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Simple Geomagnetic Field Model Forecast Assessments: Autoregressive Methods and Machine Learning

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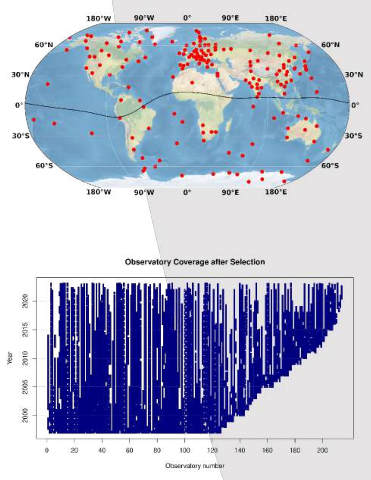
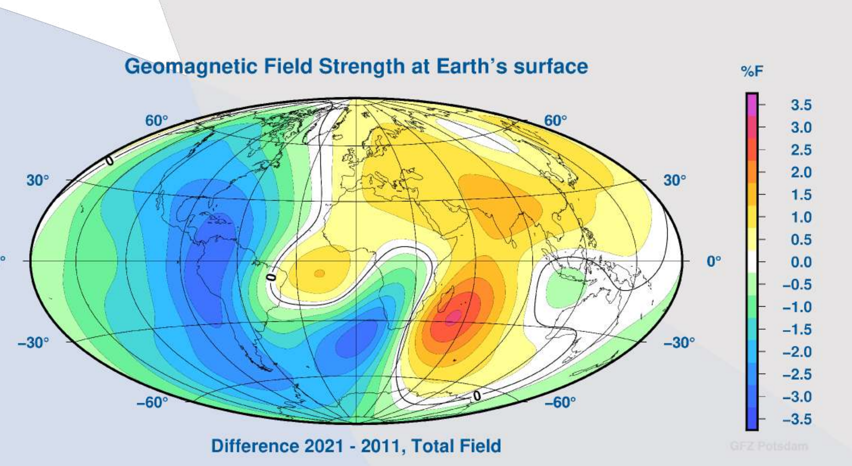
Mag.num

`Mag.num` is the magnetic *core* field model of the GFZ geomagnetism group, in particular using most recent satellite data (i.e. Swarm) and in combination with other satellite data, in particular from CHAMP, but also from less accurate calibrated platform magnetometer data. Also essential are ground observatory data, aiming to stabilize the behaviour in time, even though the global distribution is highly asymmetrical.



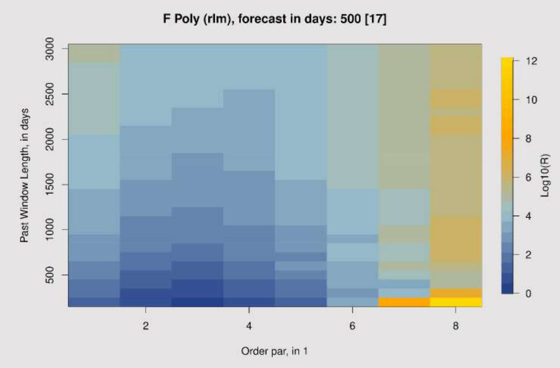
Distribution of Intermagnet observatories (top), and distribution in time after `Mag.num` selection applied (bottom) – observatories ordered by appearance in data set.

The `Mag.num` classic modelling scheme (substantial heritage from Vincent Lesur's `GRIMM` approach) will be used as *parent* model for GFZ's candidate model for the IGRF (International Geomagnetic Reference Field, a collaborative effort of groups worldwide to create a good quality geomagnetic reference model). The mapped evolution in time (example right) is a window into the Earth and needs to be forecasted for the next IGRF.

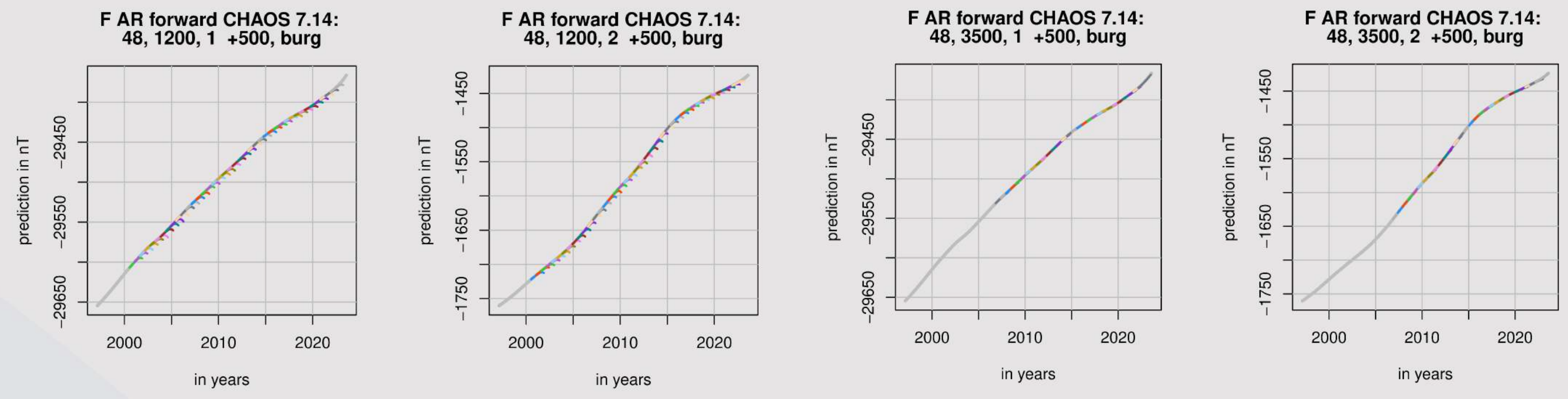


Modeling: Forecast

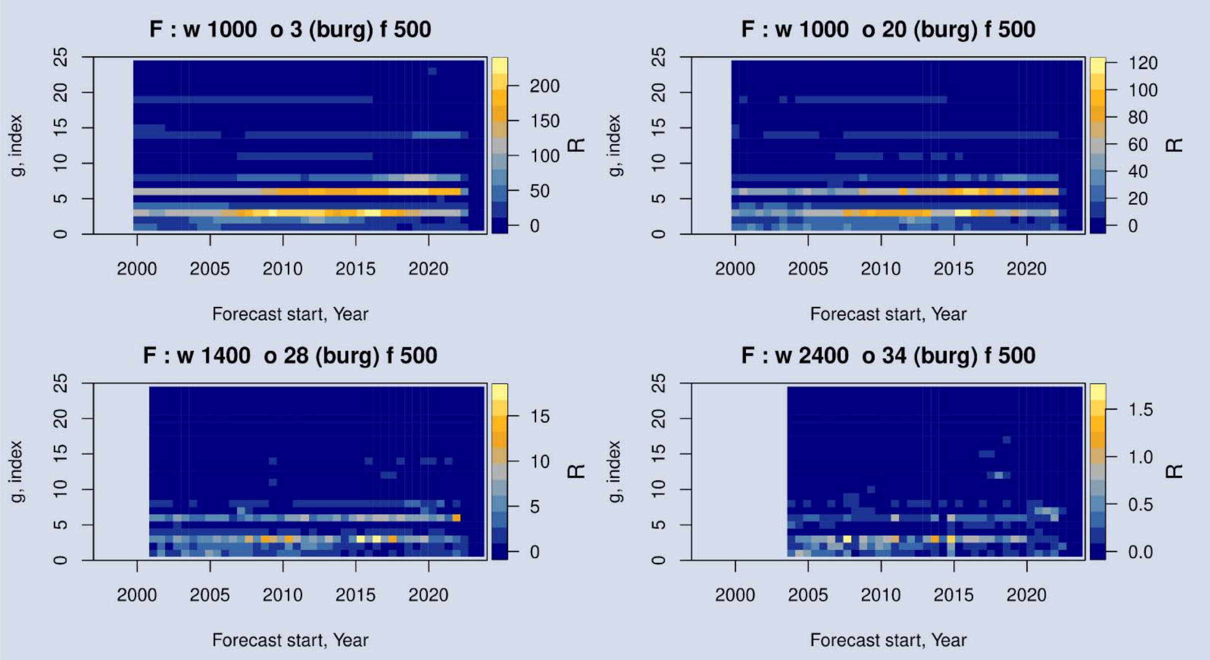
Just simply fitting polynomials to past windows for forecasting seems usable in general only for small time windows and low degree. Figure right: The overall quadratic sum *R* as a simple metric on moving windows forecasts allows to show summarized dependencies on internal parameters applied.



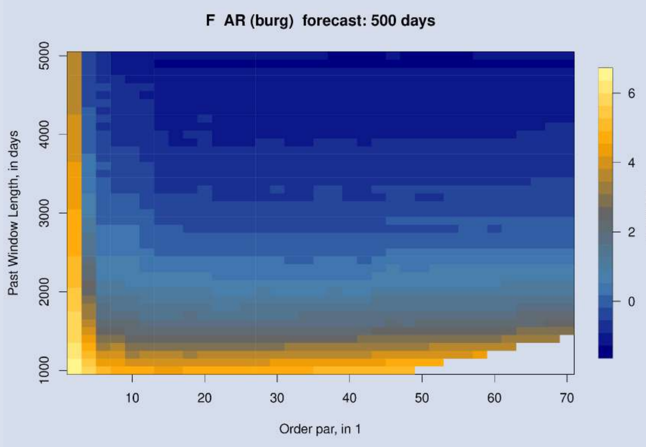
With standard AR forecast methods (using script language R, package *forecast* and *Burg* algorithm) we can check the forecasted residuals for moving windows on the smooth model coefficients (here: and `Mag.num` CHAOS-7) time series. Figure below: On AR, for the first two coefficient time series see a fit improvement with increased length of input time window.



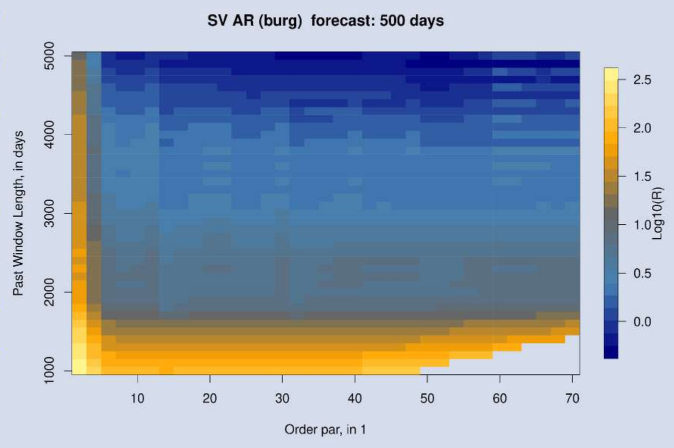
Modeling: Forecast



Color coded total error for AR algorithm burg over time for fix data window length and burg method degree. Even for this overall smooth signals, the performances still depends on coefficient index and epoch of the moving window.

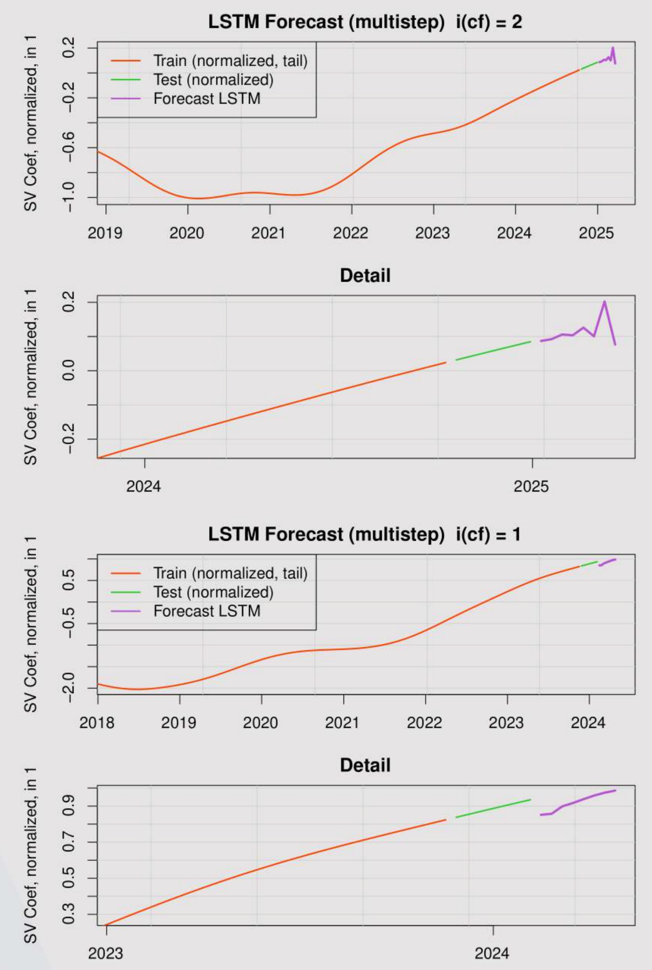


Sum over all total errors for AR all moving window attempts, for parameters window length and burg method complexity (degree)); right figure for SV.



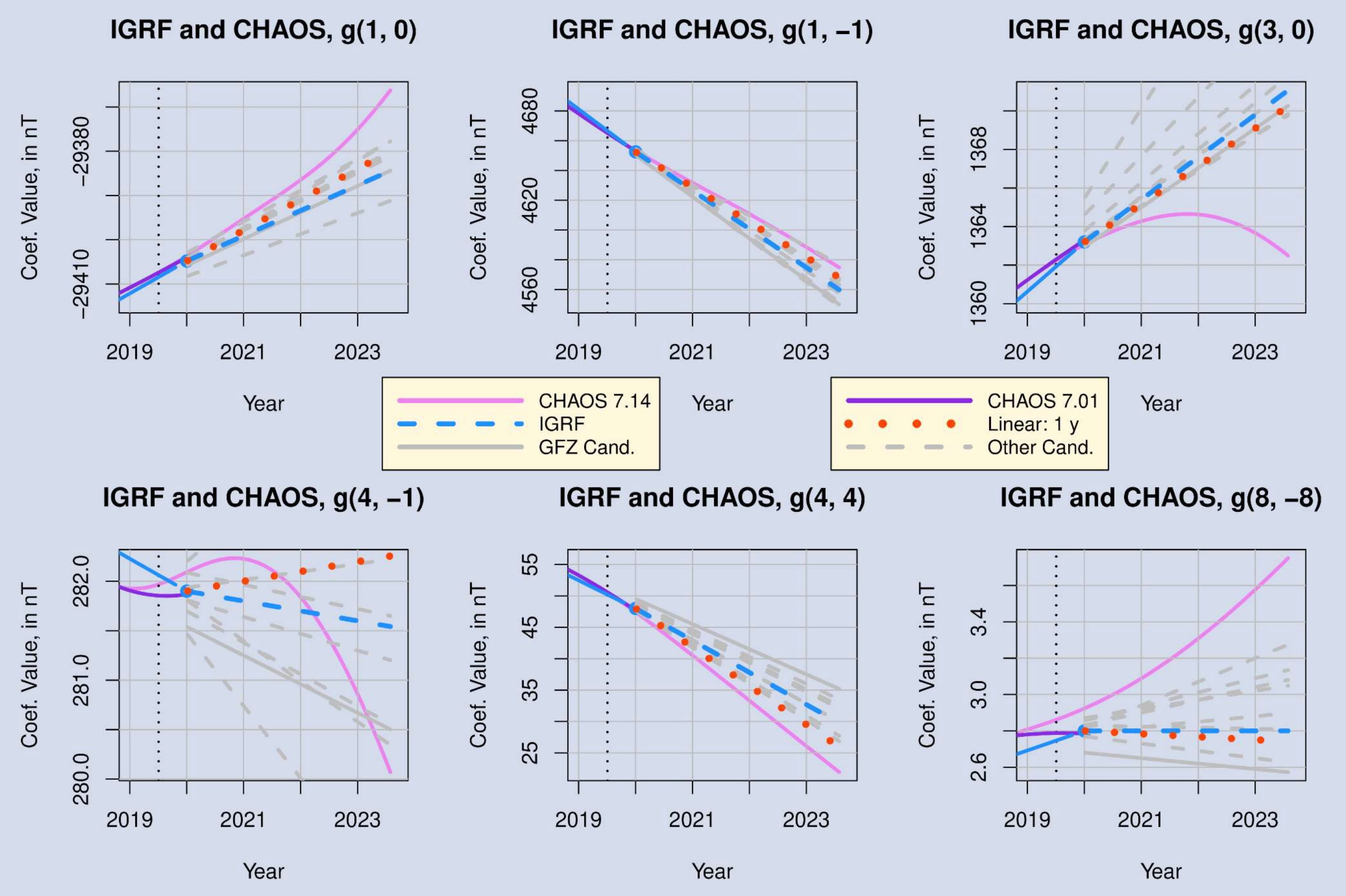
ML/Deep Learning

- To be able to extend the information used later (i.e. by the usual time series of indices and other data and information sources), we apply *Deep Learning* methods on this forecast problem. From the suggested methods suitable for time series, *Recurrent Neural Network* (`RNN`), *Long Short-term Memory* (`LSTM`), *Gated Recurrent Units* (`GRU`), and *Transformer Networks, we choose, for now, the popular and recommended* `LSTM` *approach. For this first approach we are using* `TensorFlow` *with the* `Keras API` *inside the* R *language.*
- *Currently there are no results for direct comparison with the summaries of the classic AR method, yet. For now, at least for the simplistic input sets used (F and SV time series from* `Mag.num` *and* CHAOS*), that occasional arcane numerical instabilities preventing a comprehensive review yet.*



Example (`LSTM` *forecast, on* full *coeff. time series only) for index two of the SV (upper two frames) and an example (CHAOS, index one) with a bias misfit – or numerical instability (lower two frames).*

IGRF-13... a view back



For some candidates we can now, 2023, compare the 2020 predictions with a most recent CHAOS-7 model version (for a very few coefficients, see upper frames).

The modeled recent development is rarely covered even by the significant scattering of the candidate models. The table summarizes the total integral residual error of some models, compared with the most recent model.

But a year-spanning forecast based on auto-regression (and subsequently just extrapolated), applied on the related pre-2020 model shows an improvement of the forecast.

2020.016 – 2023.576	*Years*
< 2019.507	
Other Candidates	Σ *R*
Potsdam/MaxPlanck	711
DTU	1096
ISTerre	1139
IPGP	1214
BGS	1659
NCEI	1893
GFZ	2938
NASA/GSFC	4060
IGRF final	995
Forecast on CHAOS 7.14	301
Forecast on CHAOS 7.01	1200

Summary

- `Mag.num` will be the parent model for the GFZ geomagnetism group candidates to be submitted for the next `IGRF` model. The SV seems to be the most critical product part.
- `AR` forecast seems suitable probably until *one year* forecast period. The applicability for a `IGRF SV` candidate is under testing.
- *Deep learning* seems to be a good candidate to be used in forecasting as well. It is open for embedding other sources of information.

References

Shi, J.; Jain, M. and Narasimhan, G. (2022); *Time Series Forecasting Using Various Deep Learning Models*, International Journal of Computer and Systems Engineering, Engineering and Technology, 16, 224-232.

Next steps

Further exploring machine learning/deep learning methods and available front-ends for forecasting of appropriate time periods to finally apply on estimating an `IGRF SV` candidate from own parent model.

Understanding and evaluate current spurious numerical side effects before going further.

Applied first simply on coefficient time series, but going to include also applicable indices and other suitable data sources as well.

Evaluate the available information about the significance of the input sources.