Performance of Various Data Assimilation Schemes in the Forecast of a Major Heavy Rainfall Event over the Indian Subcontinent

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Abstract

The study compares the performance of an ensemble Kalman Filter (EAKF) with three and four-dimensional variational (3DVar and 4DVar) and a hybrid ensemble-variational (3DEnVar) data assimilation systems in the forecast of a major heavy rainfall events over Indian subcontinent using Weather Research and Forecast (WRF) model. The assimilated data include conventional observations as well as cloud-tracked satellite winds in every 6 hours interval. The performance of the data assimilation schemes is evaluated against standard sounding observations and TRMM satellite observations. It is found that the advanced data assimilation schemes with implicit or explicit flow dependent error covariance have significantly reduced the forecast errors. Further, the forecast skill scores for precipitation shows improvements when initialized with data assimilation systems that incorporate flow evolving error covariance.

Introduction

Many extreme rainfall events have been reported over the Indian subcontinent in the recent decades. Studies indicate that the frequency of such events are increasing. Numerical weather prediction, being an initial value problem, the accuracy of the forecast model predominantly rely on the quality of the given initial conditions. Hence for good forecast, it is vital to obtain the best possible initial estimate of the atmosphere. Data assimilation(DA) is an effective tool to determine as accurately as possible the initial state of the system by making use of all the available information.

This work aims to provide a comparison between four DA schemes: 3DVar, 4DVar, EAKF and Hybrid(3DEnVar) and studies their impact on the forecast of heavy rainfall events over Indian subcontinent.

- 3DVar system uses intermittent assimilation technique where observations made within a specific time window are aggregated and used in analysis. This system employs a completely constant error statistics.
- 4DVar system uses a continuous approach where the observations are assimilated at the exact time of measurement, rather than in batches. 4DVar scheme uses tangent linear and adjoint models which produces the implicit propagation of error statistics.
- The Kalman Filter method also uses sequential approach but background error covariance(BEC), instead of being assumed to be constant, is updated from the previous analysis time to the new analysis time using the forecast model. In EnKF method, an ensemble of forecasts is used to calculate the error covariance
- In Hybrid system, BEC is a linear combination of the constant, isotropic 3DVar covariance and the variable EnKF covariance. The combination fill out the error covariance estimated from only a limited sample of ensemble members

Cost function for 3DVar:

$$J(\mathbf{x}) = (\mathbf{x}-\mathbf{x}_b)^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + (\mathbf{y}-H(\mathbf{x}))^T\mathbf{R}^{-1}(\mathbf{y}-H(\mathbf{x}))$$

Cost function for 4DVar:

$$J[x(t_0)] = \frac{1}{2}[x(t_0)-x_b(t_0)]^T B_0^{-1}[x(t_0)-x_b(t_0)] + \frac{1}{2}\sum_{i=0}^{n}[H(x_i)-y_i]R_i^{-1}[H(x_i)-y_i].$$

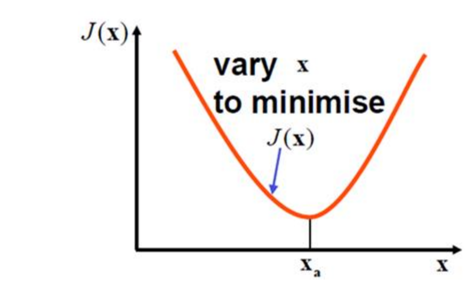
Kalman Filter:

Kalman-gain computation $\mathbf{K}(t) = \mathbf{P}_f(t)\mathbf{H}^T(t)[\mathbf{H}(t)\mathbf{P}_f(t)\mathbf{H}^T(t)+\mathbf{R}(t)]^{-1}$

State analysis $x_a(t) = x_f(t) + \mathbf{K}(t)[y(t) - H(t)x_f(t)]$

Cost function for Hybrid:

$$J(\mathbf{x}) = (\mathbf{x}-\mathbf{x}_b)^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + (\mathbf{x}-\mathbf{x}_b)^T\mathbf{E}^{-1}(\mathbf{x}-\mathbf{x}_b) + (\mathbf{y}-H(\mathbf{x}))^T\mathbf{R}^{-1}(\mathbf{y}-H(\mathbf{x}))$$



x- model state vector, x_b/x_f –background model state vector, x_a– analysis model state vector, y- observation vector, B- background error covariance, R- observation error covariance, H/*H*- observation operator, n- time of the last (n-th) observation, P_f – forecast error covariance, E- ensemble error covariance

Case overview: Uttarakhand heavy rainfall(2013)

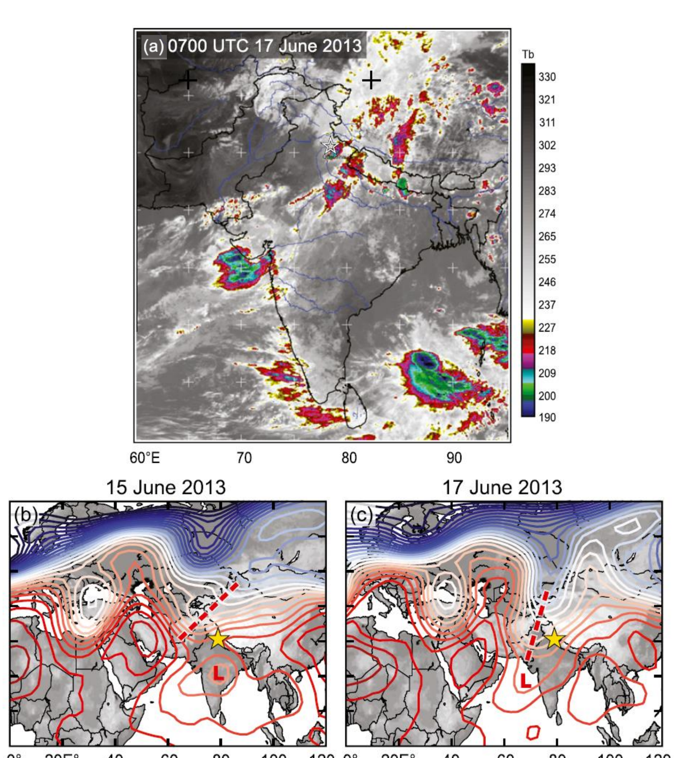


Fig.1 Meteosat-7 infrared satellite imagery for (a) 0700 UTC 17 Jun 2013. (b)&(c) Geopotential heights at 500 hPa(m). *Courtesy: R. A. Houze Jr., and Coauthors, 2017: Multiscale aspects of the storm producing the June 2013 flooding in Uttarakhand, India. Mon. Wea. Rev., Vol.145, 4448- 4466.*

From 13-17th June, Uttarakhand received Extremely-heavy rainfall. On 17th June, more than 340 mm of rainfall has been recorded, which is 375% more than the daily normal rainfall during monsoon.

Synoptic Conditions prevailed over the region:

- Interaction between WNW moving monsoon low from Odisha to Rajasthan and western disturbance and associated trough in middle and upper troposphere on 16th and 17th June,2013.
- The monsoon low provided the moisture feed and the westerly trough provided the divergence to lift the moisture. This sustained clouds on the large scale along with isolated deep convection produces extremely heavy rainfall.

Experimental Design

The WRF ARW model (version 3.8.1) has been configured with three domains having 27, 9 and 3-km horizontal resolution, with 36 vertical levels and a two-way interaction.

Model physics include:

- Kain-Fritsch scheme for cumulus physics (except for domain 3)
- WRF Single Moment 5-class scheme for microphysics
- YSU scheme for boundary layer
- Noah scheme for land surface physics
- Dudhia scheme for shortwave and
- RRTM scheme for longwave radiation.

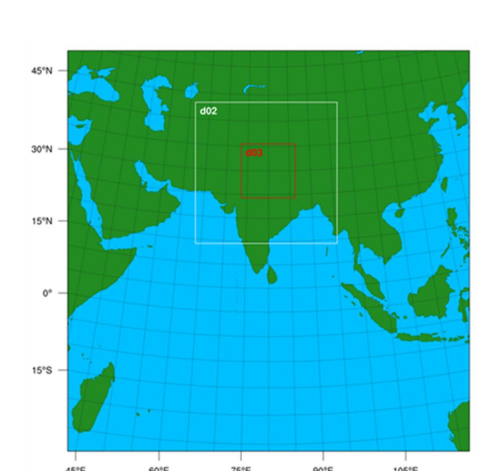
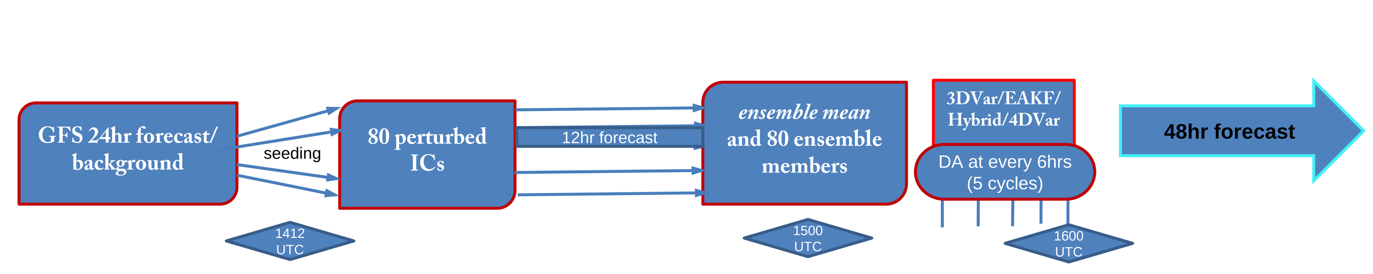


Fig.2 Model domain configuration



Observation and Results

Vertical Profile for RMSE

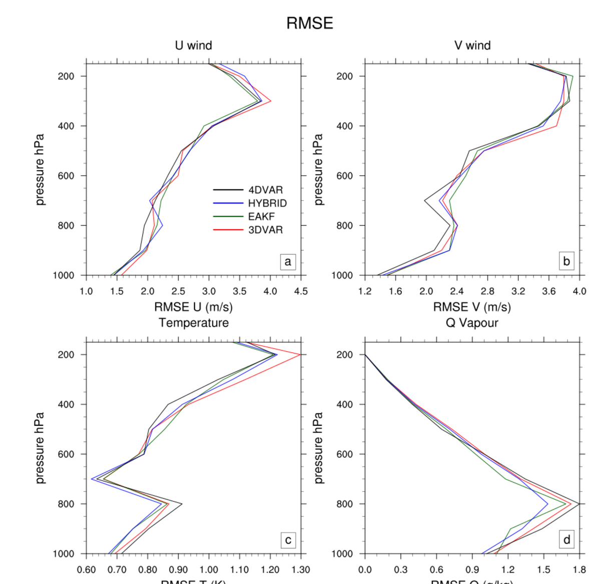


Fig.3 Domain averaged RMSE for (a) U wind (b) V wind (c) Temperature (d) Q Vapour for the 48hr forecast

Spatial distribution of Accumulated Precipitation compared to TRMM & IMD data

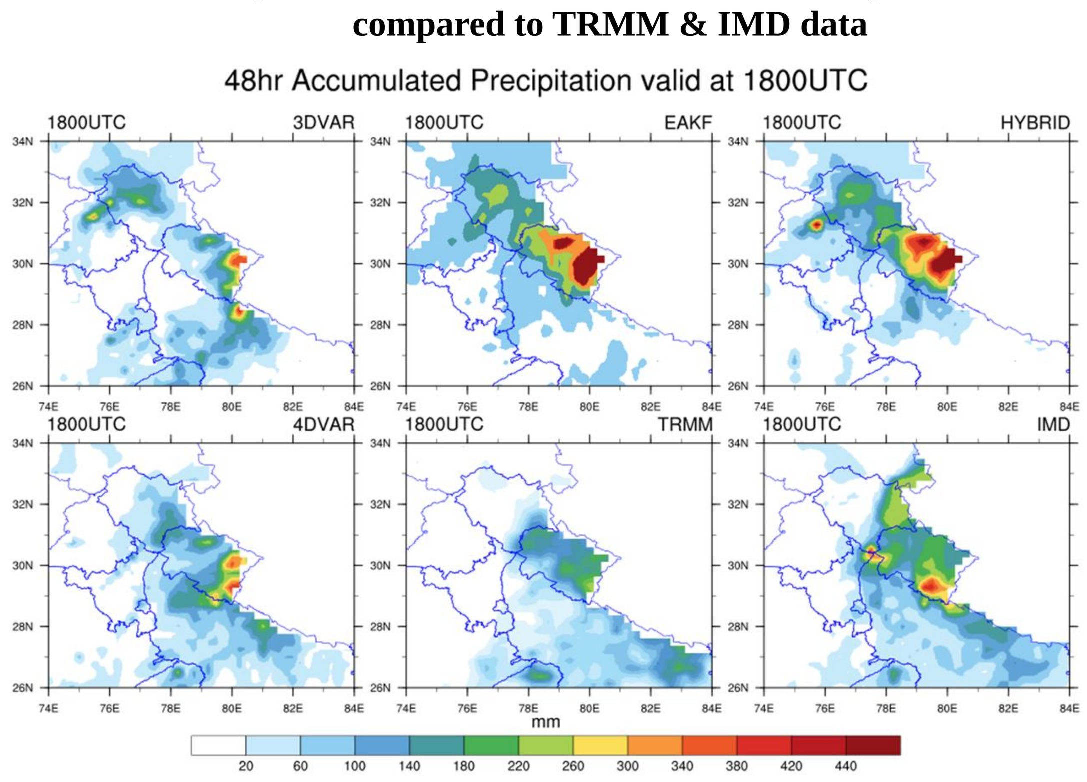


Fig.4 48hr Total accumulated precipitation for 3DVar, EAKF, Hybrid, 4DVar in comparison with TRMM satellite data and IMD gridded precipitation

Equitable Treat Score and Bias

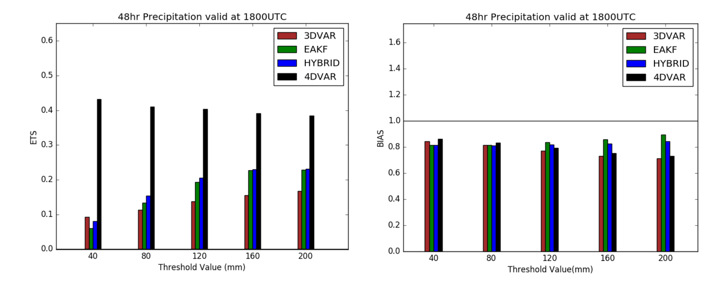


Fig.5 Statistical scores for the 48hr accumulated precipitation for 3DVar, EAKF, Hybrid, 4DVar w.r.t IMD gridded rainfall data

The two main patches of the accumulated precipitation observed on east and west side of the state has been clearly captured by the 4DVar scheme whereas EAKF and the hybrid scheme seems to have captured them by an offset(Fig.4). The statistical scores confirms the observation with maximum ETS observed for the 4DVar scheme(Fig.5)

Time series of Accumulated Precipitation

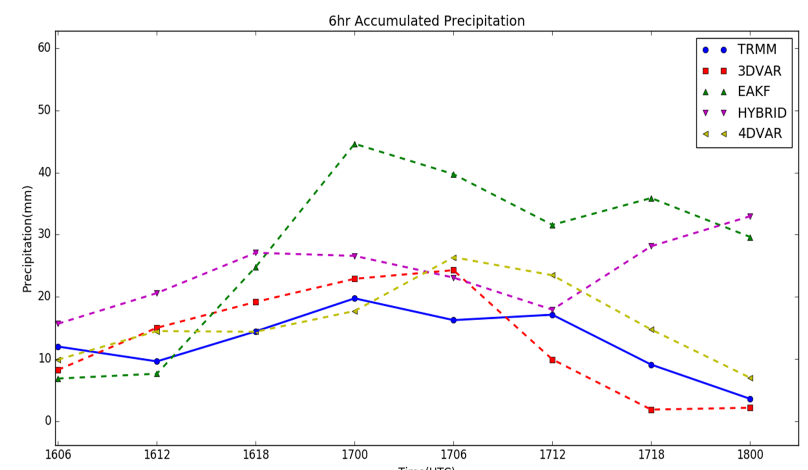


Fig.6 Time series of grid point average rainfall over Uttarakhand domain compared w.r.t TRMM data

Nested Assimilation Strategy

Configuration: WRF model has been run on nested domain at 3 km resolution for the short range forecast in between the data assimilation cycles.

The resolution is sufficient to resolve the moist convection and dynamics. Since the study adopted two-way strategy, the information from the finer resolution is fed back to coarser outer domain

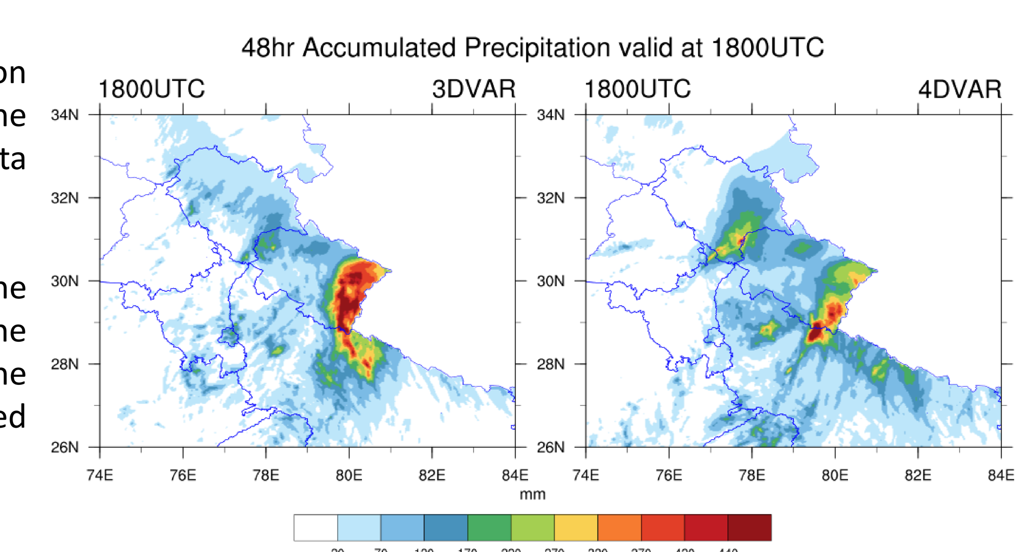


Fig.7 Total accumulated precipitation(48hr) for 3DVar and 4Dvar valid at 1800 UTC

Statistical Scores

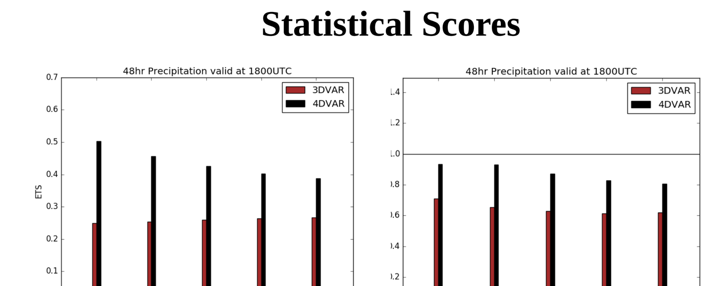


Fig.8 ETS and Bias scores for 48hr accumulated precipitation for 3DVar and 4DVar

The improved coarser resolution outer domain is further used as the background for assimilation

The results shows remarkable improvement in the performance of data assimilation schemes. This points to the importance of using high resolution data assimilation cycling in improving the prediction of heavy rainfall events

Conclusions and Remarks

- Verification with different sets of data (IMD, TRMM, Radiosonde) shows that the forecast initialized from 4DVar and ensemble based schemes perform better than 3DVar.
- Skill scores for quantitative precipitation forecasts is higher for forecasts from 4DVar analysis as compared to that of other schemes.
- For higher thresholds of rainfall, 3DVar is significantly underestimates precipitation as compared to that in other schemes.
- Results show remarkable improvement for 3DVar and 4DVar schemes for the nested assimilation strategy.

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