Assimilation of historical and paleomagnetic data into dynamo models

Sabrina Sanchez & Alexandre Fournier

Institut de Physique du Globe de Paris, France

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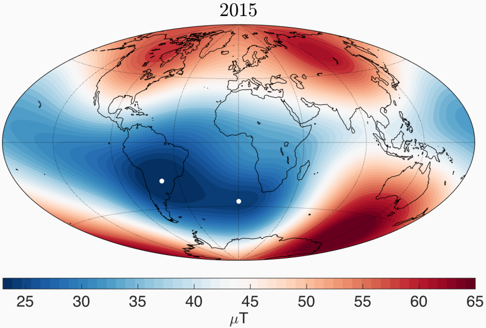
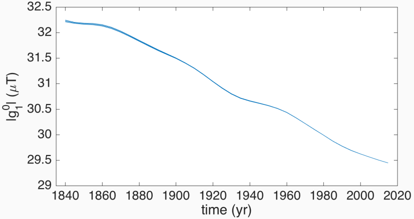
The geomagnetic field

Magnetic field intensity | **B** |
@ Earth's surface
COV-OBS (Gillet et al, 2015)



South Atlantic Anomaly (SAA)

Axial dipole magnitude

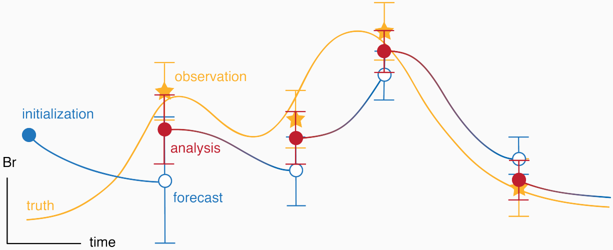


- Combine observations with information about the dynamical system
- 3D dynamo simulations as prior
- Sequential data assimilation

Data assimilation (DA)

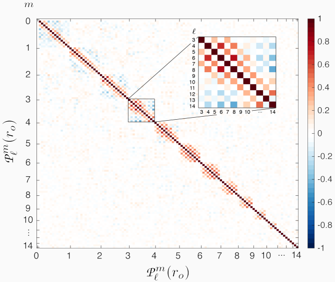
Sequential DA
(Kalman Filter, Kalman, 1960)

- First guess
- Forecast
- Analysis



Ensemble Kalman Filter (EnKF, Evensen et al., 1994)

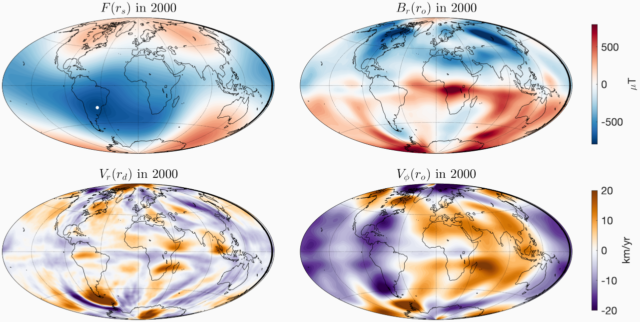
- Ensemble of models $N_e \sim \mathcal{O}(10^2)$
- Sample covariance as a proxy for true model covariance
- Covariance localization - mitigation of spurious correlations



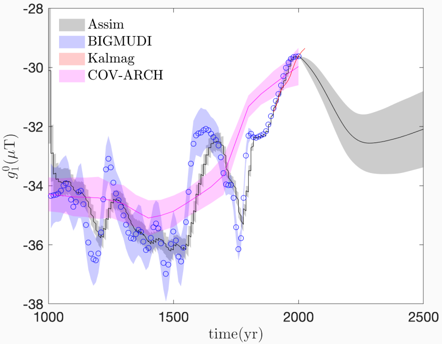
Reanalysis based on BIGMUDI

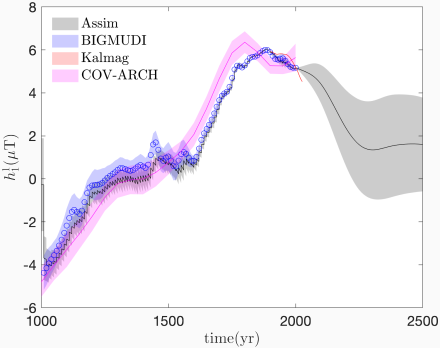
Reconstruction of core state based on the assimilation of BIGMUDI (Arneitz et al. 2019)

- Time window: 0 AD - 2000 AD
- $L = 8$, $\Delta t = 10$ yr, $N_e \approx 200$



Predictions based on BIGMUDI

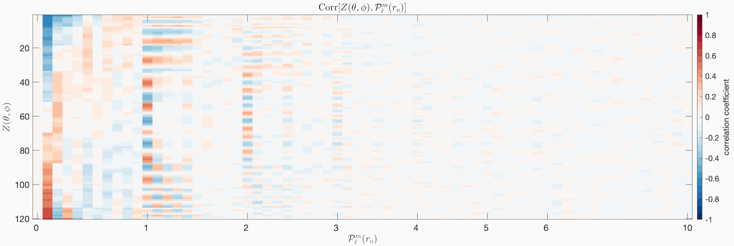




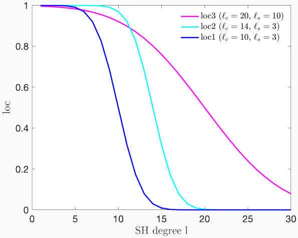
- Prediction sensitivity to background dynamo models (ongoing)
- Considerable differences with respect to other field models (possible observation unmodelled errors)
- Assimilation of point-wise paleomagnetic and historical data: sequential approach allows for very heterogeneous data distribution

Point-wise GDA

Spectral-grid covariance localization, with $\mathbf{C}(\ell) \sim erf(\frac{\ell - \ell_c}{\ell_s})$



- Works well in synthetic framework, but GDA with real point-wise data is unstable



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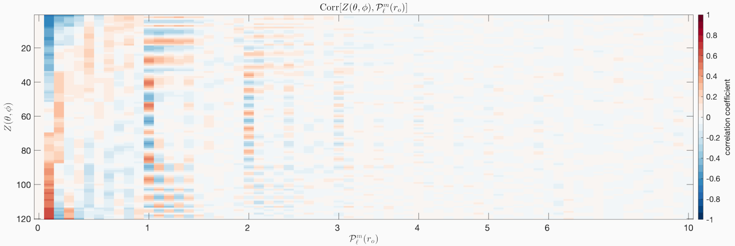
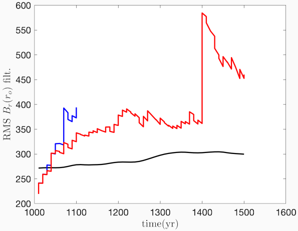
Spectral-grid covariance localization, with $\mathbf{C}(\ell) \sim erf(\frac{\ell-\ell_c}{\ell_s})$



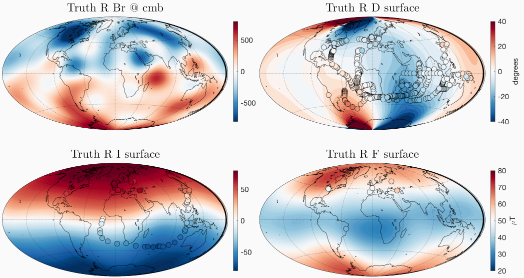
- Works well in synthetic framework, but GDA with real point-wise data is unstable
- Inconsistencies in the dataset (outliers and wrong uncertainties)

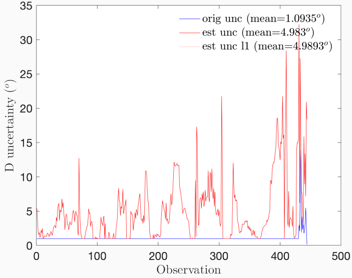


Point-wise GDA

Historical + paleomagnetic data from HISTMAG (Arneitz et al. 2017) and Geomagia (Brown et al., 2015)

- Historical data usually not provided with uncertainties
- Paleomagnetic data with questionable uncertainties
- Snapshot tests of only B_r @ CMB with dynamo prior (example for 1700 AD)
- Co-estimation of observation uncertainties $\epsilon^f \approx \sigma^f + \sigma^o$





Summary

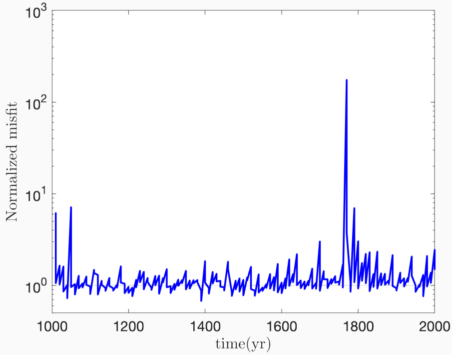
- Assimilation of geomagnetic field models have the potential to provide reconstructions of hidden core dynamics
- Reconstruction and prediction depend on background model; assess impact of model setup and track systematic model errors
- Paleomagnetic field models also bear important errors; attempt at assimilating point-wise observations
- Assimilation of point-wise data work well in synthetic framework, but fail with real data, due to inconsistencies within the dataset
- Spectral-spatial covariance localization mitigates, but does not solve the problem
- Forecast errors statistics to correct underestimated observation uncertainties and infer non-provided uncertainties (most historical data)

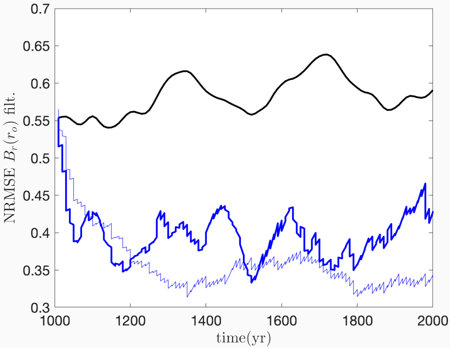
Thank you!

Questions?

Impact of age uncertainties

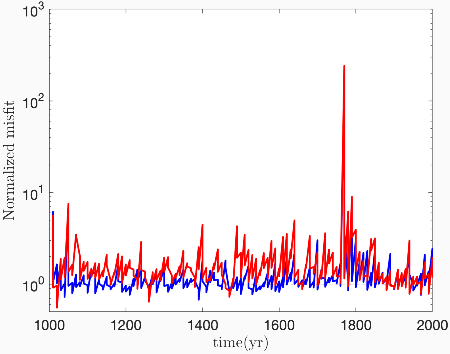
- Synthetic data base mimicking paleo + historical data: only data with assigned measurements and age uncertainties

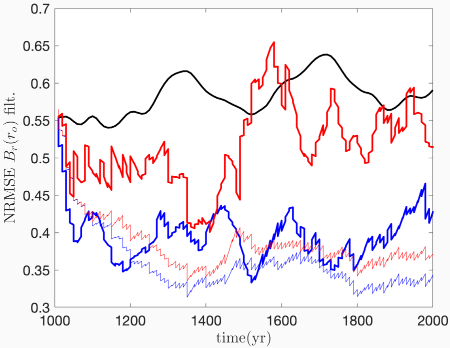




Impact of age uncertainties

- Synthetic data base mimicking paleo + historical data: only data with assigned measurements and age uncertainties
- Random sampling of age based on age uncertainties





Impact of age uncertainties

- Synthetic data base mimicking paleo + historical data: only data with assigned measurements and age uncertainties
- Random sampling of age based on age uncertainties
- Uncertainty propagation: $\sigma_T^2 = \sigma_o^2 + (\delta \mathbf{y}_o/\delta t)^2 \sigma_a^2$