

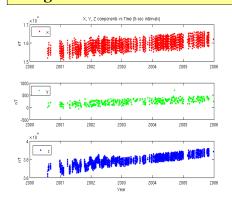
Core flow modelling from satellite-derived 'Virtual Observatories'

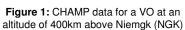
1. Introduction

The last decade has seen a significant improvement in the capability to observe the global field at high spatial resolution using data from satellite missions including CHAMP, Oersted and SAC-C. These data complement the existing record of ground-based observatories, which have continuous temporal coverage at a single point. We wish to exploit these new data to model the secular variation (SV) globally and improve the flow models that have been constructed to date.

Using the approach developed by Mandea and Olsen (2006) we create a set of 648 evenly distributed 'Virtual Observatories' (VO), at 400km above the Earth's surface, encompassing satellite measurements from the CHAMP satellite over five years (2001-2005). We invert the SV calculated at each VO to infer flow along the core-mantle boundary. Direct comparison of the SV generated by the flow model to the SV at individual VO can be made.

Using Virtual Observatories to derive SV





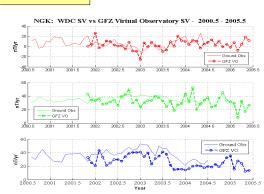


Figure 2: Comparison of Secular Variation from the Niemgk ground observatory (Ground Obs) and associated Virtual Observatory (GFZ VO) in the $\dot{X} \dot{Y} \dot{Z}$ components

2. Method

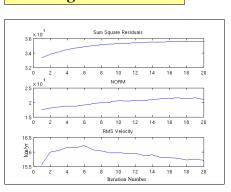
CHAMP Vector Data (release v50) for 2001.4 to 2005.9 were obtained from the GFZ Potsdam web server. A global 10° regular grid of 648 VO at an altitude of 400km was created ($\theta = 5^{\circ}$, ..., 175° ; $\Phi = -180^{\circ}$, ..., 170°). All data within a 400km radius of the grid point were included in the VO 'cylinder' [Figure 1].

We used the method of Mandea and Olsen (2006) to reduce the ~86,000 measurements (all times) per day for a month to one-monthly value for each VO above the Earth. The field is assumed to approximate a Laplacian potential field.

An internal magnetic field model (CHAOS from Olsen et al. (2006)) is removed from each data vector measurement (to pre-whiten the data). A robust leastsquares algorithm is then used to find the polynomial coefficients which best fit the field residuals within the cylinder. The magnetic field model is added back to coefficients to produce the average values of the field at the VO for the particular month.

SV is calculated as the yearly change in the strength of the three vector components $(\dot{x} \ \dot{y} \ \dot{z})$ [e.g. Figure 2]. The SV dataset consists of 44 months from November 2001 to Feb 2005. Core flow models are calculated using the methods of Whaler (1986) and Walker and Jackson (2000) [for an overview, see Figure 3], directly inverting the SV data using a regularised iterative L₁ minimisation algorithm.

Inferring Flow from SV



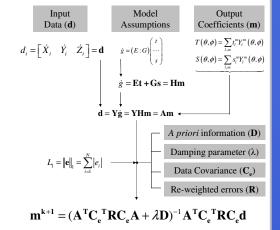


Figure 3: Iteration Metrics and Mathematical Model used to calculate core flow from Secular Variation.

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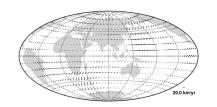


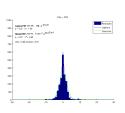
3. Results

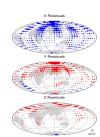
Figure 4 shows an example of three flow models (Nov. 2001; Feb. 2003; May 2005) in the left column. The associated residuals (difference between the SV predicted by the flow and the input data) are plotted as both a histogram (centre) and vector component distribution (right) [N.B. blue indicates negative residual, red is positive residual, with marker size indicating the absolute residual size].

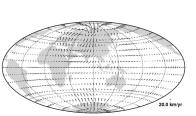
We find that the resulting core flows are influenced by some signal, which varies in time giving unrealistic monthly changes in the flow. In Figure 4 (b), the contamination produces a bimodal distributed histogram, with strong negative bias in the \dot{X} component. Note the sectorial banding in the residuals.

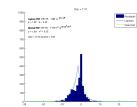
Flow Results from SV



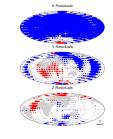


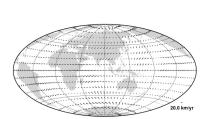


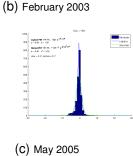




(a) November 2001







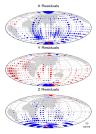


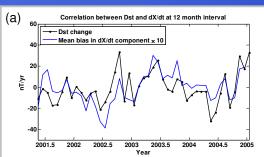
Figure 4: Core flow Models, Residuals and Distribution of residuals Left: Flow Models, Centre: Residual Histogram, Right: Residual Distribution (Red: Positive; Blue: Negative)

4. Discussion

Using this direct SV inversion method, residuals can be investigated in detail. Suggested explanations for the obvious biases in the vector components include contamination from external field currents and ionospheric (internal to the satellite) combined with satellite orbit configuration in local time.

Figure 5 (a) shows the pattern in yearly *Dst* change. Overlaid is the mean *bias* in the dX/dt component (multiplied by 10 to improve visual comparison). The change in the bias is correlated to that of the *Dst*, suggesting that external magnetic fields may be one source of error. Figure 5 (b) shows the mean bias in dX/dt compared to the mean satellite local time for each month – these curves bear little resemblance to each other.

Different data selection (e.g. using night-side only) indicate that day-side current systems also have an effect on the residuals, although tests to remove estimates of these from the day-side data using the Comprehensive Model (Sabaka et al., 2004) have proved inconclusive.



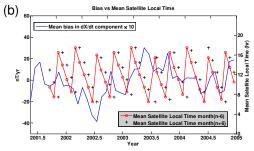


Figure 5: Correlation between the Change in Dst and the Mean bias in the X component

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