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Using Ensemble Kalman Filtering to improve magnetic field models during vector satellite data ‘gaps’?

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Overview

Kalman filtering can be used to combine data optimally from different sources assuming that the error or variance of each data type is suitably understood. Typically a physical model is combined with occasional real measurements. **Ensemble Kalman Filters (EnKF)** extend this idea by making multiple simulations with randomly perturbed models drawn from probability distribution of fixed variance [1]. Here we use EnKF to combine steady core ***surface flow models*** of the fluid outer core with ***magnetic field models*** derived from periods when no vector satellite data were available. We test if there is an optimal combination of flow and field that minimises the overall root-mean-square misfit to a ‘true’ magnetic field calculated after the resumption of satellite vector measurements.

What ‘gap’?

After almost a decade in low Earth orbit, the CHAMP mission ended in September 2010. The Ørsted mission at a higher altitude provided a small amount of scalar-only data for the next three years but main field models had to rely on vector data solely from ground observatories. In November 2013, the ESA Swarm mission launched and began providing global vector data in early 2014. Hence for around three years, there was a gap or lack of satellite vector measurements which are essential for making high-quality models of the main field.

For our main field models, we use five annual updates from the BGS MEME model created with the magnetic global data available at the time in 2010, 2011 etc. up to 2014 (Figure 1). In 2015, the MEME code changed to a smoother high-degree spline representation. SV predictions for one year from the release dates are shown. Fig.1 also shows the CHAOS-X field models, which are retrospective rather than predictive.

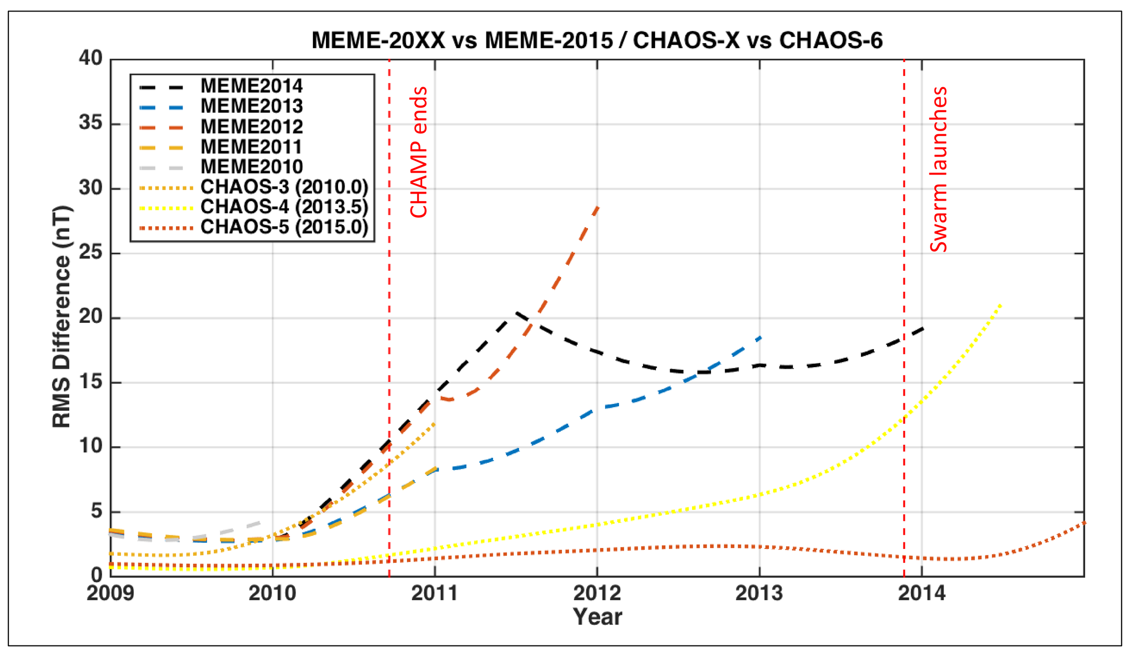

Figure 1: Comparison of root-mean-square (RMS) differences of MEME-201X with MEME-2015 and CHAOS-X with CHAOS-6. MEME-201X models are computed from the available data at the time. Differences are to degree and order 14. MEME-2015 and CHAOS-5/6 use both CHAMP and Swarm data while CHAOS-3/4 and MEME-2010/1/2/3 use CHAMP and observatory vector data, and some Ørsted scalar data. MEME-2014 uses some initial Swarm data. Model release dates are shown in the legend.

Going with the flow

The secular variation (SV) of the magnetic field can, on short timescales, be ascribed to advective motion of the liquid iron core carrying an embedded magnetic field. Core flow models which incorporate a steady flow and steady acceleration component have been shown to perform best at predicting the SV of the magnetic field over five year periods [2].

We use a steady core flow and acceleration model derived from satellite and ground magnetic SV and secular acceleration data spanning 2007-2010. This consists of flow to spherical harmonic degree 14 and acceleration to degree 8 in its toroidal and poloidal components and a weakly applied tangentially geostrophic flow constraint.

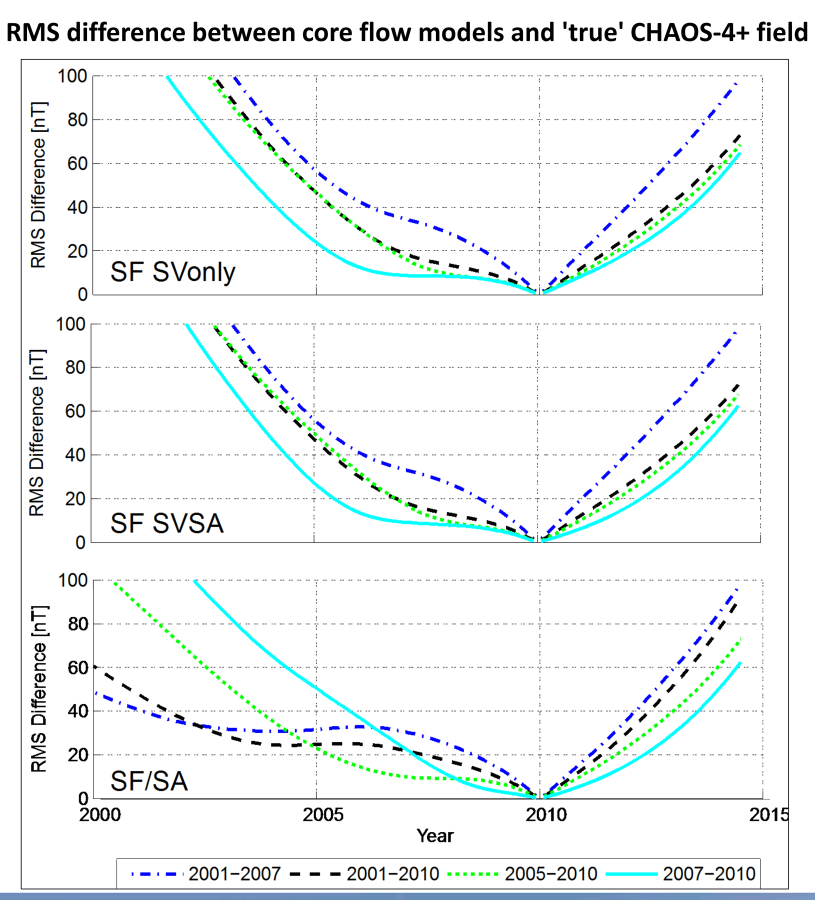

Figure 2 (from Ref [2]): Forecast and hindcast of magnetic field change from a starting time of 2010.0 using different core flow models. The magnetic field data SV and SA has been inverted using three types of assumption about the flow:

- **SF SV only: using magnetic SV data for a steady flow only**
- **SF SVSA: using magnetic SV and SA data for a steady flow only**
- **SF/SA: using magnetic SV and SA data to invert for both a steady flow and acceleration**

The different colours show the coverage of magnetic field data used for each flow. From inspection, it can be seen that the SF/SA flow using 2007-2010 magnetic data gives the lowest RMS difference with CHAOS-4+ between 2010.0 and 2015.0

Forecast and assimilation

An EnKF progresses in two stages : (i) a forecast step based upon the model of the physical system and (ii) an assimilation step to infuse a measurement into the model in order to update and correct the trajectory. We use the **flow models** inverted from the 2007-2010 magnetic field data to drive the EnKF in forecast mode for one year and the Gauss coefficients of the MEME-201X **field models** computed from the available data at the time for the annual assimilation.

The key questions are:

- Can we improve on a flow-only forecast over five years?
- What is the best balance between the errors assigned to the flow and field to produce an optimal forecast trajectory?

To initialise the system, we start at 2009 and use the annual differences (per coefficient) in magnetic field between a flow forecast and the poorest (*a posteriori*) field model to set the allowed variance. We use 1000 ensemble and run for six years from 2009.1 to 2015.1 [Ref. 3]. The resulting forecasts are shown in Figure 3.

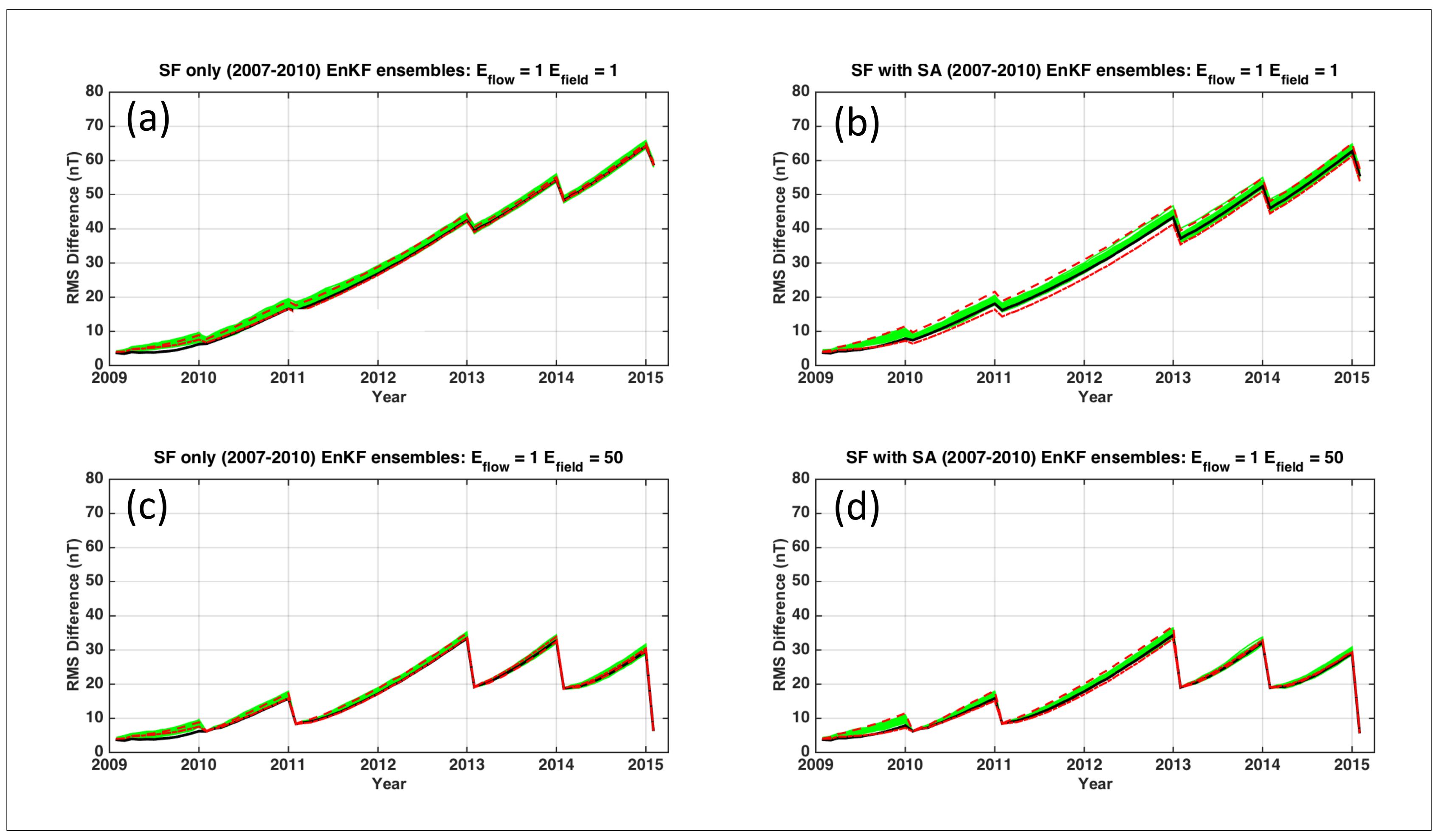

Figure 3: (a) EnKF forecast using a *Steady Flow only* model and a ratio of 1:1 between flow and field variance and (c) forecast using a SF only model and a ratio of 1:50 between flow and field variance. (b) EnKF forecast using a *Steady Flow and Steady Acceleration* model and a ratio of 1:1 between flow and field variance and (d) forecast using a SF and SA model and a ratio of 1:50 between flow and field variance. The RMS difference is with respect to MEME-2015 magnetic field model to degree 14. The black line is the ensemble mean, the red lines are ±1σ standard deviation. The green lines are the individual ensemble forecasts. Note, no field model was assimilated in 2012.0.

There is no ‘free lunch’ ...

The RMS differences in the forecasts in Figure 3 show that if we have equal ’belief’ in the error models of the flow and main field [panels (a) and (b)], we are not using the field model optimally. On the other hand, if we essentially ignore flow model in the assimilation step [panels (c) and (d)] we can only reduce the RMS difference to that of the field model.

Hence, we can only do as well as the ‘better’ model in the system. Given that the field models produced during periods of no-vector satellite data are just as good as the annual predictions from a flow model, there appears to be no overall benefit to using an EnKF. Until flow models can better predict the SV, this will remain the case.

Conclusions

We used an Ensemble Kalman Filter to combine forecasts from a **core flow model** with those from **main field models** built without vector satellite data during the CHAMP-Swarm gap. We find that these field models and flow model forecasts have similar RMS differences (compared to the ‘true’ field) and hence are not strongly improved by using an EnKF approach.

References

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