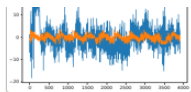
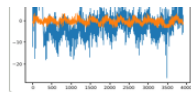


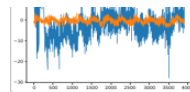
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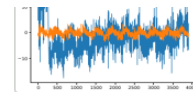
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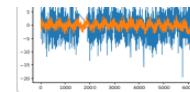
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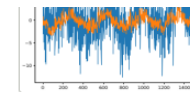
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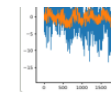
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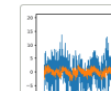
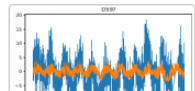
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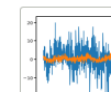
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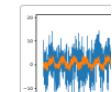
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Modeling of Residual GNSS Station Motions through Meteorological Data in a Machine Learning Approach

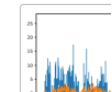
Pia Ruttner, Roland Hohensinn, Stefano D'Aronco , Jan Dirk Wegner and Benedikt Soja
EGU General Assembly
27.05.2022



KIRN_t



MAR3_t



OSTE_t

MOXA_test.pdf

MRON_test.pdf

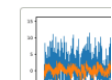
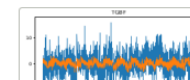
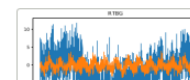
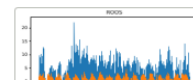
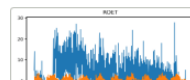
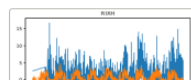
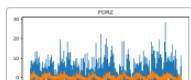
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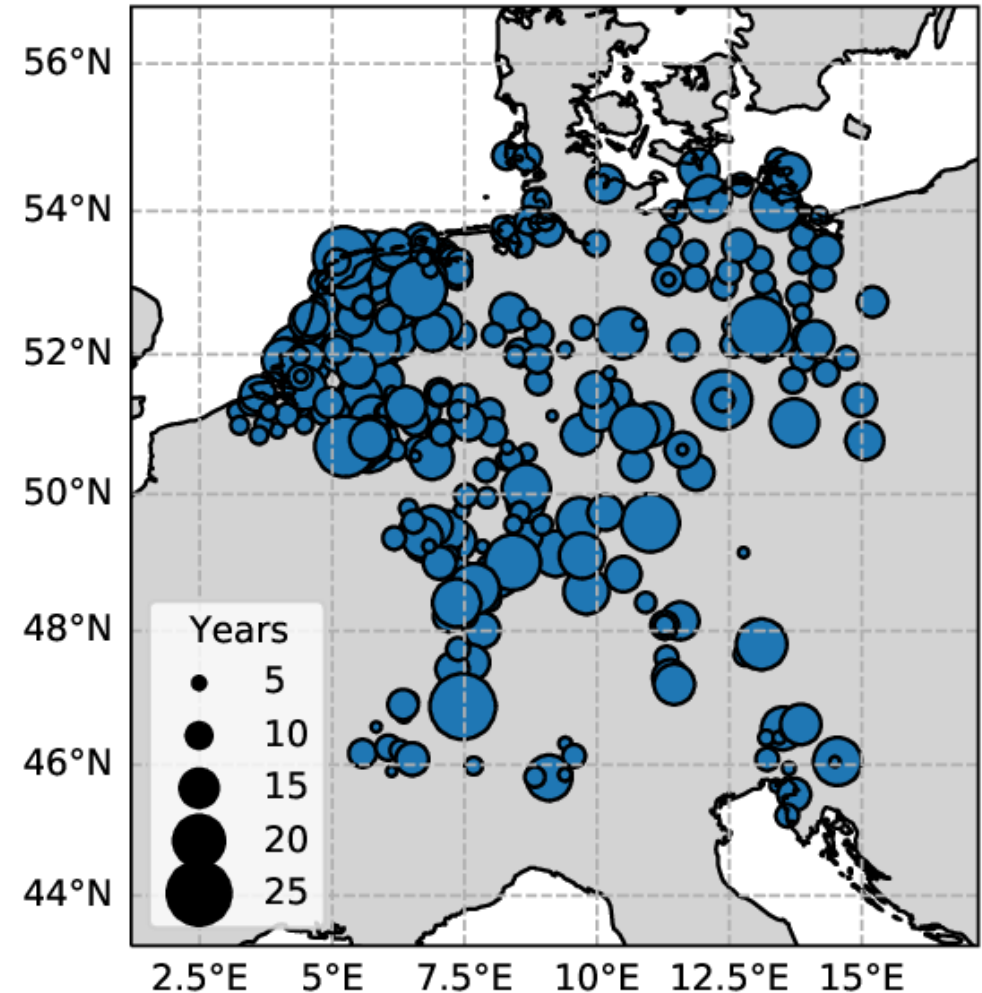


Motivation & Objective

- Long-term GNSS observations
- Signals related to environmental influences
- Improve RMS of GNSS height residual time series by taking into account:
 - Environmental Loading Data (physical models)
 - Meteorological Data (Machine Learning approach)

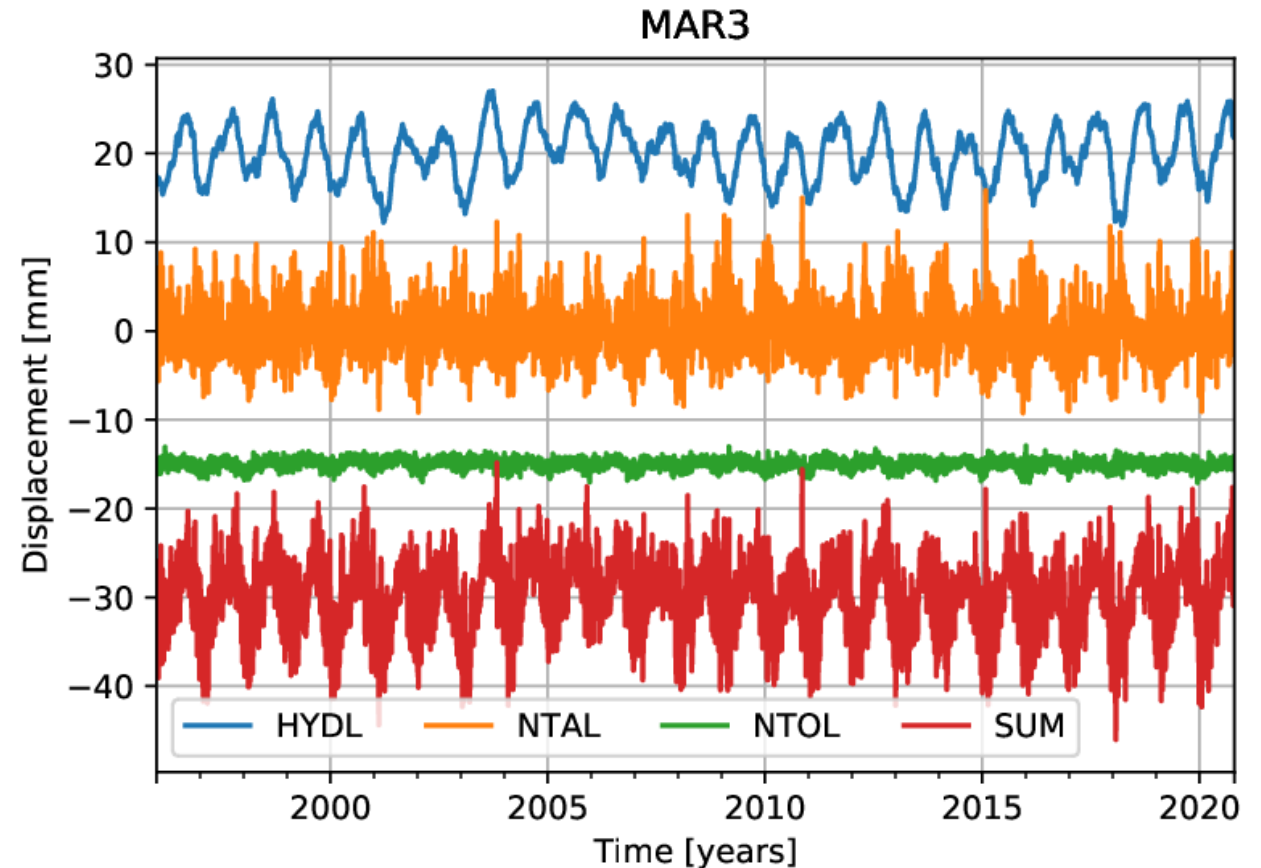
GNSS Data - NEVADA

- Nevada Geodetic Laboratory
- Sampling: 24h
- Data Range: 01.01.1994 - 31.10.2020
- Preprocessing:
 - Remove Jumps, Outliers, linear Trend
 - min. 3.5 Years
 - max. 20% missing Data

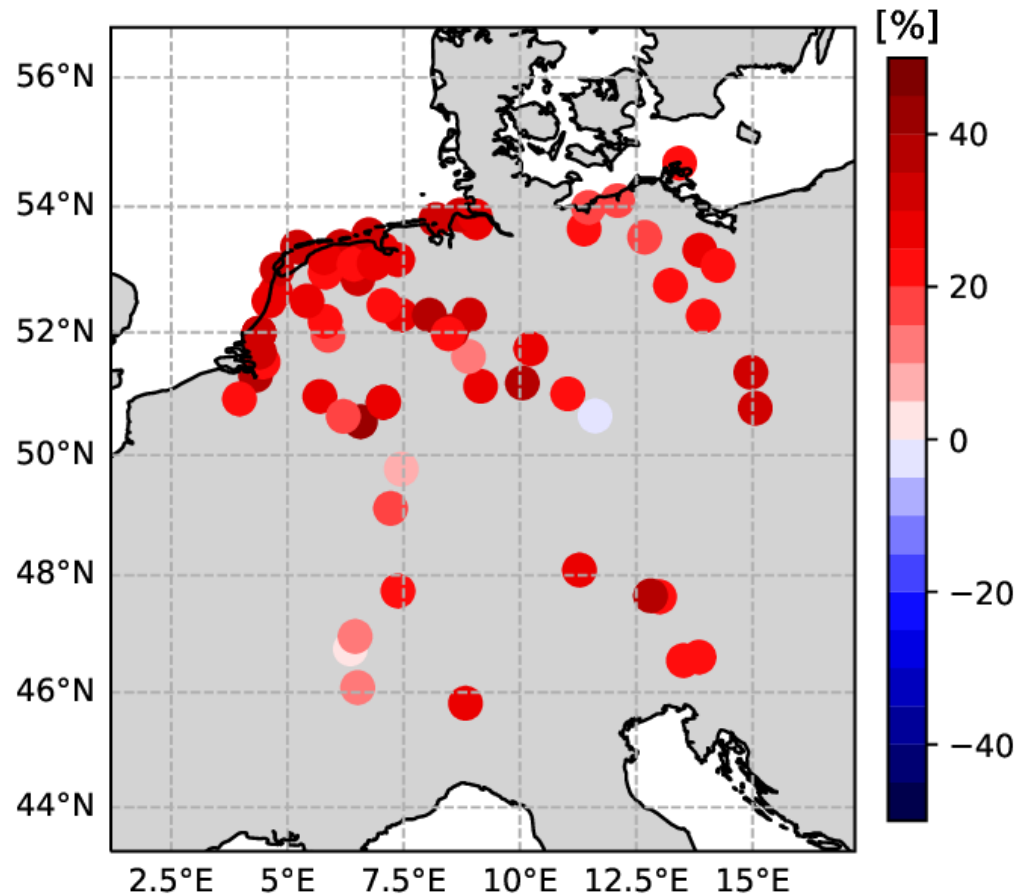


Environmental Loading Data - GFZ

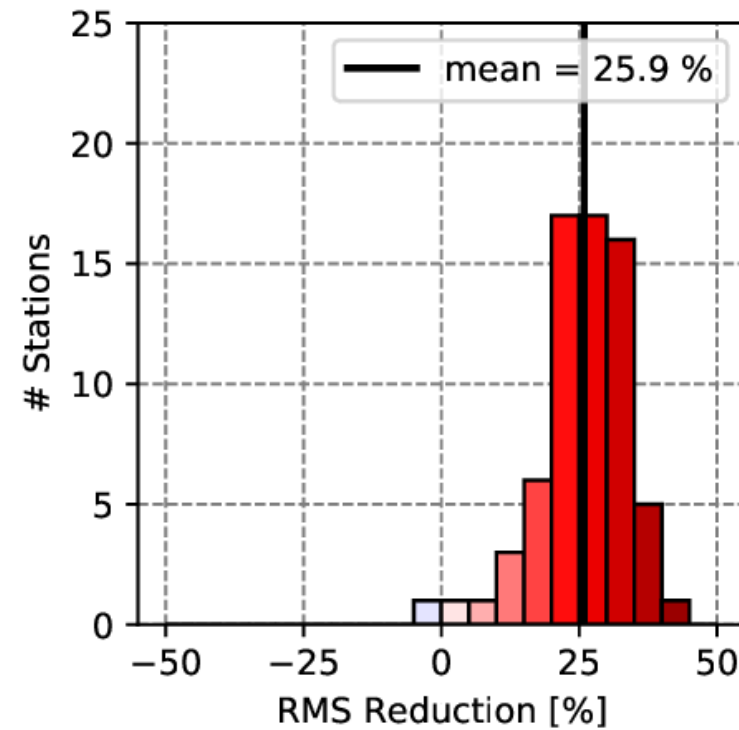
- German Research Center for Geosciences
- Sampling: 24h / 3h
- $0.5^\circ \times 0.5^\circ$ regular grid
- Data Range: 01.01.1996 – 19.10.2020
- Preprocessing:
 - Downsampling
 - Bilinear Interpolation



RMS Reduction Environmental Loadings

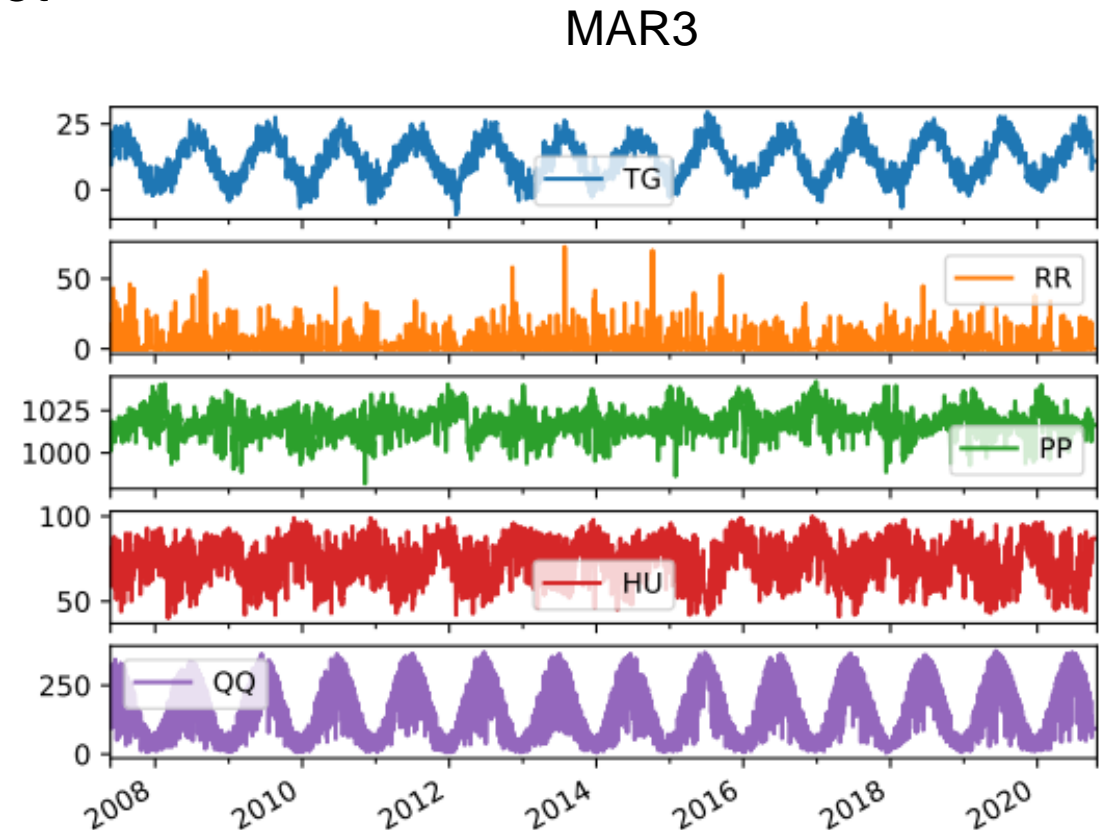


$$RMS\ Reduction = \left(1 - \frac{RMS(GNSS - Loading)}{RMS(GNSS)} \right)$$



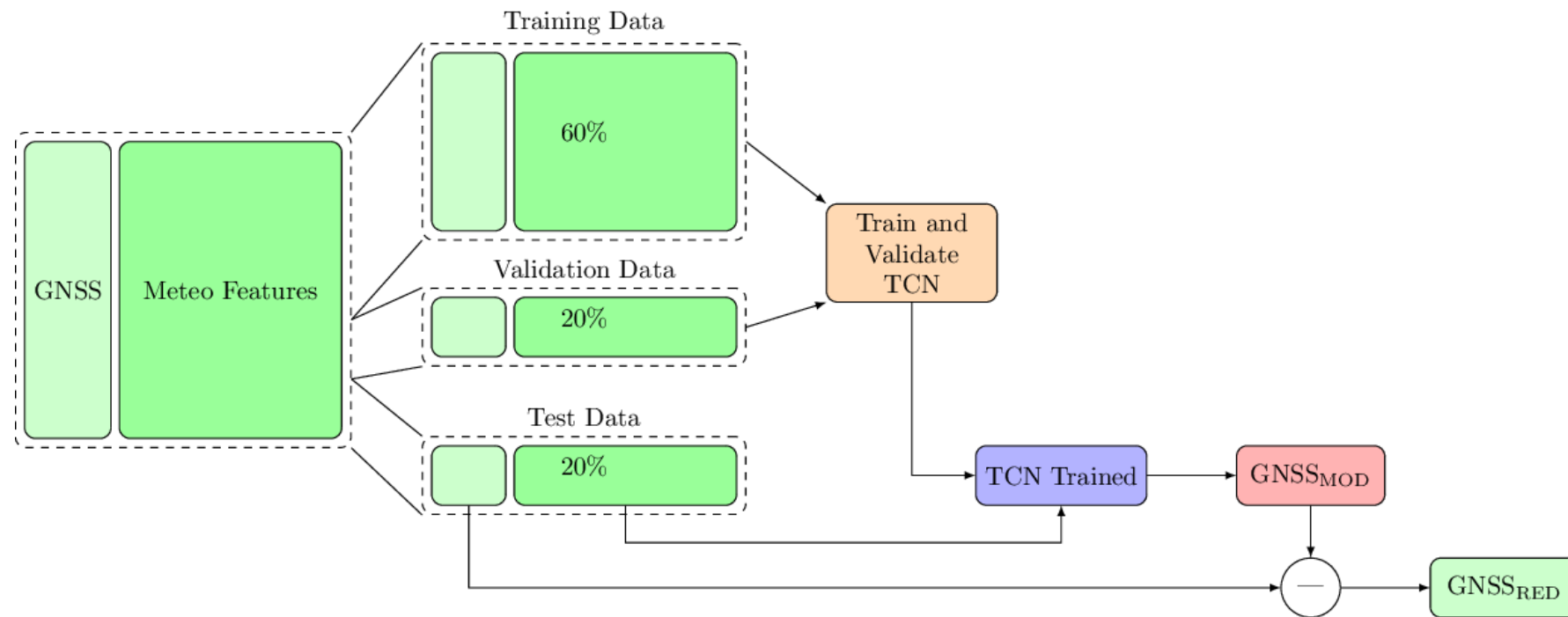
Meteorological Data - ECAD

- European Climate Assessment and Dataset
 - Mean Temperature [$^{\circ}\text{C}$] (TG)
 - Precipitation [mm] (RR)
 - Sea Level Pressure [hPa] (PP)
 - Humidity [%] (HU)
 - Radiation [W/m^2] (QQ)
- Sampling: 24h
- Data Range: 01.01.1994 - 31.10.2020



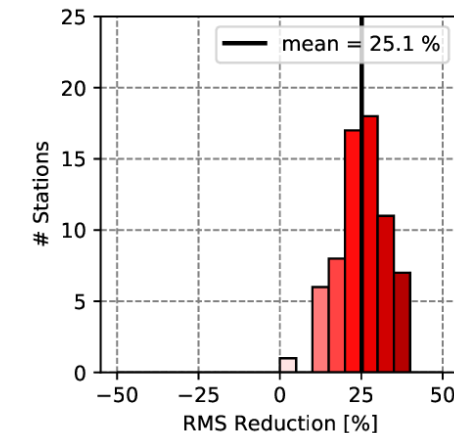
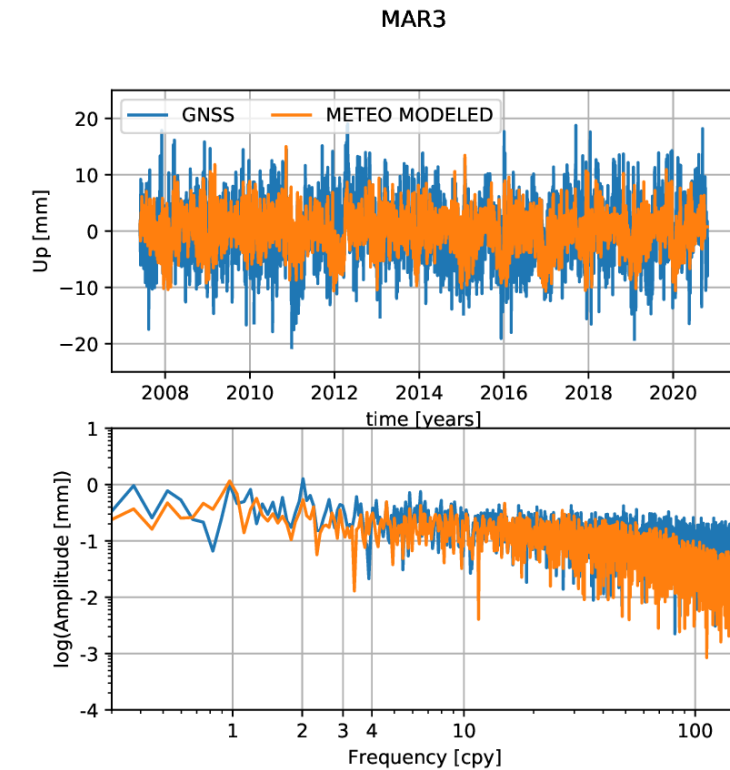
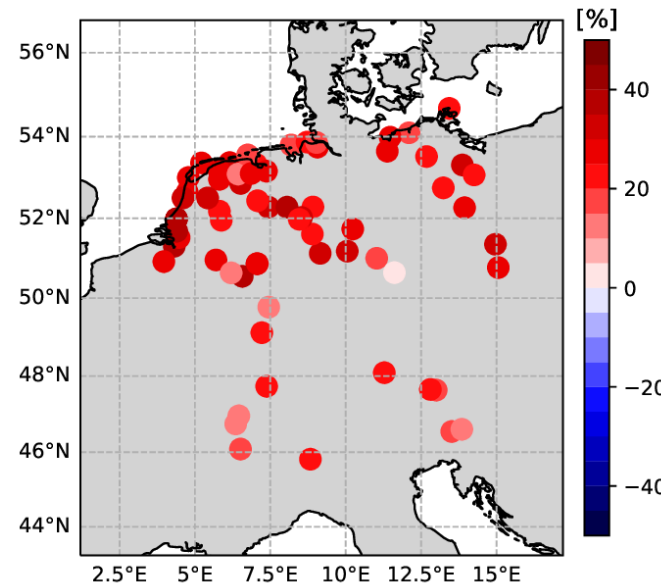
TCN training pipeline

- Temporal Convolutional Neural Network
- Model GNSS height residual time series with raw meteorological data as input features



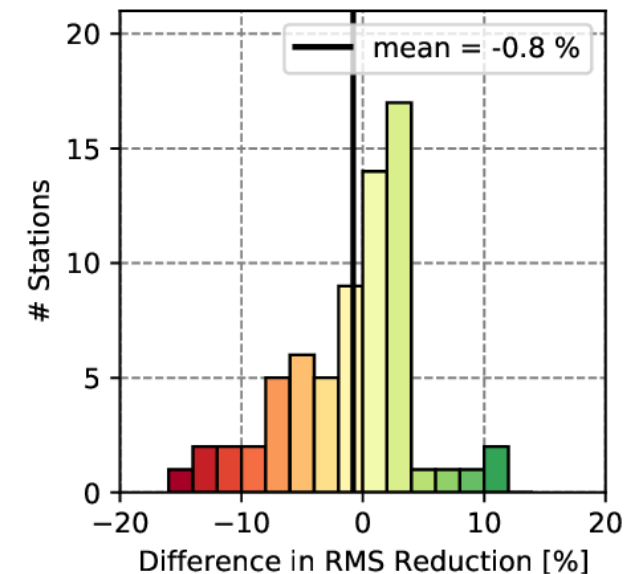
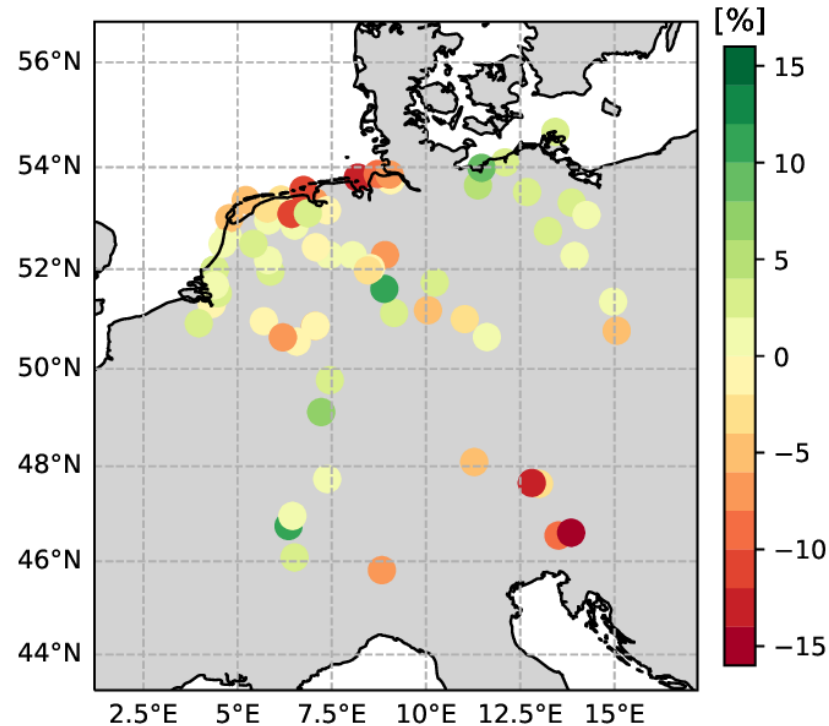
RMS Reduction TCN

- TCN trained on original GNSS height residual time series
- Result on similar level as reduction through environmental loading data
 - TCN is able to reconstruct physical models



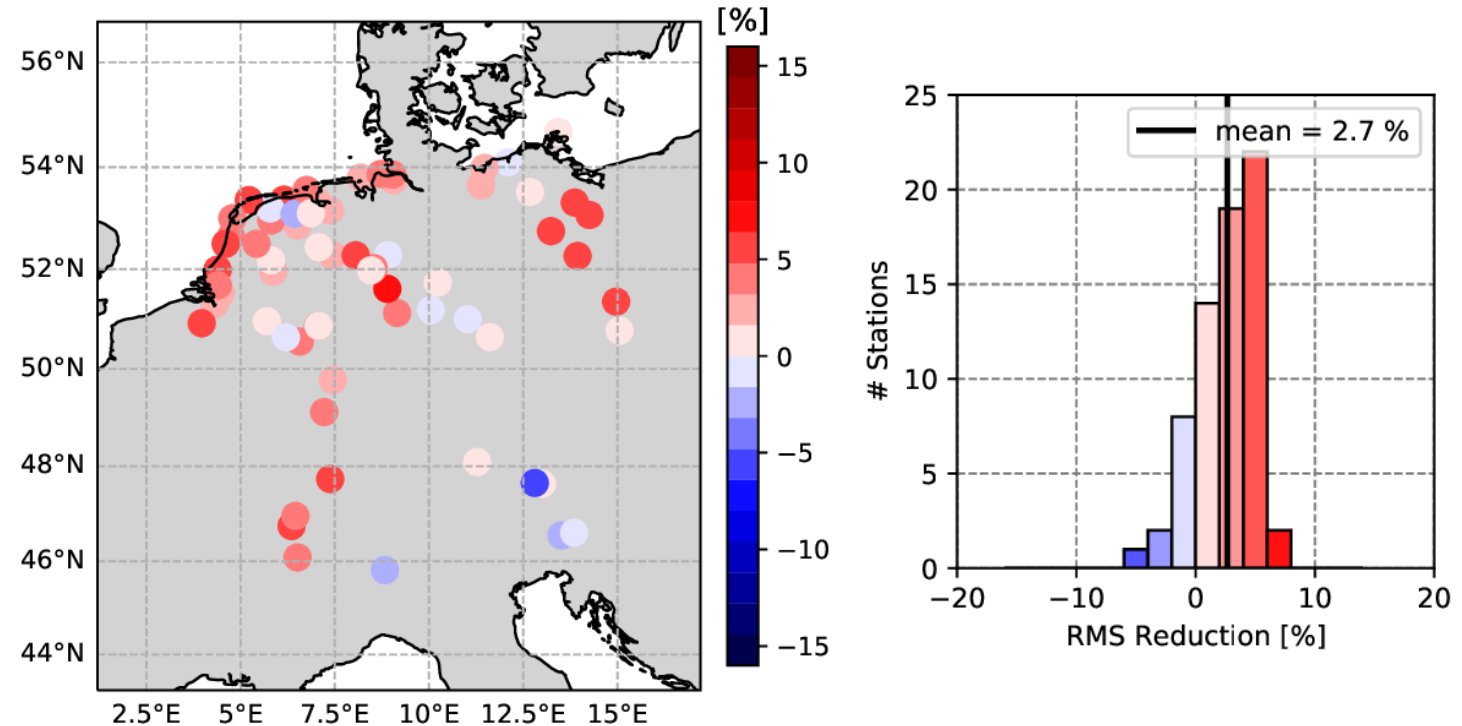
Difference in achieved RMS reductions

- RMS reduction rate using TCN modeled signal minus RMS reduction rate using environmental loadings
- Positive difference → TCN performed better
- Mean: slightly lower when using TCN modeled signal
- More stations with positive reduction rate when using TCN modeled signal



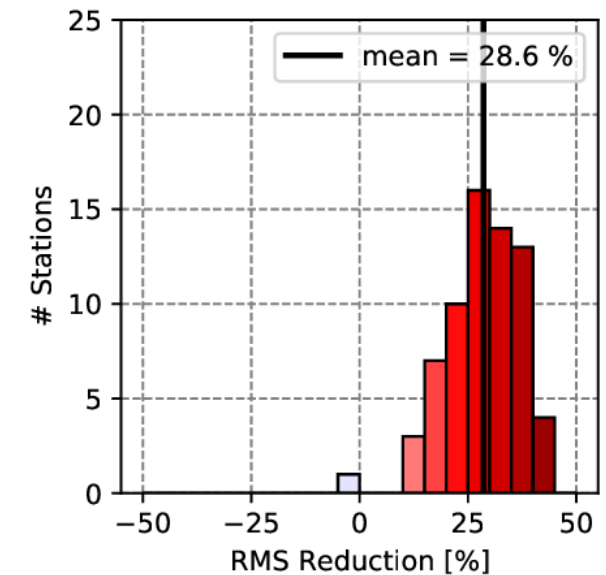
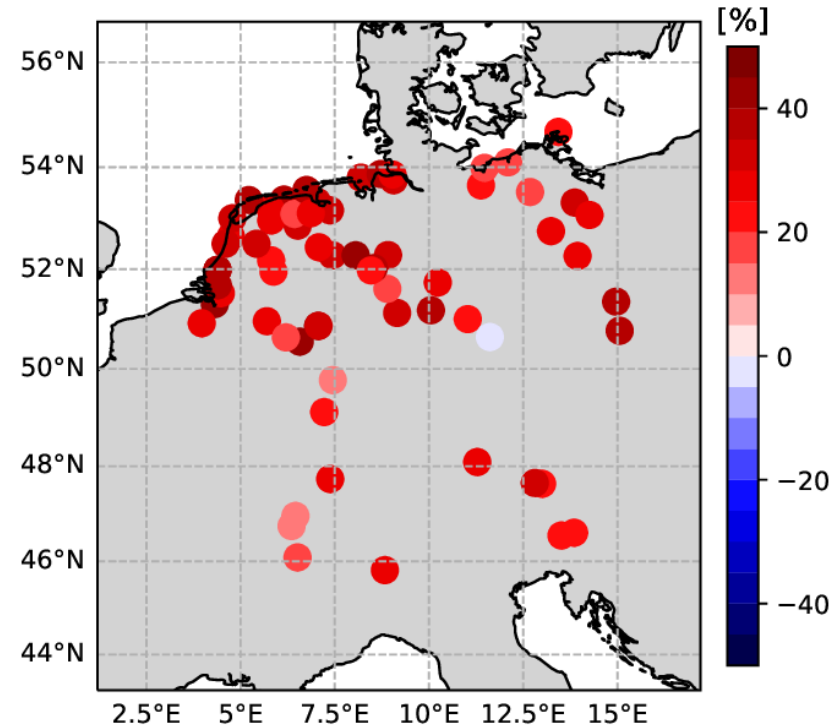
RMS Reductions TCN (reduced residuals)

- TCN trained on reduced GNSS height residual time series (environmental loadings subtracted)
- Additional RMS reduction possible



RMS Reductions Total

- Sum of RMS reductions
- Only one station slightly worse RMS after all reductions
- Overall mean reduction: 28.6%
- Max: 44 %



Take Home

- RMS reduction by environmental loadings and by TCN modeled signal using meteorological features on similar level
- Additional RMS reduction possible through TCN using meteorological data when using reduced GNSS time series (by environmental loadings)
- Potential of machine learning models for GNSS time series modeling

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[Ruttner, Pia, et al. "Modeling of Residual GNSS Station Motions through Meteorological Data in a Machine Learning Approach." Remote Sensing 14.1 \(2021\): 17.](#)