REQUEST FOR A SPECIAL PROJECT 2012–2014

MEMBER STATE: Italy……………..…………………………………………..…

Principal Investigator[1]**:** Lucio Torrisi, Francesca Marcucci…………………………….……

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Project Title: Data Assimilation and Short-Range Forecast with a Limited Area Ensemble Kalman Filter

If this is a continuation of an existing project, please state the computer project account assigned previously.	**SPITLEKF**	
Starting year: (Each project will have a well defined duration, up to a maximum of 3 years, agreed at the beginning of the project.)	2012	
Would you accept support for 1 year only, if necessary?	YES ☒	NO ☐

Computer resources required for 2012-2014: (The maximum project duration is 3 years, therefore a continuation project cannot request resources for 2014.)	**2012**	**2013**	**2014**
High Performance Computing Facility (units)	3000000	4000000	4500000
Data storage capacity (total archive volume) (gigabytes)	1000	1500	2000

An electronic copy of this form ***must be sent*** *via e-mail to:* *special_projects@ecmwf.int*

Electronic copy of the form sent on (please specify date): 23-04-12

Continue overleaf

[1] The Principal Investigator will act as contact person for this Special Project and, in particular, will be asked to register the project, provide an annual progress report of the project's activities, etc.

Principal Investigator: Lucio Torrisi, Francesca Marcucci

Project Title: Data Assimilation and Short-Range Forecast with a Limited Area Ensemble Kalman Filter

Extended abstract

The goal of this project is to investigate methodologies to improve analysis and forecast skill in the field of operational limited area NWP models through the use of a variation of the Ensemble Kalman Filter (EnKF) approach. This is an important current research topic in meteorology and many competing approaches are currently under study and experimentation.

The Local Ensemble Transform Kalman Filter (LETKF, Hunt et al., 2007) is one representative of a large family of ensemble Kalman filters which are collectively known as ensemble square-root filters, or “deterministic filters”. This type of filters do not perturb observations, as is characteristic of the original (“stochastic”) version of the EnKF (Evensen, 1994; Houtekamer et al., 2005), but apply the Kalman Filter update equations in the forecast error subspace spanned by the ensemble. The LETKF offers the theoretical advantage of choosing the analysis ensemble which is closer to the forecast ensemble and, in its local implementation, provides an ensemble analysis which varies continuously between adjacent regions. As noted elsewhere, the LETKF offers some practical advantages for operational NWP applications. In the LETKF scheme, parallelization is natural and relatively simple to implement and computational scalability is theoretically close to 100%.

The CNMCA has recently implemented and tested the ensemble data assimilation algorithm based on the LETKF approach (Bonavita, Torrisi and Marcucci, Q.J.R.M.S. 2008,2010). The LETKF ensemble mean analysis and forecast has proved to be of superior quality with respect to the CNMCA operational 3DVar. The LETKF algorithm is of rather straightforward implementation but, as with many other ensemble based systems, it requires careful tuning of a number of parameters (notably horizontal and vertical localization lengths, covariance inflation parameters, ensemble size) to obtain a calibrated system.

The CNMCA-LETKF data assimilation system is used to initialise the COSMO-ME model (7km) and it is operational (since 1 June 2011) with these characteristics:

a) 6-hourly assimilation cycle
b) 40 ensemble members + control run with 0.09° (~10Km) grid spacing (HRM model), 40 hybrid p-sigma vertical levels (top at 10 hPa);
c) Model domain: European-Mediterranean area;
d) (T,u,v,qv,ps) set of control variables ;
e) Observations: RAOB, SYNOP, SHIP, BUOY, AIREP, AMDAR, ACAR, AMV (MSG), WindPROF, SCATwinds (ERS2, METOP);
f) State Dependent Multiplicative Inflation according to Whitaker et al (2010);
g) Climatological Additive Noise;
h) Lateral Boundary Condition Perturbation using EPS;
i) Climatological Perturbed SST.

The work plan for the project is:

1. Perform a more thorough exploration of the filter's parameter space, finding the “optimal” values for our operational setup. The increase of resolution in the operational configuration from 28 km to 10 km requires a tuning of horizontal and vertical localization length scales, that at moment are maintained unchanged. Moreover a smart selection of the observations in the local patch has to be optimized in order to reduce the computation time without loss of information. One

idea is to guarantee a minimum sample for each class of observation (raob,aircraft, etc), another one is use only those that significantly change the background following the idea of an adaptive patch (Whitaker et al. 2008) or, finally, take into account only information from nearest observations. The impact of localization over the analysis ensemble balance should be also investigated.

2. Improve the model error representation in the filter; so far an adaptive multiplicative and a climatological additive inflation parameterization of model error are used. At moment two different versions of multiplicative inflation have been implemented in the code. The first one is the 3D Adaptive Multiplicative Inflation with temporal smoothing according to Li et al (2009) acting on background/analysis perturbations, based on the relationships:

$$\mathbf{x}_i^b \leftarrow r\left(\mathbf{x}_i^b - \overline{\mathbf{x}}_i^b\right) + \overline{\mathbf{x}}_i^b \qquad r = \frac{\mathbf{d}_{o-b}^T \mathbf{d}_{o-b} - Tr(\mathbf{R})}{Tr(\mathbf{HP}^b \mathbf{H})}$$

The second one is the State Dependent Covariance Inflation according to Whitaker and Hamill (2010) acting on analysis perturbations, expressed by:

an. pert. $$\mathbf{x}_\mathrm{a}' = \mathbf{x}_\mathrm{a}' \sqrt{\alpha \frac{\sigma_\mathrm{b}^2 - \sigma_\mathrm{a}^2}{\sigma_\mathrm{a}^2} + 1}$$

$\alpha = 0.95$
σ^2 = variance

Other promising options need to be explored: evolved additive perturbation (Hamill and Whitaker 2011), stochastic kinetic energy backscatter, an improved version of the stochastic physics parameterization (Palmer et al, 2009).

3. Continue investigation of the use of nonlocal observations (I.e., radiances and precipitation) which is not computationally straightforward to implement in a local algorithm such as LETKF. For the AMSU-A observation we would compare two different methods proposed in Fertig 2007: the “maximum based method”, that threat the AMSU-A as a single level observation localized at the model level for which the magnitude of the weighting function is largest, and the “cut-off based selection”, whose idea is to examine the weighting function for each nonlocal observation, and choose to assimilate it if a “significant” weight is assigned to any model state vector component within the local region. The assimilation of AMSU-B/MHS and HIRS observations, already monitored in our system, will be investigated.
As regard IASI radiances, the large volume of data and amount of computations required to treat all channels is prohibitive in our small operational context, for this reason IASI retrievals (temperature and humidity profiles reconstructed from the radiances and prior information) will be assimilated.

4. Handle system non-linearities through iterative EnKF techniques such as the *quasi outer-loop /running in place* algorithms (Yang and Kalnay, 2011) and the Snyder iterated EnKF that mimics the 4D-Var outer-loop (Snyder, ECMWF Annual Seminar 2011).

The future work will be to develop a local area ensemble prediction system based on LETKF analysis perturbations.

The following F90 codes will be used:

- “ANA_TUVH_FIELDS_LETKF”, an in-house code that perform the LETKF analysis, parallelised using the MPI libraries. Some of the ESSL routines have been used to optimize expensive matrix operations. The code is running in the current version using 160 processors.
- “HRM” and “COSMO”, the numerical models parallelised using the MPI libraries.

This activity is obviously CPU intensive in that it requires repeated trials of the assimilation and prediction systems in various configurations over an optimization period which cannot be too short for the results to have statistical significance.
In order to have an idea of the computation effort, it can be assumed that 1-day run of the operational configuration takes about 33000 BU. A guess is to perform 2 test runs for each one of the 4 points previously described, for a total of 8 experiments.

As we expect to run at least 20 days for each test (700.000 BU), assuming that each one should be repeated at least for two different seasons of the year, the total cost for the 16 (2 x 8) planned runs will be about 11.000.000 BU. The resources have been spread out in the 3 year period in the following way: 3.000.000 BU on 2012, 3.500.000 on 2013, 4.000.000 on 2014.

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