Local Ensemble Transform Kalman Filter data assimilation: shallow water model tests

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In this work, the local ensemble transform Kalman filter (LETKF) that is a local square root filter [2] suggested in [1] was implemented. The localization means that the analysis can be carried out independently at each grid point with the use of only local observations, which naturally decreases the problem size and reduces spurious correlations. One other distinctive feature of the LETKF is that it solves the problem in the ensemble space, using transformation from the physical to the ensemble space.

The LETKF assimilation scheme was tested with the shallow water model with forcing [3] on the sphere. The external forcing was chosen so that the mean state of the atmosphere on the specific pressure level was close to the NCEP/NCAR 2 reanalysis data for a given date (the approach similar to that of the tests with the barotropic vorticity model [4]). Model resolution is 1.5°×1.5°, the time step is equal to 45 minutes.

The assimilation scheme was tested in assimilation cycle. Pseudoobservations (wind components and geopotential) were generated from NCEP/NCAR 2 reanalysis in the randomly chosen grid points. We used NCEP/NCAR Reanalysis 2 data as first guesses at the first assimilation step. The localization function was piecewise linear, the influence distance being different for the wind components and for the geopotential.In the experimental set, the ensemble size was 40-60 members. The assimilation scheme is parallelized via MPI (each process calculates analysis for a chosen set of the latitude circles)

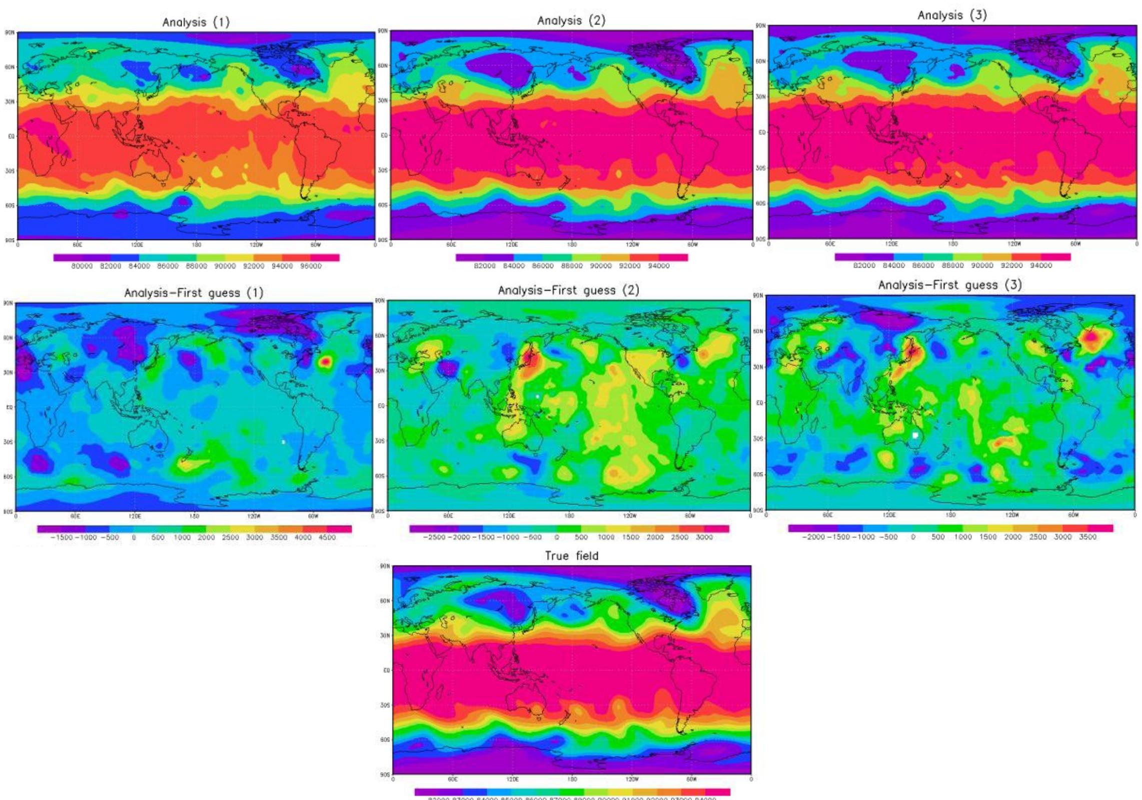

Figure 1 - Analysis (upper row), analysis increments (middle row) and true field (lower row) for the 250th assimilation step (left: inflation factor set to 1.1, middle: inflation factor set to 2, right: inflation factor set to 1.1, each ensemble member uses different forcings)

One of the most challenging points in the test suite was a serious underestimation of the analysis error covariance, which is a regular problem for the square root filter assimilation. Two possible solutions of the problem were devised. For the first one, we used a greater covariance inflation coefficient (equal to 2 or greater), artificially making the analysis error covariance greater by the factor of inflation. For the other one, we applied the model operator with different external forcing for different ensemble members (see Figure 1). Both approaches showed acceptable result, while using different external forcing seems to be more physical and is somewhat similar to the 'stochastic physics' approach [6].

The system proved to be stable for not less than 500 assimilation cycles.

The implemented LETKF assimilation scheme is now being tested with the 3D weather forecast model.

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