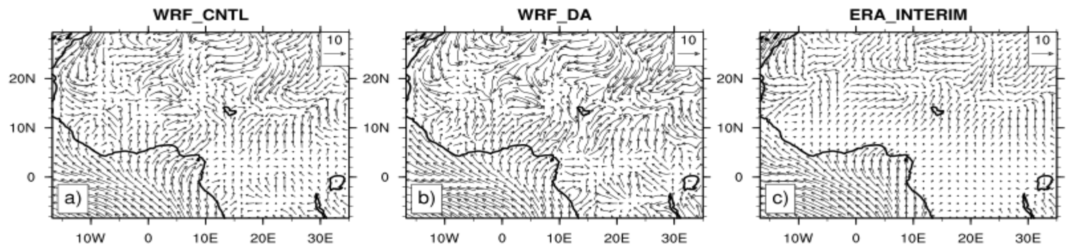

Fig. 7: Horizontal wind vectors derived from surface pressure at 1000 hpa valid on 2011-08-16_21:00:00

5-Conclusion

The WRF model was used to simulate atmospheric parameters for the period 15-17 August 2011 over Western Africa. Two numerical experiments were performed to assessing the impact of data assimilation. Ensemble forecasts tests of the model to different physics packages was performed. As stated by Flaounas et al., (2010) and Pohl et al., (2011) in their respective studies on Western and East Africa, WRF simulations are slightly sensitive to the choice of physics packages. This study revealed that spatial and temporal precipitation patterns are most sensitive to the choice of cumulus parameterizations in the study domain and that some microphysics schemes have comparable skill and are superior to the other schemes as found by Changhai et al. (2011). As a results of WRF_CNTL and WRF_DA experiments, we found that the WRF_DA experiment improved the overall simulation over Western Africa. The WRF_DA represented well the location and the intensity of rainfall even if the model still overestimated the rainfall intensity. The Sahelian rain belt was well reproduced by the model. Simulations of relative humidity, zonal and meridional winds components, 2 metre temperature and surface pressure have been slightly improved by the order of 5%-10%. But forecasting rainfall is one of the most difficult tasks in weather prediction, due to their rather small spatial and temporal scale and the inherent non-continuity of their dynamic. The enhancement in the simulation of atmospheric parameters is a clear depiction of the additional observation data as found by Mohanthy et al (2011) over Indian. Data assimilation is a promising tool of reducing systematic model error before application in impact studies.

.Acknowledgment

Authors want to thank ERAD12 for the financial support of the conference fees. We also thank WRF team and WRF users for documentation.

References

Adejuwon, Oladipo, J., Odekunle, Odeyemi, T., Omotayo, Omoluke, M., 2007. Extended-range weather forecasting in sub-saharan west africa: Assessing a potential tool for adapting food production to climate variability and climate change. *AIACC Working Paper*, **NO. 46**.
Baik, J.-J., M.-D., Raman, S., 1991: Tropical cyclone simulations with the betts convective adjustement scheme. part iii: Comparisons with the Kuo convective parameterization. *Mon. Wea.Rev*., **119**, 2889-2899.

Barker, D., M., Huang, W., Guo Y., R., Bourgeois A., J., Xiao Q., N., 2004: A three-dimensional variational data assimilation system for mm5: Implementation and initial results. *Mon. Wea. Rew.,* **132**, 897-914.

Betts, A. K., Miller, M. J., 1993: The betts-miller scheme. the representation of cumulus convection in numerical models.
Amer. Meteor. Soc., **24**, 107-121.

Changhai, L., Kyoko, I., Gregory, T., Roy, R., Dudhia, J., 2011: High-resolution simulations of wintertime precipitations in the Colorado headwaters regions: Sensitivity to physics parameterizations. *Mon. Wea. Rev.* , **139**, 3533-3553.

Chen, F., Dudhia, J., 2001b. Coupling an advanced land-surface/hydrology model with the Penn State/NCAR MM5 modeling system. part i: model description and implementation. *Mon Weather Rev.* **129**, 569-585.

Djiotang, Tchotchou, L. A., Mkankam, Kamga, F., 2010. Sensitivity of the simulated african monsoon of summers 1993 and 1999 to convective parameterization schemes in regcm3. *Theor Appl Climatol.,***100,** 207-220.

Dong-Kyou, L., Dae-Yong, E., Joo-Wan, K., Jae-Bok, L., 2010: High-resolution summer rainfall prediction in the JHWC real-time system. *Asia-Pacifc J. Atmosp. Sci.*, **46 (3)**, 341-353.

Dudhia, J., Hong, S., Lim, K., 2008: A new method for representing mixed-phase particle fall speeds in bulk microphysics parameterizations. *J. Met Soc Japan*, **86**, 33-44.
Emmanuel, K. A., Zivkovic-Rothman, M., 1999. Development and evaluation of a convection scheme for use in climate *models. J. Atms. Sci.* **56**, 1766-1782.

Fink Andre H, Anna Agusti-Panareda, Douglas J. Parker, Jean-Philippe Lafore, Jean-Blaise Ngamini et al, 2011, Operational meteorology in West Africa: observational networks, weather analysis and forecasting. *Atmos. Sci. Let*., **12**, 135-141.

Flaounas, E., Bastin, S., Janicot, S., 2010: Regional climate modelling of the 2006 west african monsoon: sensitivity to convection and planetary boundary layer parameterisation using WRF. *Clim. Dynamics*, **363**., 1083-1105.

Grell, G., Dudhia, J., Stauffer, D., 1994: A description of the fifth-generation Penn State/NCAR mesoscale model (MM5). *NCAR Tech. Note NCAR/TN-398+STR*, **138**.
Grell, G. A., Devenyi, D., 2002: A generalized approach to parameterizing convection combining ensemble and data assimilation techniques. *Geophys. Res. Lett*., **29**, 1693-1696.

Ide, K., Courtier, P., Ghil, M., Lorenc, A., C., 1997: Unifed notation for data assimilation: Operiational, sequential and variational.
J. *Meteor. Soc. Japan* **75,** 181-189.

Kamga A., S. Fongang, A. Viltard, 2005: Systematics errors of the ECMWF operational model over tropical Africa. *Mon. Wea. Rev*., **18**, 1949-1959

Lenoue, A., Mkankam, Kamga, F., 2008: Sensitivity of african easterly waves to boundary layer conditions. *Ann. Geophys*, **26,** 1355-1363.

Mohanthy, U., C., A., R., Krishna, K., O., S., Kiran, P., 2011: A study on simulation of heavy rainfall events over Indian region with ARW-3DVAR modeling system. *Pure Appl. Geophysics*. Pages 1-19, DOI 10.1007/s00024-011-0376-1

Nicholson, S., Some, B., Kone, B., 2000: An analysis of recent rainfall conditions in West Africa, including the rainy seasons of the 1997 el Niño and the 1998 la Niña years. *J Clim*, **13**, 2628-2640.

Nicholson, S. E., and J. P. Grist, 2002: On the seasonal evolution of atmospheric circulation over West Africa and Equatorial Africa.
J. Climate, **16**, 1013-1030.

Nicholson, S. E., and P. J. Webster, 2007: A Physical Basis for the Inter annual Variability of Rainfall in the Sahel. *Quart. J. Appl. Meteor. Soc,**133,** 2065–2084*

Pohl, B., Crétat, J., Camberlin, P., 2011: Testing WRF capability in simulating the atmospheric water cycle over equatorial East Africa. *Clim. Dyn.*,**37,** 1357-1379.

Talagrand, O, 2003: Bayesian estimation. optical interpolation. statistical linear estimation. *Data Assimilation for the Earth System*, 21-35.
Tomas, R. A., and P. J. Webster, 1997: The role of inertial instability in determining the location and strength of near-equatorial convection. *Quart. J. Roy. Meteor. Soc*., **123**, 1445-1482.

Vinod, Kumar, A., Chandrasekar, A., Alapaty, K., Niyogi, D., 2007: The impact of assimilating soil moisture, surface temperature, and humidity and the traditional four dimensional data assimilation on the simulation of a monsoon depression over India using a mesoscale model. *J Appl Meteorol Climatol*, **47**, 1393-1412.

Wheatley, Dustan M., David J. Stensrud, David C. Dowell, Nusrat Yussouf, 2012: Application of a WRF mesoscale data assimilation system to springtime severe weather events 2007–09. *Mon. Wea. Rev.*, **140**, 1539–1557.