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Predicting Seasonal Oscillations in Daily GNSS Displacement Time Series from Geophysical Fluid Loading Data using Machine Learning

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Introduction

- Seasonal oscillations in GNSS time series are a significant source of noise for interpreting tectonic signals and are challenging to remove using established methods - e.g. classic regression models - especially with regards to (interannually) varying seasonals **[1]**.
- Non-tidal fluid loading was identified as a main cause of seasonality in tectonic geodesy, but the exact interactions are still unknown **[1]**.
- We use machine learning to analyse the predictive capabilities of non-tidal fluid loading on the seasonal noise and provide insights on their complex relationship.

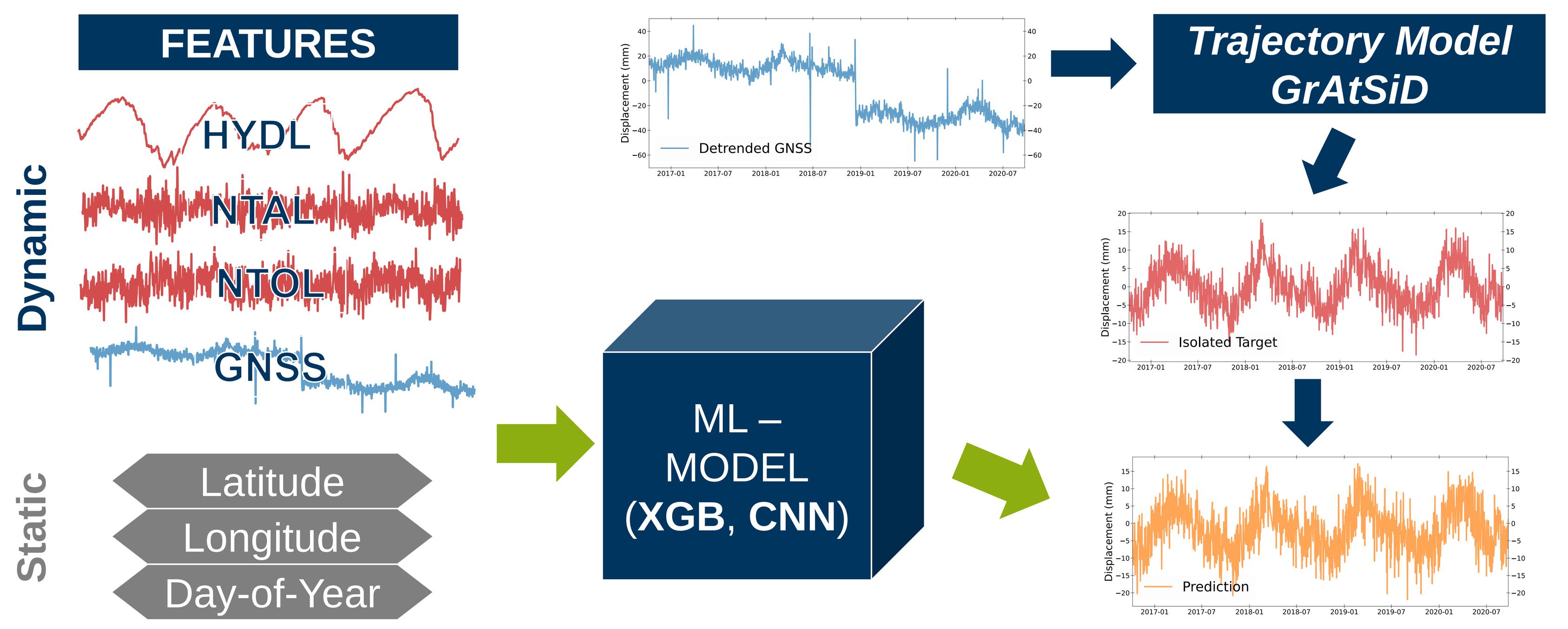

Fig.2 Algorithm to obtain ML predictions from the shown features and the target isolated from trajectory modelling

Methods

- 134 daily, vertical (PPP-) time series in South America from NGL **[2]** with at least 4 years of data from 2010 – 2022
- ***GrAtSiD*** trajectory model to isolate seasonal and residual non-tectonic signal **[3]** as the learning target
- **Time-windowed input features**:
  - Waveforms of ***ESMGFZ*** surface loading products at the respective station **[4]**
  - Detrended GNSS at respective station
- **Auxiliary inputs for stabilization**:
  Trigonometric encodings of latitude, longitude and day-of-year

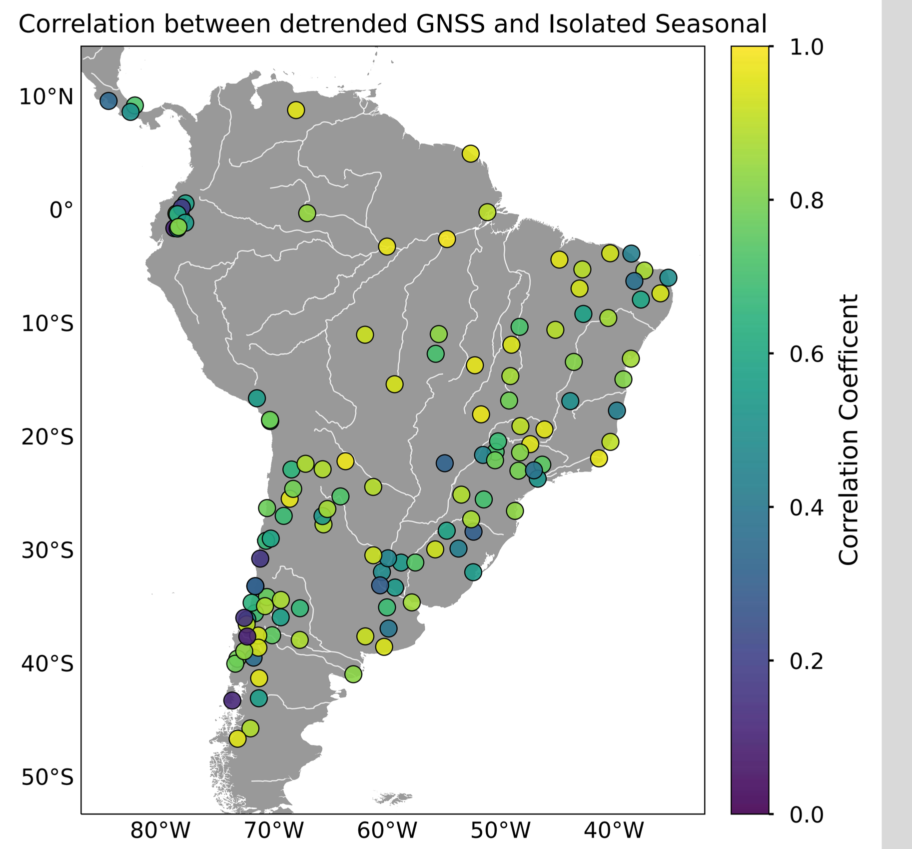

Fig.1 *Map showing the 134 stations in South America and the corelation coefficient of the GNSS signal at these stations with the isolated seasonal target signal*

- Temporal data set split into training before 2018 and test after 2018 to avoid temporal leakage between training and evaluation stages
- We use two machine learning models to demonstrate their potential in predicting the non-tectonic signals in GNSS time series:
  - **XGB:** Gradient Boosted Regression Trees **[5]** **→ time window 7 days into past**
  - **CNN:** Convolutional Neural Network **→ time window 14 days into past**

Prediction Results

- Machine learning models generally fit the target closer than the sum of ESMGFZ loading products
- Removing the machine learning predictions from the GNSS signal surpasses the reduction of seasonals compared to the sum of loading products
- CNN and XGB also significantly reduces the high-frequency scatter in the original GNSS time series

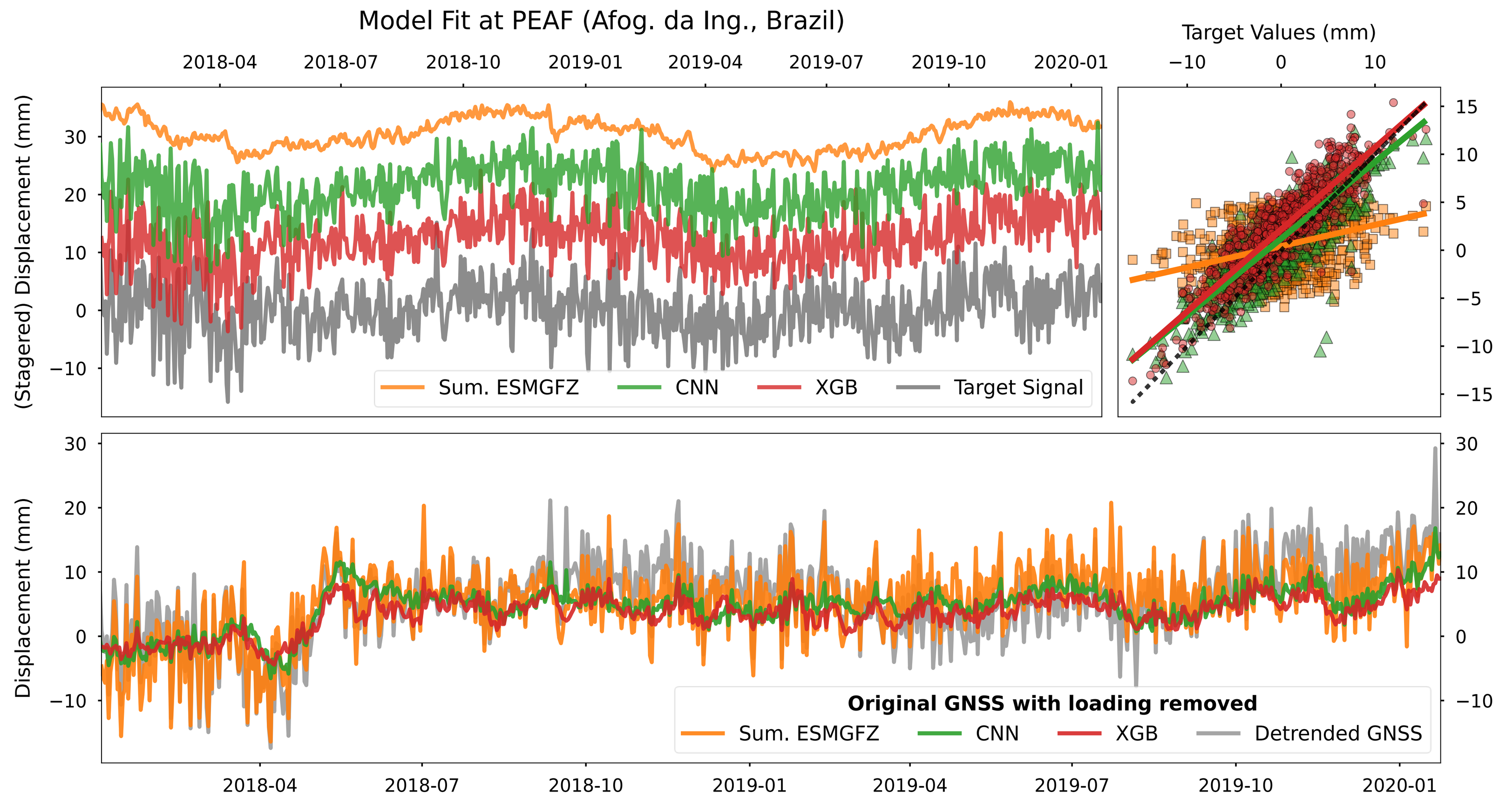

Fig.3 *(top left) Target and predictions from the respective models. (top right) cross-plot showing fit quality from the three models. (bottom) Original GNSS and GNSS with predictions from the three models removed.*

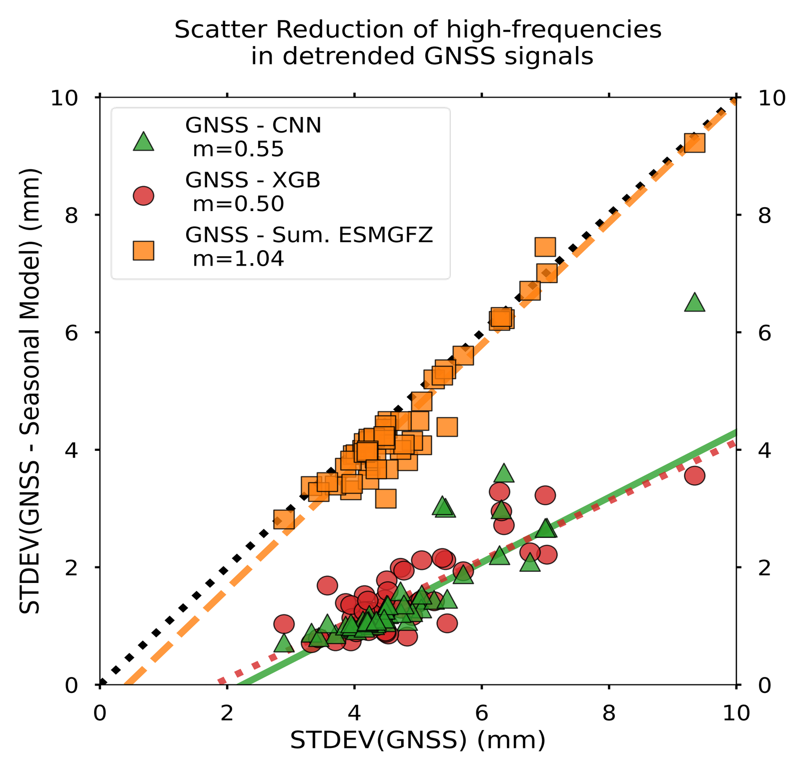

Fig.5 *Standard deviation of GNSS against the standard deviation of the loading removed GNSS for all test stations. Both signals are high-pass filtered at 10 cpy*

- Example station PEAF shows good performance even in the presence of steps
- Amplitude spectra show all models retrieving the annual signal but the best reduction is achieved with XGB and CNN,
- CNN and XGB also fit well to the higher-frequencies while the ESMGFZ loading falls off considerably after 10 cpy

- We high-pass filter the GNSS and predicted signals of all test stations at 10 cpy to investigate the behaviour at high-frequencies
- Comparing the standard deviation of the filtered original GNSS with predictions from CNN, XGB, and ESMGFZ removed shows that ESMGFZ has little effect on high-frequency scatter, while XGB predictions significantly reduce scattered noise.

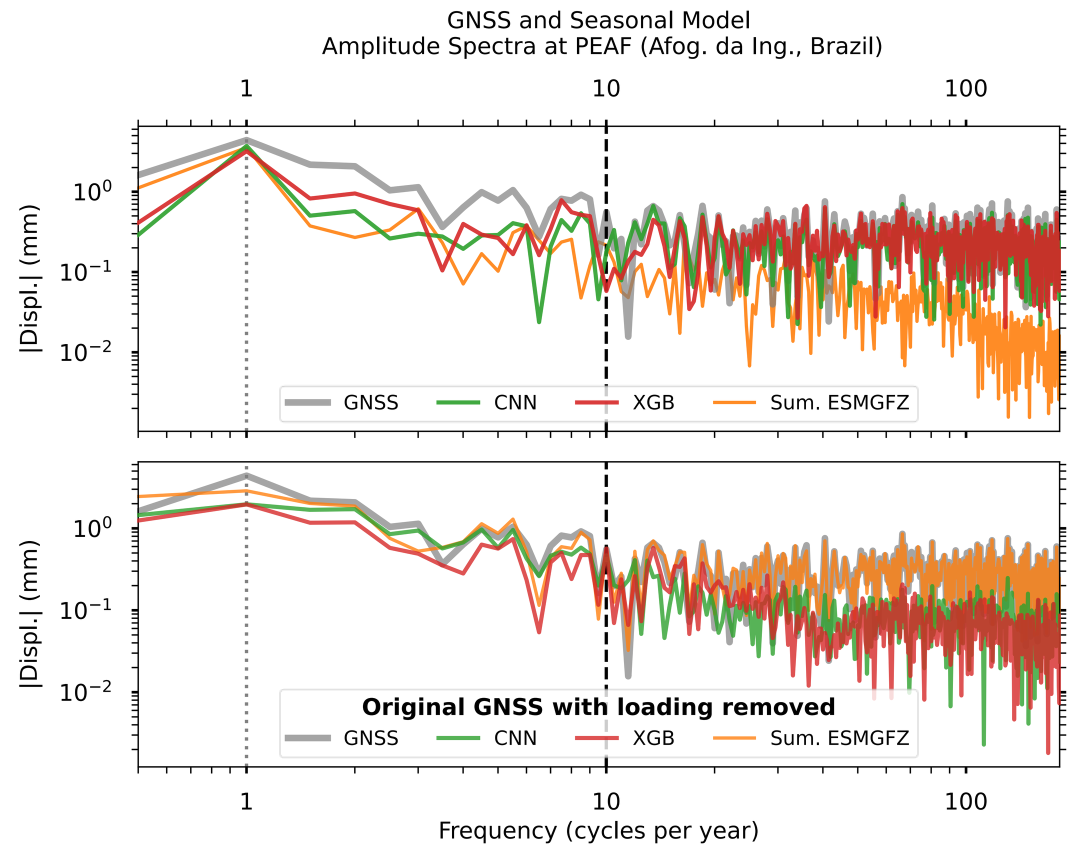

Fig.4 *(top) Amplitude spectra of the GNSS signal and the three model predictions. (bottom) Spectra of the GNSS and GNSS with predictions from the three models removed.*

Discussion & Outlook

- Machine learning predictions provide improved removal of the seasonal signal compared to simple subtraction of the ESMGFZ loading products
- Using the GNSS signal as an input feature helps to improve fits
  - ► Hints towards a complex relation between surface loading and ground displacement
  - ► Surface loading alone might not be able to explain the seasonal while the GNSS signal contains additional, seemingly important information that were not isolated by our trajectory model
  - ► High correlation between GNSS and target could bias the prediction through information leakage in case of loading dominated stations
- Interpretable XGB reveals non-tidal atmospheric loading as very important feature which might be partially related to high-frequency scatter in the GNSS
- For future development: ► Try with global data set (transfer learning) and more data
  ► Interpretability of DNN (e.g. Temporal Fusion Transformer **[6]**)

Digital Poster Version & Further Information

Get *GrAtSiD* Trajectory Model on GitHub

Get *ESMGFZ* Loading Products

References

[1] **Männel, B., et. al (2019).** Correcting surface loading at the observation level: impact on global GNSS and VLBI station networks. *Journal of Geodesy, 93*(10), 2003-2017.

[2] **Blewitt, G., et. al (2018).** Harnessing the GPS data explosion for interdisciplinary science, *Eos*, 99

[3] **Bedford, J., & Bevis, M. (2018).** Greedy automatic signal decomposition and its application to daily GPS time series. *Journal of Geophysical Research: Solid Earth*,123, 6992–7003.

[4] **Dill, R., & Dobslaw,H. (2013).** Numerical simulations of global-scale high-resolution hydrological crustal deformations. *Journal of Geophysical Research: Solid Earth*, 118, 5008-5017.

[5] **Chen, T., & Guestrin, C. (2016).** XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785-794).

[6] **Lim, B. et. al (2021).** Temporal fusion transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting*, 37(4), 1748-1764.

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