Impact of hybrid GSI analysis using ETR ensembles

V S PRASAD* and C J JOHNY

National Centre for Medium Range Weather Forecasting, A-50, Sector-62, Noida, India.

**Corresponding author. e-mail: vsprasad@ncmrwf.gov.in*

Performance of a hybrid assimilation system combining 3D Var based NGFS (NCMRWF Global Forecast System) with ETR (Ensemble Transform with Rescaling) based Global Ensemble Forecast (GEFS) of resolution T-190L28 is investigated. The experiment is conducted for a period of one week in June 2013 and forecast skills over different spatial domains are compared with respect to mean analysis state. Rainfall forecast is verified over Indian region against combined observations of IMD and NCMRWF. Hybrid assimilation produced marginal improvements in overall forecast skill in comparison with 3D Var. Hybrid experiment made significant improvement in wind forecasts in all the regions on verification against mean analysis. The verification of forecasts with radiosonde observations also show improvement in wind forecasts with the hybrid assimilation. On verification against observations, hybrid experiment shows more improvement in temperature and wind forecasts at upper levels. Both hybrid and operational 3D Var failed in prediction of extreme rainfall event over Uttarakhand on 17 June, 2013.

1. Introduction

Numerical weather prediction (NWP) forecasts depend on initial conditions which are created by combining a short-term forecast from previous cycle (known as background state) with observations. Data assimilation (DA) is employed to compute an optimal correction to the background state, referred to as the analysis increment, using the observations and estimates of the uncertainty associated with the background state and the observations. The uncertainty is typically characterized by covariance matrices for the error in the background state and the observations. These covariance matrices determine the level of influence each observation has on the analysis and how this influence is distributed both spatially and among the different types of analysis variables (Buehner 2010). This method is optimal only if both the observation and background error covariance matrices are correctly specified in the analysis.

Accurate specification of these covariance matrices is very important for the quality of the assimilation system. In a variational scheme, the background error is typically computed using NMC (National Meteorological Center) method (Parrish and Derber 1992) and static background error covariance, used here, does not reflect the flow-dependent error statistics. This background error covariance is time-independent and therefore does not include errors of the day. Variational scheme assumes that the background forecast-error covariances are static and nearly homogeneous and isotropic (Parrish and Derber 1992; Courtier *et al.* 1998). In reality, the background-error covariances may vary substantially depending on the flow of the day (Wang *et al.* 2007a). In order to address this issue, there were attempts to include some amount of spatial inhomogeneity and anisotropy in standard covariance models used in 3D Var (Wu *et al.* 2002; Purser *et al.* 2003). Ensemble based data assimilation in various forms of ensemble Kalman filter (EnKF) is an

Keywords. Hybrid; assimilation; GSI; ensemble.

alternative to variational approaches. The ensemble forecasts also provide a means of estimating all the flow dependent multi-variate correlations which are ignored in the static covariance matrix used for 3D Var. The analysis increments from 3D Var have an isotropic structure that is centered on observation location and completely independent of background flow. As EnKF requires sequential assimilation of observations to avoid large matrix inversion during each update cycle, computational expense scales linearly with the amount of data (Zhang *et al.* 2013). Certain schemes of EnKF like local ensemble transform Kalman filter (LETKF), reduced the computational cost significantly updating the analysis of each grid point independently by assimilating the observations in the local region centered at each grid point (Liu *et al.* 2008). Another approach was to blend flow-dependent error from ensemble into the variational framework known as hybrid (Barker 1998; Hamill and Snyder 2000).

In the EnVar, the variational framework is used to conduct data assimilation within which the flow-dependent ensemble covariances are effectively incorporated to estimate the background error covariance (Wang 2010). Ensemble data assimilation schemes adopt a framework completely different from existing variational scheme, while the hybrid EnVar schemes build upon existing variational systems and ensemble information can be included relatively easily. Hamill and Snyder (2000) proposed a hybrid DA scheme by combining 3D Var with an EnKF, showing significant improvements in the analysis due to the flow-dependent information provided by the ensemble-based estimate of the background error covariance matrix. They showed that the ensemble-based background error covariance can completely replace the background error covariance of 3D Var if the ensemble size is large enough. In their hybrid scheme, the assimilation process is necessary for each ensemble member with perturbed observation at every analysis step, and therefore the computational cost may be unaffordable, if a large ensemble size is required. Lorenc (2003) proposed another form of the variational scheme for updating the state, where the control variables in the cost function were augmented by another set of control variables, preconditioned upon the square root of the ensemble covariance. Although both the hybrid schemes differ in the way they include ensemble information into the cost function, their equivalence is mathematically proved (Wang *et al.* 2007a). On the other hand, Patil *et al.* (2001) showed that the flow dependent atmospheric instabilities (the errors of the day) tend to be locally confined to a low-dimensional subspace with respect to the global system phase space. Such evidence

supports the construction of an ensemble to span the unstable subspace of the system by representing such space with an ensemble size much smaller than the model dimension, thus contributing to reduce the computational cost. The differences between the perturbed and non-perturbed nonlinear runs, represent the fast growing dynamical instabilities of the evolving flow and naturally carry information on ‘errors of the day’ (Toth and Kalnay 1993, 1997). Wang and Bishop (2003) showed that Ensemble Transform Kalman Filter (ETKF) can provide ensemble perturbations that produce skillful ensemble forecasts at relatively inexpensive cost. Wang *et al.* (2007b) showed assimilation with ETKF ensembles produced analysis almost accurate as EnKF. Penny (2014) introduced an EnVar method by augmenting LETKF with information from 3D Var by combining gain matrices of ensemble and variational method rather than linearly combining their respective background error covariance as done in traditional approaches. Kretschmer *et al.* (2015) introduced a method to improve the performance of EnKF by increasing size of ensemble members at the analysis time, created by adding climatological perturbations to forecast ensemble mean. As climatological perturbations are calculated once, there is negligible computational expense involved in obtaining additional ensemble members. There are many studies which suggest potential advantages of the EnVar in comparison with a stand-alone EnKF. For example, Wang *et al.* (2007b, 2009) suggested that for large-scale application, the EnKF-3D Var was more robust than the EnKF for small ensemble size and large model errors since the static covariance used in 3D Var helped to reduce the sampling errors, which indicates smaller ensemble size may be utilized by the hybrid than by the EnKFs to achieve similar performance. This is particularly attractive for operational forecasts for which the size of the ensemble may be constrained by the availability of the computational resources and the timing of the forecasts (Wang 2010). Hybrid systems applying physical space localization has the advantage over EnKF algorithm that performs localization in observation space in assimilating nonlocal observations like brightness temperature. Zhang *et al.* (2013) using WRF model found EnVar methods (3D Var ensemble and 4D Var ensemble) produced better forecasts than both 3D Var and 4D Var. Hybrid ETKF-3D Var with real observations in WRF model produced more improvements in data sparse regions and in wind field (Wang *et al.* 2008b). Hamill *et al.* (2011) found that cyclone track errors with GSI hybrid assimilation system (3D Var-EnKF) is similar to those from EnKF ensemble mean forecast and much superior to operational deterministic forecasts. Buehner *et al.* (2010a, b) using

Environment Canada's operational model found hybrid assimilation produced significant improvement in southern extra tropics and moderate improvement in tropics. Buehner *et al.* (2013) using Environment Canada's operational model found 4D Var ensemble produced only small improvement over 3D Var ensemble and performance of 3D Var ensemble is superior to 3D Var and produced similar or better forecasts than that of 4D Var in the tropical region. Kuhl *et al.* (2013) with 4D Var-ETKF hybrid system found improvement of hybrid assimilation is more pronounced in the forecasts of tropical winds. Kleist and Ide (2015) with NCEP-GFS found 3D Var EnVar assimilation reduced analysis error in wind and moisture especially in tropics. In this study, impact of hybrid assimilation system is investigated by combining 3D Var (T574) with low resolution 20 member ETR ensemble (T190) for a period of 7 days spanning 10–18 June 2013.

2. Experimental setup

In this study, we performed two numerical experiments, one with operational 3D Var (CTL) configuration and other with one-way coupled hybrid configuration (EXP) and forecasts are issued up to 5 days at 00UTC. Operational 3D Var system has 64 hybrid sigma pressure vertical levels and dimension Gaussian grid with 1760×880 points. Details of the operational 3D Var system in the centre can be seen in the technical reports (Prasad *et al.* 2011). Gridpoint Statistical Interpolation (GSI) system implemented in centre in 2009 and implementation details can be seen in Surya and Prasad (2011). It is a physical space based variational analysis scheme (Wu *et al.* 2002; Kleist *et al.* 2009; Hu *et al.* 2013) DA system for both global and regional applications. Updated version of GSI (GSI 3.2) assimilation system used in our numerical experiments use three-dimensional variational method to assimilate observations. The assimilation system is capable of running in 4D Var mode coupled with forecast and their adjoint models and in hybrid mode. Although, the system is capable of using hybrid assimilation, 3D Var option is used considering computational aspects. It is capable of assimilating conventional and satellite observations. The GSI, version used in the experiment is capable of assimilating TDR (Tail Doppler RADAR) and CrIS (Cross track infrared sounder) observations. The assimilation system used in the experiment is at a horizontal resolution of T382 and interpolated to T574 resolution for all practical purposes. In GSI, analysis is done using Gaussian grid with dimension of 1152×576 . In hybrid system, horizontal localization is done at 2828 km and for

vertical localization 30 grids are used (Wang *et al.* 2008a) and it is adopted from the NCEP GSI system. Hybrid system can be implemented with one-way or two-way coupling of ensemble and deterministic models. In one-way coupling, perturbations from ensemble forecast are used in hybrid analysis but does not re-center ensemble analyses to hybrid analysis. In two-way coupling, additionally ensemble analysis is re-centered to the control hybrid analysis. The two-way coupling implicitly assumes that the hybrid control analysis is better than the ensemble mean analysis, and the re-centering should help to prevent the divergence between the ensemble and hybrid analyses so that the ensemble perturbations can sample the control forecast uncertainty well (Pan *et al.* 2014). In the hybrid configuration we have chosen, ensemble system is not an independent full data assimilation system and ensemble analyses are generated by perturbing control analysis (hybrid analysis).

Hybrid system utilizes the forecast from 20 member ETR based global ensemble forecast system (GEFS) T190L28 to obtain flow dependent error characteristics. Ensemble system is of 28 vertical levels with model top at 2.35 mb and operational 3D Var is of 64 vertical levels with model top at 0.27 mb pressure. In order to address this discrepancy, an interpolation algorithm is used for changing 28 vertical levels in ensemble system to 64 levels in the deterministic system. This low resolution 28 level forecast is interpolated to corresponding 64 vertical levels of T574 using an interpolator program and fed to hybrid assimilation system. In hybrid assimilation, weightage of 0.75 is given to static error and 0.25 to flow dependent error in estimation of background error covariance matrix. As ensemble is of low resolution and has less vertical levels than operational system, only small weightage is given to flow dependent error covariance in the hybrid system. In this system, we have used same weighing coefficient for all vertical layers. Model top in our deterministic and ensemble system is different and above the ensemble top our deterministic system is having three vertical levels at 1.79, 0.99 and 0.27 mb pressure levels. In order to address model top discrepancy, Buehner *et al.* (2013) adopted a system of fixed weighing parameters for flow dependent and static background error covariance from surface to 40 mb, which then gradually changes to fully static covariance above 10 mb up to model top. It can be seen from their results that effect of choosing such a varying weighing coefficient at different vertical levels is only felt above 10 mb. Similarly, in this study any such influence of model top is expected at similar altitudes and all our discussions are confined up to 200 mb pressure levels only. The assimilation system used in hybrid experiment is the same one that is used in

the CTL experiment. The analysis produced from hybrid system is used as initial condition for the forecast and generating ensembles.

In ETR method, perturbed initial conditions for ensembles are generated by method of ensemble transform with rescaling. In this method, perturbations are transformed using analysis error variances from the best possible data assimilation system and perturbations are re-scaled to have an initial spread distribution similar to an estimate of the analysis error variance (Wei *et al.* 2008). Using the 20 perturbed initial conditions short range forecast for 6 hours is issued. Forecasts are compared with the analysis valid at the time and differences are determined. These 20 differences are then made orthogonal and rescaled to the size representative of known observational and forecast errors. Below 500 mb, a rescaling factor for the initial perturbation is increased linearly to a final value 20% at the model surface. Procedure is repeated every 6 hr, creating a new set of perturbations in every 6 hr (Raghavendra Ashrit *et al.* 2013). ETR method is considerably cheaper than other ensemble methods, if the analysis variance information is available. Again, initial perturbations are centered around the analysis field generated by the data assimilation system and in this way ensemble system will be consistent with DA.

3. Results

Model rainfall, vector wind, temperature and humidity in the two numerical experiments are verified against observations and mean analysis. Analysis is the best estimate of the weather condition unless accurate very high resolution observation network is available. Here, mean of the analysis of the experiments 'EXP' and 'CTL' is used as reference for verifying forecasts. In our investigation temperature, wind and relative humidity are verified against mean analysis. Rainfall forecast is compared over Indian region against merged gridded rainfall product (0.5° resolution), combining IMD rain gauge observations and TRMM rain estimates. Technical details of this rainfall data can be seen in Mitra *et al.* (2009). Performances of the experiments are compared in different spatial domains global, tropics (20°S–20°N, 180°E–180°W) and RSMC (20°S–45°N, 30°–120°E) to find out regional biases in forecast skill.

3.1 Wind

Stability of atmospheric flow in models is limited by errors in initial conditions (Ferranti *et al.* 2002). Hybrid assimilation modifies the errors in atmospheric flow by incorporating flow dependent error

covariance. Due to the nature of global observing system with large number of mass-type observations, assimilation system can anchor temperature analysis errors through assimilation of satellite radiances (Kleist and Ide 2015) and more improvement with hybrid experiment is expected in wind. It is noted in some previous studies that hybrid assimilation produced largest improvement in wind than other variables (Wang *et al.* 2008b; Wang and Lei 2014). In this section, model wind at different pressure levels in the analysis and forecasts are compared against conventional observations assimilated in the model. Forecasts are also verified against mean analysis. Analysis U wind and V wind of the hybrid and 3D Var experiments are inter-compared. A difference plot of the experiments (3D Var-Hybrid) for U wind and V wind for pressure levels 850, 500 and 200 mb is shown in figure 1. It can be seen that around 80°S latitude, in all the vertical levels, the difference between the experiments are more, which is more evident for U wind. In tropics, the difference between the experiments are more in 200 mb pressure level especially over Indian region. It is reported in some previous studies, hybrid assimilation increased analysis errors in the U wind analysis in southern polar cap region, in middle and upper troposphere and reduced errors in upper troposphere over tropics, especially over Indian Ocean region (Kleist 2012). RMSE of wind in model first guess analysis, 24 and 48 hr forecasts are compared against radiosonde observations over the global (GL) and tropical (Tropics) regions. Vertical profile of mean RMSE difference between the experiments (EXP-CTL) in analysis wind and first guess against radiosonde observations averaged over the global and tropical regions are shown in figure 2. Black line indicates zero difference position. Blue coloured error bars represent the differences significant at 95% confidence level. Mean RMSE difference values beyond the error bars are significant at 95% confidence level. Figure 3 shows vertical profile of RMSE difference in wind forecasts (24 and 48 hr) with respect to radiosonde observations in global and tropical region. Negative RMSE differences indicate the region where hybrid experiment performed better than 3D Var and *vice versa*.

Plots show that the difference between the experiments are very minute for analysis wind and at majority of vertical levels, CTL experiment fit to observations more closely. But it can be seen that in forecasts (first guess, 24 and 48 hr), hybrid experiment fits observations more closely. It is noted in some previous studies that analysis produced by variational system fits observations more closely than hybrid (Wang *et al.* 2008b; Zhang and Zhang 2012). Comparison of analysis with observations cannot be considered as a measure of analysis

Figure 1. Mean difference in analysis (3DVar-Hybrid) for U wind (m/s) and V wind (m/s) at pressure levels 850, 500 and 200 mb (left panel is for U wind and right panel is for V wind) computed for the entire study period.

error characteristics, since observations used for comparison are also part of analysis system. But for comparing the forecasts, these observations can be considered as independent observations. It can be seen that hybrid experiment improved forecast in majority of cases. It can also be seen that the

general pattern of errors are similar for both the domains vertically, while in tropics, at lower levels, hybrid experiment reduced errors. It can be seen that in general, hybrid experiment improved forecasts with respect to observations, although there are some slight variation from general pattern

Figure 2. Vertical profile of RMSE difference between the experiments (EXP-CTL) in analysis and first guess wind (m/s) against radiosonde observations in global domain (bottom) and tropical region (top) (mean value computed for the entire study period). Black line indicates zero difference position. Blue coloured error bars represent the differences significant at 95% confidence level. Mean RMSE difference values beyond the error bars are significant at 95% confidence level. Negative RMSE differences indicate the region where hybrid experiment performed better than 3D Var and *vice versa*.

at some vertical levels. The differences between the experiments are significant at 95% confidence level in majority of the cases. The improvement can be seen more in upper levels than at lower levels. These variations may be associated with quality and availability of observations at different vertical levels. Improvement in 24 hr wind forecast with hybrid assimilation is more impressive

in global domain than in tropics. Both in tropics and global domain, at lower altitudes, hybrid experiment shows minor degradation in 24-hr wind forecasts, while in 48-hr forecast, minor degradation is observed at middle levels. The magnitude of improvements in wind forecast, at upper levels is more in tropical region than in global domain. Again, it can be seen that RMSE values are increasing

Figure 3. Vertical profile of RMSE difference between the experiments (EXP-CTL) in wind forecast (24 and 48 hr) against radiosonde observations in global domain (bottom) and tropical region (top) (mean value computed for the entire study period). Black line indicates zero difference position. Blue coloured error bars represent the differences significant at 95% confidence level. Mean RMSE difference values beyond the error bars are significant at 95% confidence level. Negative RMSE differences indicate the region where hybrid experiment performed better than 3D Var and *vice versa*.

with the altitude in both the experiments. Figure 4 shows anomaly correlation plots of vector wind with respect to mean analysis and their statistical significance over the regions global, tropics and RSMC at 850, 500 and 250 mb pressure levels. It can be seen that wind forecast improved with hybrid assimilation over all the regions global, tropics and RSMC and improvement is significant

at 95% confidence level in most of the cases. In global domain, wind forecast showed significant improvement in all the vertical levels and at all lead times. Time series data of 200 mb wind forecasts of 72 hr with respect to mean analysis over the domains global, tropics and RSMC region is shown in table 1. This has been done to find out if any spin-up related issue exists. It can be seen

Figure 4. Anomaly correlation of model wind forecasts at 850 mb (bottom panel), 500 mb (middle) and 250 mb (top) pressure levels with respect to mean analysis in the domains Global (left), tropics (middle) and RSMC region (right). Bottom panel shows the difference with respect to CTL and their statistical significance. The line above bar is significant at 95% confidence level.

Table 1. RMSE in 200 mb wind with respect to mean analysis averaged over Global (G2), Tropical and RSMC regions in each day.

Day	G2			Tropics			RSMC		
	EXP	CTL	EXP-CTL	EXP	CTL	EXP-CTL	EXP	CTL	EXP-CTL
15 June	7.63	8.09	-0.46	7.29	7.58	-0.29	7.44	7.71	-0.27
16 June	7.30	7.73	-0.43	7.6	8.03	-0.43	7.90	8.47	-0.57
17 June	7.31	7.84	-0.53	7.81	7.69	0.12	7.84	8.15	-0.31
18 June	7.96	8.31	-0.35	8.14	8.33	-0.19	7.96	8.60	-0.64

Figure 5. Vertical profile of RMSE difference between the experiments (EXP-CTL) analysis and first guess temperature (K) against radiosonde observations in global domain (bottom) and tropical region (top) (mean value computed for the entire study period). Black line indicates zero difference position. Blue coloured error bars represent the differences significant at 95% confidence level. Mean RMSE difference values beyond the error bars are significant at 95% confidence level. Negative RMSE differences indicate the region where hybrid experiment performed better than 3D Var and *vice versa*.

that hybrid experiment improved wind forecast consistently in all the regions except one day (17th June) in tropics. Error characteristics do not exhibit any time-dependent signal.

3.2 Temperature

Model temperatures at different vertical levels are compared against observations and mean analysis.

RMSE of temperature in model first guess, analysis, 24 and 48-hr forecasts are compared against radiosonde observations over the regions, global (GL) and tropics (Tropics). Figure 5 shows vertical profile of mean RMSE difference between the experiments (EXP-CTL) in analysis and first guess temperature against radiosonde observations and their statistical significance in the domains global and tropics, respectively. Similar plots for forecasts

Figure 6. Vertical profile of RMSE difference between the experiments (EXP-CTL) in temperature (K) forecast (24 and 48 hr) against radiosonde observations in global domain (bottom) and tropical region (top) (mean value computed for the entire study period). Black line indicates zero difference position. Blue coloured error bars represent the differences significant at 95% confidence level. Mean RMSE difference values beyond the error bars are significant at 95% confidence level. Negative RMSE differences indicate the region where hybrid experiment performed better than 3D Var and *vice versa*.

Figure 7. Anomaly correlation of model temperature forecasts at 850 mb (bottom), 500 mb (middle) and 250 mb (top) pressure levels with respect to mean analysis in the domains Global (left), tropics (middle) and RSMC region (right). Bottom panel shows the difference with respect to CTL and their statistical significance. The line above bar is significant at 95% confidence level.

of 24 and 48 hr in the domains global and tropics is shown in figure 6. Unlike wind, temperature behaves differently with respect to observations in different regions. It can be seen that hybrid analysis fit observations more closely at upper levels in global domain, while in tropics hybrid experiment fit observations more closely in both upper and lower levels. Forecasts show improvement with hybrid assimilation in middle and upper levels in

global domain, while in tropics, improvement can be seen at upper levels. In tropics, hybrid forecasts are inferior to CTL at middle levels. It can be seen that improvement with hybrid experiment can be seen at all levels on taking global average, while in tropics middle levels, hybrid experiment performs inferior to 3D Var in comparison with radiosonde observations. Using NCEP/GSI system it is observed in previous studies that hybrid produced

Figure 8. Vertical profile RMSE difference between experiments (EXP-CTL) in analysis and first guess specific humidity against radiosonde observations in global domain (bottom) and tropical region (top) (mean value computed for the entire study period). Black dashed line indicates zero difference position. Blue coloured error bars represent the differences significant at 95% confidence level. Mean RMSE difference values beyond the error bars are significant at 95% confidence level. Negative RMSE differences indicate the region where hybrid experiment performed better than 3D Var and *vice versa*.

neutral or negative impact on temperature forecasts in tropics at some vertical levels in comparison with 3D Var (Wang *et al.* 2013; Wang and Lei 2014). The improvement in wind field not seen in temperature at some vertical levels might be due to improper coupling of wind and mass fields in tropics. Figure 7 shows anomaly correlation plots

of temperature with respect to mean analysis and their statistical significance (95% confidence) in the global, tropics and RSMC regions at pressure levels 850, 500 and 250 mb. It can be seen that hybrid experiment improved the forecasts significantly in all the cases in global region, while in the regions of RSMC and tropics, the improvement is not up

Figure 9. Vertical profile RMSE in specific humidity forecast (24 and 48 hr) against radiosonde observations in global domain (bottom) and tropical region (top) (mean value computed for the entire study period). Black dashed line indicates zero difference position. Blue coloured error bars represent the differences significant at 95% confidence level. Mean RMSE difference values beyond the error bars are significant at 95% confidence level. Negative RMSE differences indicate the region where hybrid experiment performed better than 3D Var and *vice versa*.

to significant level in many cases. In RSMC region at 250 mb pressure level, significant improvement with hybrid assimilation is seen only in the 72-hr forecast. But it has to be noted that the comparison of forecasts with mean analysis did not show any middle level degradation in tropical region as observed in comparison with observations.

3.3 Humidity

Model-specific humidity in analysis and forecasts at different vertical levels are compared with radiosonde observations. RMSE of specific humidity in model first guess, analysis, 24 and 48-hr forecasts against radiosonde observations is computed for entire global domain and tropics separately for both experiments. As the difference between the experiments is small, for better visualization, RMSE differences are plotted. Figure 8 shows vertical profile of RMSE difference in analysis and first guess specific humidity (EXP-CTL) with respect to radiosonde observations for global (GL) and tropical (Tropics) regions. It can be seen that hybrid experiment fits observations more closely than 3D Var in most of vertical levels and the magnitude of RMSE difference between the experiments are more in the tropical region compared to the global

domain. In tropics, both first guess and analysis fit observation more closely in hybrid experiment, except at 700 mb level. This variation at 700 mb level can be seen in the analysis in global domain also. In global domain at lower levels, hybrid shows more deviation than 3D Var with respect to observations. Figure 9 shows the difference in RMSE (EXP-CTL) in specific humidity forecasts of 24 and 48 hr with respect to radiosonde observations. In 24-hr forecasts, hybrid experiment improves the forecast, except at lower levels both in tropics and global domain. In 48-hr forecasts, hybrid experiment improves the forecast globally except at lower levels, while in tropics improvement is seen except at surface and 400 mb pressure levels. In tropics, at middle levels (700 mb), hybrid analysis and first guess fit observations less closely than 3D Var. This is not seen in the case of 24 and 48-hr forecasts. This discrepancy at 700 mb can be seen in the analysis in global scale also. On comparison with observations globally, relative humidity is improved by hybrid assimilation at 95% confidence level in middle levels. Figure 10 shows RMSE plots of relative humidity with respect to mean analysis over different domains at pressure levels 850, 700 and 200 mb. The black line above the bars indicates, differences are significant at 95% confidence level.

Figure 10. RMSE in model forecasted RH with respect to mean analysis over domains global (left), RSMC region (middle) and tropics (right) at pressure levels 850, 700 and 200 mb. Green bars indicate 95% confidence interval. Black line indicates mean absolute difference in RMSE between experiments. Black line above green bars indicates the differences that are significant at 95% confidence level.

It can be seen that hybrid experiment improved RMSE scores at all lead times in global domain and are significant at 95% confidence level. Over tropics, hybrid assimilation improved RMSE scores except day-4 and day-5 forecast at 200 mb. But differences between the experiments are not significant in most of the cases. Relative humidity

Table 2. Mean RMSE in model forecasted 24 hr accumulated rainfall with respect to IMD-TRMM merged rainfall data.

Forecast Day	Experiment	
	CTL	EXP
Day-1	17.17	16.58
Day-2	18.43	17.91
Day-3	20.71	19.80
Day-4	22.06	20.81
Day-5	20.58	20.38

difference between experiments in tropical region are significant only in day-1 and day-2 forecast at 850 and 700 mb pressure levels and in day-1 forecast at 200 mb pressure level. Over RSMC region, hybrid assimilation improved model performance at 850 and 700 mb pressure levels but at 200 mb level it deteriorated performance in day-2, day-4 and day-5 forecasts. In RSMC region, significant differences between experiments are seen in day-1 and day-2 forecasts at 200 and 850 mb pressure levels and in day-1 forecast at 700 mb pressure level.

3.4 Rainfall

Model forecasted rainfall compared with IMD-NCMRWF merged rainfall over the domain 8° – 38° N and 68° – 98° E. Table 2 shows average RMSE values of model forecasted rainfall with the observations. It can be seen that hybrid experiment performed

Figure 11. Day-1 forecast of 24 hr accumulated rainfall (mm) in the numerical experiments and their differences (EXP-CTL) along with observations valid for 03 UTC 17 June 2013. Top left shows observations, top right shows difference in the numerical experiment (EXP-CTL), bottom left shows hybrid experiment and bottom right shows CTL. Uttarakhand region is indicated in red circle.

relatively better than 3D Var experiment for forecasts of all lead times. During the investigation period, on 17 June, extremely heavy rainfall occurred in Uttarakhand region as a result of interaction of two synoptic systems (Anumeha *et al.* 2014). Figure 11 shows day-1 forecast of 24 hr accumulated rainfall of both experiments and their differences along with the merged observations of IMD-NCMRWF. It can be seen that hybrid assimilation was not able to give much improvement in forecast of this extreme rainfall event. Both the experiments failed to pick the peak intensity of the rainfall event and spatial pattern. The precipitation process depends on processes that are not explicitly considered by NWP models, like condensation, vertical convective transport of heat and moisture and phase transitions of water between vapour, clouds and ice (Damrath *et al.* 2000). These processes need to be evaluated at sufficiently high resolution to have accurate precipitation forecast.

3.5 Monsoon index

In order to find out how monsoon circulation in the Indian region is modified by the experiment, monsoon circulation index of the NWP experiments are compared using Webster and Yang (1992) criterion. Mean zonal wind shear (U850–U200) that averaged over the region 5–20°N and 40–80°E, during the investigation period is estimated. It is observed that mean wind shear is 31.14 for hybrid and 30.87 for operational 3D Var. Hybrid experiment shows comparatively stronger circulation index than operational 3D Var. The changes produced in atmospheric flow characteristics by hybrid assimilation strengthened monsoon flow marginally. Regression plot of monsoon index and rainfall is given in figure 12 which shows higher regression values for the hybrid experiment. This shows relationship between monsoon index and rainfall is more linear in case of hybrid experiment which implies better predictability of

Figure 12. Plot of south Asian monsoon index computed from analysis against accumulated rainfall over Indian region (mean value computed for the entire study period).

rainfall in the region with monsoon circulation index.

4. Conclusions

The results show that the one-way coupled dual resolution hybrid assimilation did show moderate improvement in the model forecast skill on comparison with 3D Var during the investigation period. Average statistics show marginal improvement in forecast skill of temperature, relative humidity, wind and rainfall. It can be seen from the results that more improvement is seen in upper level wind and temperature. The difference plots of analysis wind show large difference between the experiments around 200 mb pressure level in tropics, especially over the Indian region. Comparison of forecasts against observations also shows large decrease in error at 200 mb pressure level with hybrid experiment. In temperature also more improvement is seen around 200 mb pressure level. But, in case of humidity such an improvement is not seen in upper levels. In global domain, humidity forecast is improved with hybrid assimilation in middle levels. Wang *et al.* (2013) reported that hybrid assimilation produced more improvement in upper level wind and temperature. Kleist (2012) suggested multivariate aspects of hybrid assimilation in analysis increments as the reason for non-uniform improvement in analysis variables. In their investigation, improvement in analysis with hybrid assimilation is seen in wind and humidity but not in temperature. Improvement in rainfall is statistically important but not significant in synoptic scale. Prediction of these types of extreme rainfall depends on model resolution and parameterization schemes. The use of two-way coupled hybrid system and fine tuning of the background error coefficients may improve the forecast skill of system.

Acknowledgements

Authors wish to thank Director, NCMRWF for providing constant support and encouragement. They are also thankful to Daryl Kleist, NCEP for the discussions.

References

- Anumeha D N, Raghavendra Ashrit, Amit Ashish, Kuldeep Sharma, Iyengar G R, Rajagopal E N and Swati Basu 2014 Forecasting the heavy rainfall during Himalayan flooding – June 2013; *Weather and Climate Extremes* **4** 22–34.
- Barker D M 1998 Var scientific development paper 25: The use of synoptic-dependent error structure in 3D Var; UK MetOffice Tech. Rep. [Available from the Met. Office, Saughton House, Broomhouse Dr., Edinburgh EH11 3XQ, United Kingdom].
- Buehner M 2010 Error statistics in data assimilation, estimation and modeling; *Data Assimilation* (Springer: Berlin Heidelberg), pp. 93–112.
- Buehner M, Houtekamer P L, Charette C, Mitchell H L and He B 2010a Intercomparison of variational data assimilation and the ensemble Kalman filter for global deterministic NWP. Part 1: Description and single observation experiments; *Mon. Wea. Rev.* **138** 1550–1566.
- Buehner M, Houtekamer P L, Charette C, Mitchell H L and He B 2010b Intercomparison of variational data assimilation and the ensemble Kalman filter for global deterministic NWP. Part 2: One month experiment with real observations; *Mon. Wea. Rev.* **138** 1567–1586.
- Buehner M, Morneau J and Charette C 2013 Four-dimensional ensemble-variational data assimilation for global deterministic weather prediction; *Nonlin. Process. Geophys.* **20** 669–682.
- Courtier P *et al.* 1998 The ECMWF implementation of three-dimensional variational assimilation (3DVAR) I: Formulation; *Quart. J. Roy. Meteor. Soc.* **124** 1783–1807.
- Damrath U, Doms G, Fruhwald D, Heise E, Richter B and Steppeler J 2000 Operational quantitative precipitation forecasting at the German Weather Service; *J. Hydrol.* **239** 260–285.
- Ferranti L, Klinker E, Hollingsworth A and Hoskins B J 2002 Diagnosis of systematic forecast errors dependent on flow pattern; *Quart. J. Roy. Meteorol. Soc.* **128** 1623–1640.
- Hamill T M and Snyder C 2000 A hybrid ensemble Kalman filter-3D variational analysis scheme; *Mon. Wea. Rev.* **128** 2905–2919.
- Hamill T M, Whitaker J S, Kleist D T, Fiorino M and Benjamin S 2011 Prediction of 2010's tropical cyclones using the GFS and ensemble based data assimilation methods; *Mon. Wea. Rev.* **139** 3243–3247.
- Hu M, Hui Shao, Donald Stark and Kathryn Newman 2013 Gridpoint Statistical Interpolation (GSI) Version 3.2 User's Guide, Developmental Testbed Centre, NCAR, NOAA, USA, <http://www.dtcenter.org/com-GSI/users/index.php>.
- Kleist D T 2012 An evaluation of hybrid variational-ensemble data assimilation for the NCEP GFS; PhD Thesis, Dept. Atmospheric and Oceanic Science, University of Maryland-College Park, 149p, <http://drum.lib.umd.edu/handle/1903/13135>.
- Kleist D T and Ide K 2015 An OSSE-based evaluation of hybrid variational-ensemble data assimilation for the NCEP GFS. Part I: System description and 3D-hybrid results; *Mon. Wea. Rev.* **143** 443–451.
- Kleist D T, Parrish D F, Derber J C, Treadon R, Wu W S and Lord S J 2009 Introduction of the GSI into the NCEP Global Data Assimilation System; *Wea. Forecasting* **24** 1691–1705.
- Kretschmer M, Hunt B R and Ott E 2015 Data assimilation using a climatologically augmented local ensemble transform Kalman filter; *Tellus A* **67** 26617.
- Kuhl D D, Rosmond T E, Bishop C H, McClay J and Baker N L 2013 Comparison of hybrid ensemble/4DVar and 4DVar within the NAVDAS-AR data assimilation framework; *Mon. Wea. Rev.* **141** 2740–2750.
- Liu J, Fertig E J, Li H, Kalnay E, Hunt B R, Kostelich E J, Szunyogh I and Todling R 2008 Comparison between local ensemble transform Kalman filter and PSAS in the NASA finite volume GCM perfect model experiments; *Nonlin. Process. Geophys.* **15** 645–659.
- Lorenc A C 2003 The potential of the ensemble Kalman filter for NWP – a comparison with 4D-VAR; *Quart. J. Roy. Meteor. Soc.* **129** 3183–3203.

- Mitra A K, Bohra A K, Rajeevan M and Krishnamurti T N 2009 Daily Indian precipitation analyses formed from a merge of rain-gauge with TRMM TMPA satellite derived rainfall estimates; *J. Meteor. Soc. Japan* **87A** 265–279.
- Pan Y, Zhu K, Xue M, Wang X, Hu M, Benjamin S G, Weygandt S S and Whitaker J S 2014 A GSI-based coupled EnSRF–En3DVar hybrid data assimilation system for the operational rapid refresh model: Tests at a reduced resolution; *Mon. Wea. Rev.* **142** 3756–3780.
- Parrish D F and Derber J C 1992 The National Meteorological Center's spectral statistical interpolation analysis system; *Mon. Wea. Rev.* **120** 1747–1763.
- Patil D, Hunt B R, Kalnay E, Yorke J A and Ott E 2001 Local low dimensionality at atmospheric dynamics; *Phys. Rev. Lett.* **86** 5878–5881.
- Penny S G 2014 The hybrid local ensemble transform Kalman filter; *Mon. Wea. Rev.* **142** 2139–2149.
- Prasad V S, Saji Mohandas, Munmun Das Gupta, Rajagopal E N and Surya Kanti Dutta 2011 Implementation of upgraded global forecasting systems (T382L64 and T574L64) at NCMRWF, NCMRWF Technical report, NCMR/TR/5/2011.
- Purser J R, Wu W S, Parrish D F and Roberts N M 2003 Numerical aspects of the application of recursive filters to variational statistical analysis. Part II: Spatially inhomogeneous and anisotropic general covariances; *Mon. Wea. Rev.* **131** 1536–1548.
- Raghavendra Ashrit, Iyengar G R, Syam Sankar, Amit Ashish, Anumeha Dube, Surya Kanti Dutta, Prasad V S, Rajagopal E N and Swati Basu 2013 Performance of Global Ensemble Forecast System (GEFS) during monsoon 2012; NCMRWF Research report, NCMR/RR/1/2013.
- Surya K Dutta and Prasad V S 2011 Impact of gridpoint statistical interpolation scheme over Indian region; *J. Earth Syst. Sci.* **120** 1095–1112.
- Toth Z and Kalnay E 1993 Ensemble forecasting at NMC: The generation of perturbations; *Bull. Am. Meteor. Soc.* **74** 2317–2330.
- Toth Z and Kalnay E 1997 Ensemble forecast at NCEP and the breeding method; *Mon. Wea. Rev.* **125** 3297–3319.
- Wang X 2010 Incorporating ensemble covariance in the gridpoint statistical interpolation variational minimization: A mathematical framework; *Mon. Wea. Rev.* **138** 2990–2995.
- Wang X and Bishop C H 2003 A comparison of breeding and ensemble transform Kalman filter ensemble forecast schemes; *J. Atmos. Sci.* **60** 1140–1158.
- Wang X and Lei T 2014 GSI-based Four-dimensional Ensemble-Variational (4DEnsVar) data assimilation: Formulation and single-resolution experiments with real data for NCEP Global Forecast System; **142** 3303–3325.
- Wang X, Snyder C and Hamill T M 2007a On theoretical equivalence of differently proposed ensemble/3D-Var hybrid analysis schemes; *Mon. Wea. Rev.* **135** 222–227.
- Wang X, Hamill T M, Whitaker J S and Bishop C H 2007b A comparison of hybrid ensemble transform Kalman filter-OI and ensemble square-root filter analysis schemes; *Mon. Wea. Rev.* **135** 1055–1076.
- Wang X, Barker D M, Snyder C and Hamill T M 2008a A hybrid ETKF-3DVar data assimilation scheme for WRF model part 1: Observing system simulation experiment; *Mon. Wea. Rev.* **136** 5116–5131.
- Wang X, Barker D M, Snyder C and Hamill T M 2008b A hybrid ETKF-3DVar data assimilation scheme for WRF model part 2: Real observation experiments; *Mon. Wea. Rev.* **136** 5132–5147.
- Wang X, Hamill T M, Whitaker J S and Bishop C H 2009 A comparison of the hybrid and EnSRF analysis schemes in the presence of model errors due to unresolved scales; *Mon. Wea. Rev.* **137** 3219–3232.
- Wang X, Parrish David, Kleist Daryl and Whitaker J S 2013 GSI 3DVar-based Ensemble-Variational hybrid data assimilation for NCEP global forecast system: Single-resolution experiments; *Mon. Wea. Rev.* **141** 4098–4117.
- Webster P J and Yang S 1992 Monsoon and ENSO: Selectively interactive systems; *Quart. J. Roy. Meteor. Soc.* **118** 877–926.
- Wei M, Toth Z, Wobus R and Zhu Y 2008 Initial perturbations based on the ensemble transform (ET) technique in the NCEP global operational forecast system; *Tellus* **60A** 62–79.
- Wu W S, Purser R J and Parrish D F 2002 Three-dimensional variational analysis with spatially inhomogeneous covariances; *Mon. Weather Rev.* **130** 2905–2916.
- Zhang M and Zhang F 2012 E4DVar: Coupling an ensemble Kalman filter with four-dimensional variational data assimilation in a limited-area weather prediction model; *Mon. Wea. Rev.* **140** 587–600.
- Zhang F, Zhang M and Poterjoy J 2013 E3DVar: Coupling an ensemble Kalman filter with three-dimensional variational data assimilation in a limited area weather prediction model and comparison to 4DVar; *Mon. Wea. Rev.* **141** 900–917.