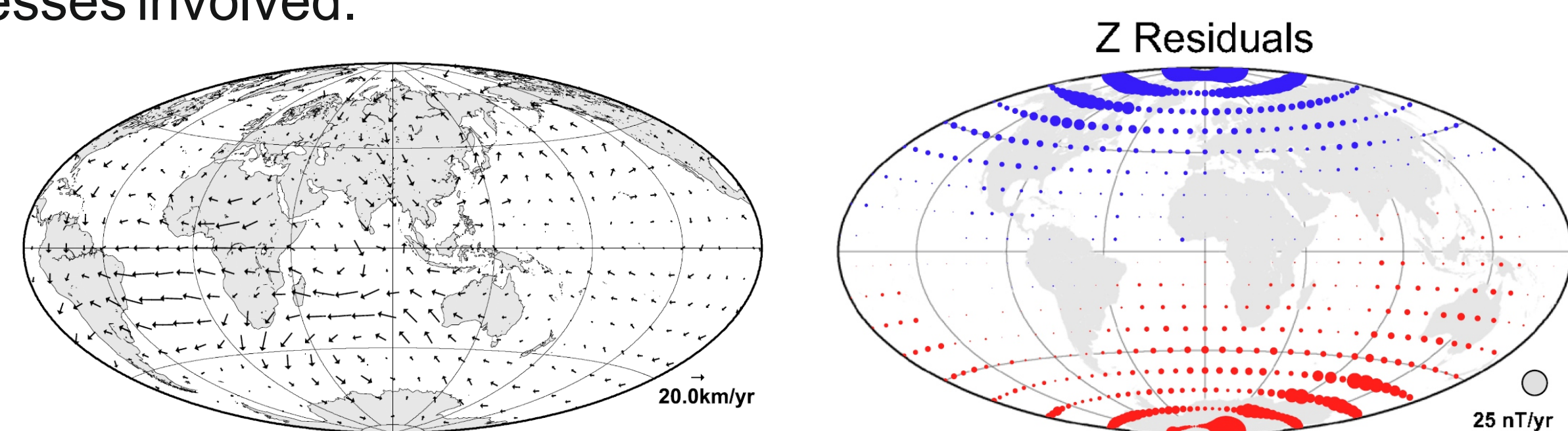


The secular variation (SV) of the geomagnetic field is difficult to accurately predict with our current incomplete knowledge of its governing physics. Field models fit to observations are necessary to separate the various sources of fields. Many academic and applied studies rely on the extrapolation of these global core field models beyond their data constrained period.

We investigate using time series forecasting methods to pre-process predictions of observations, with a view to including these predictions within the constraints of a field model inversion. This would allow us to use the most recent data to govern our predictions, without the impact of temporal damping effects from the field modelling process. We can also choose to apply any spatial and physical constraints of our model to these predictions as part of the model inversion. We show an application of forecasting to ground observatories (GO) and satellite “virtual observatories” (VO) from the CHAMP and Swarm missions.

1. Current forecasting methods

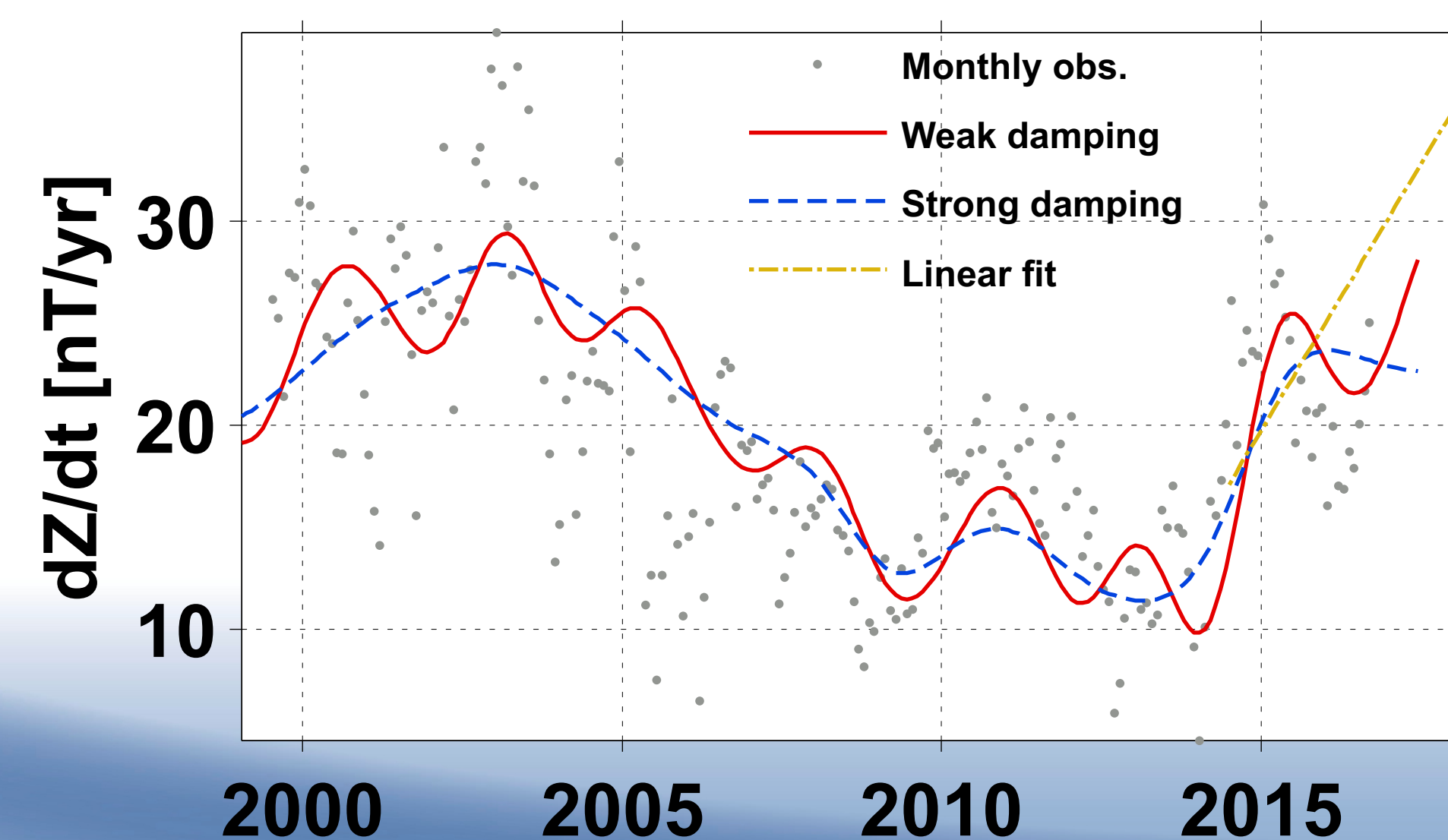
There have been many attempts to forecast the geomagnetic core field via physics-based methods. Studies such as Whaler & Beggan [2015] advect core flow estimates (Fig. below) derived from field models, while Fournier et al [2015] used the forward propagation of a geodynamo simulation, assimilating satellite observations. Such methods are continually developing but are currently limited by a lack of knowledge or resolution of the physical processes involved.



Flow at CMB (left) and VO residuals to model (right), from Whaler & Beggan [2015].

Frequently, predictions of the field are made based on simple extrapolations of a field model approximation to the observations. Where these models are parameterised by temporal B-splines, an extrapolation of the field is often heavily dependent on the damping chosen for the model, specifically at the model ends (Fig. below).

HAD: 51°N 356°E



Example field model with data at Hartland GO, UK. To control the temporal variation of a spline model, damping is used, particularly at the ends of the model. This strong damping leads to a poor fit to data at the model ends, which can lead to extrapolations, (yellow), which may not be a good approximation of the observations (grey).

2. Time series forecasting

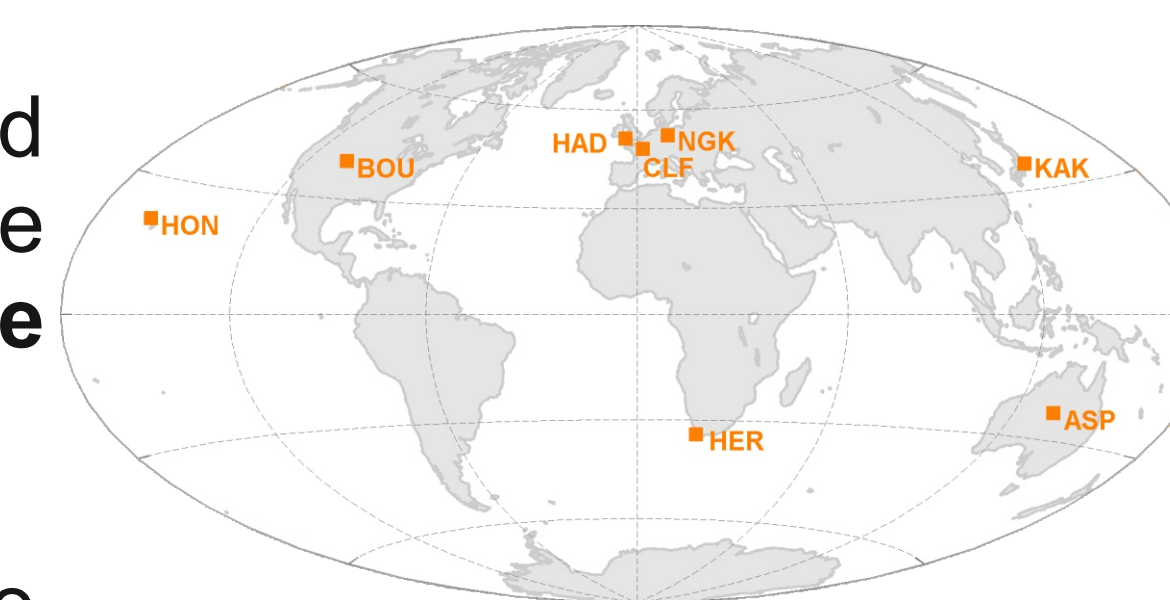
Time series modelling and forecasting is prevalent in a surprisingly wide array of activities in our modern world, from science to finance to social media. As such a vast array of tools and methods have been developed, we focus on the Prophet algorithm, developed by Facebook (Taylor & Letham, 2017). Prophet is procedure of additive regression modelling, capable of handling irregularly sampled data with irregular variations, with four model terms:

$$y(t) = p(t) + s(t) + i(t) + \epsilon_t$$

signal piecewise trend periodic variations irregular variations Gaussian residual

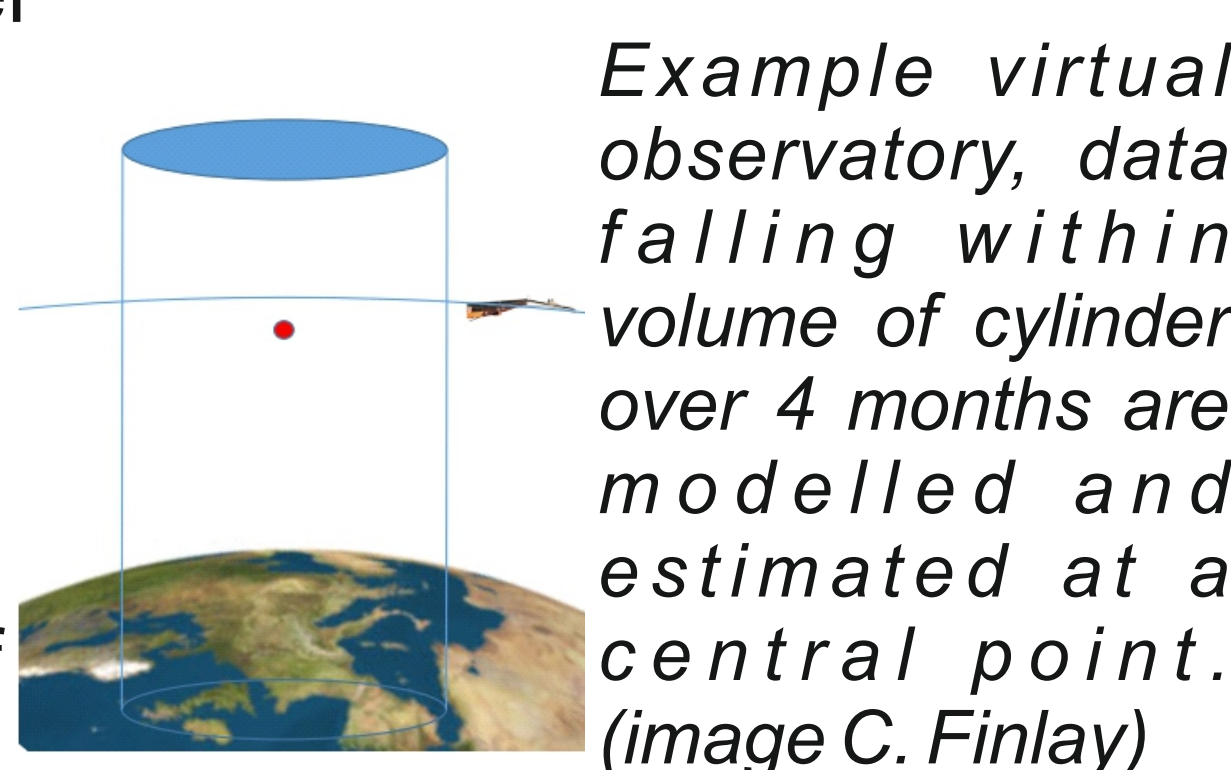
fit well with geomagnetic data, where periodic external signals overlap irregular anomalies, longer term SV punctuated by unpredictable jerks, instrument and environment noise. We have performed a preliminary study into the suitability of such models to fit GO and VO data.

GO provide continuous time series in fixed locations, sparsely distributed across the continents. We use a subset shown to the right.



Ground observatory subset used for this study.

VO (e.g. Manda & Olsen, 2006) provide approximated time series of a potential field fit to satellite data which falls inside a cylinder of space (Fig. right) over a period of time, in an evenly distributed grid across Earth. We use VO developed by M. Hammer and C. Finlay, using CHAMP and Swarm satellite data. A cubic potential field is fit to data residuals after the subtraction of a field model, in each of a grid of cylindrical bins of radius 700km, every 4 months. CHAMP VOs are fit at 300km altitude, and Swarm VOs at 500km, we use a subset of 30 VOs from the even geographic distribution of 300.



We compare our forecasts to a traditional field model – MEME2010. MEME2010 is built using GO, CHAMP, and Oersted data, and constrained by an order-6 temporal spline, with damping of the 2nd and 3rd time derivatives of the radial field at the CMB (after Hamilton et al, 2015). The model is fit to data from 1999–2010, and linearly extrapolated to give predictions to 2018.

Acknowledgements and References

The Swarm mission and data centre are operated by ESA, CHAMP data is provided by GFZ, Oersted data by DTU. Many institutes and agencies are involved in the operation of geomagnetic observatories around the world. INTERMAGNET and the World Data Centre (WDC) for Geomagnetism (Edinburgh) assist in dissemination of these data from which AUX_OBS_2 are produced by BGS for ESA. The work here not have been produced without the

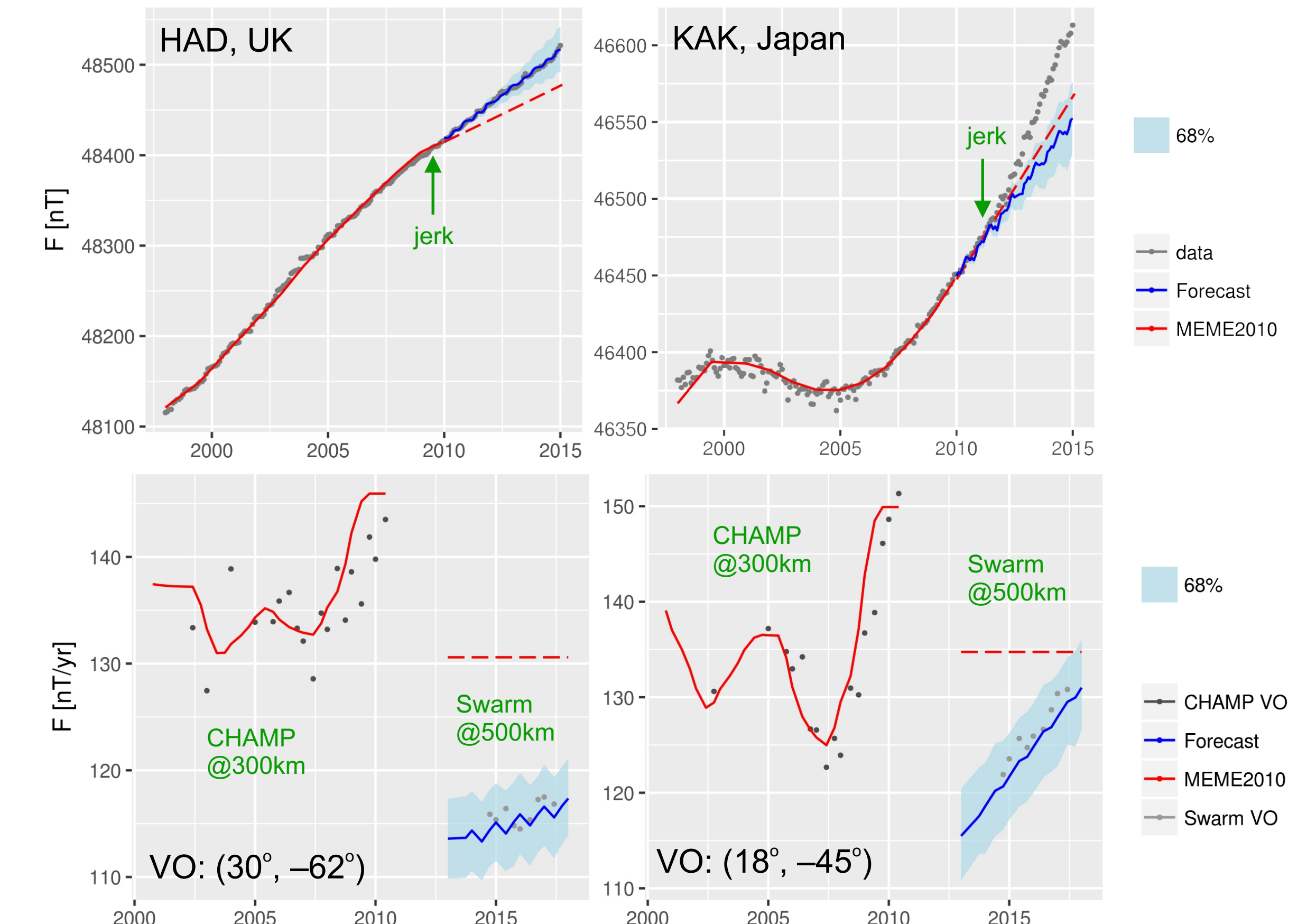
efforts of all of these bodies.

- [1] Whaler & Beggan, 2015, JGR: SE, doi:10.1002/2014JB011697.
- [2] Fournier et al, 2015, EPS, doi:10.1186/s40623-015-0245-x.
- [3] Taylor & Letham, 2017, PeerJ Preprints, doi:10.7287/peerj.preprints.3190v2.
- [4] Manda & Olsen, 2006, GRL, doi:10.1029/2006GL026616.
- [5] Hamilton et al, 2015, doi:10.1186/s40623-015-0227-x.

3. Preliminary results

Two tests have been conducted:

1. Time series modelling of 8 GO MF data from 1999–2010, forecast 2011–2015, and compared to observations and extrapolation of MEME2010.
2. Time series modelling of 30 evenly distributed CHAMP VO SV data, forecast during Swarm era, and compared to Swarm VO and extrapolation of MEME2010. To allow for the differing altitudes of CHAMP and Swarm VO, we use SV data, and perform a crude altitude levelling by removing the mean SV and adding it back to the forecasts.



Above examples of GO and VO data (grey), forecasts (blue), and field model approximations (red). Summary statistics for the time series models and predictions, compared to the MEME2010 field model as show to the right.

Despite no prior knowledge of the physical properties of the data, the time series models can fit GO and VO data to within 3nT RMSE, and are as effective as extrapolating a field model, with fewer model parameters. The forecasts can still easily be thrown by jerks beyond the modelled period, as seen at KAK, but cope better with jerks near model ends, as at HAD.

Obs.	Training RMSE [nT]	% data within 1σ of forecast		Prediction-data RMSE [nT]	
		Prophet	MEME2010	Prophet	MEME2010
ASP	2.1	49	23.6	11.4	
BOU	1.4	0	45.6	34.4	
CLF	1.2	98	1.4	26.2	
HAD	1.5	98	1.8	23.5	
HER	2.6	35	17.3	3.7	
HON	4.8	0	30.4	5.4	
KAK	2.9	28	31.4	23.5	
NGK	1.5	52	8.6	26.5	
Mean	2.3	45	20.0	19.3	
Median	1.8	42	20.5	23.5	
VO		Prophet	MEME2010		
Mean	2.6	30	6.0	6.0	
Median	2.4	20	4.9	4.9	

4. Summary and future work

Time series forecasts can produce results on par with linear extrapolations of field models, with no physical knowledge of the system, but are more responsive to crucial data close to the end of the modelled period. We may be able to refinement our forecasts by adding some prior knowledge of the expected periodic variations to our time series models, and by cleaning the GO and VO data series of contaminating external signal.

The next step is to include forecast GO and VO data and their uncertainties as constraints on a field model inversion, to see if the model ends can be more closely fit to data and thus predictions can better capture future SV.