Imprints of climate variability drivers in multi-centennial central European temperature series

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Motivation

While instrumental measurements of the climate system and its potential drivers provide a key source of data for climate variability assessment, additional information can also be obtained from proxy-based versions of the relevant variables. In this contribution, reconstructions covering five centuries of data are analysed through linear and nonlinear regression, with the following primary aims:

To identify temporal temperature variability patterns attributable to different climate drivers, both external and internal

To investigate whether the eventual links can be sufficiently approximated by purely linear functions, or whether application of a more complex, non-linear and non-parametric approach is warranted

To compare results obtained from different sources of temperature data, specifically to determine how similar the temperature signal is between the ModE-RA paleo-reanalysis (Valler et al. 2024) and the documentary-based temperature reconstruction by Dobrovolný et al. (2010)

Analysis setup

For detection and quantification of links between central European annual temperature and data approximating activity of external forcings and internal climate variability modes, two regression models were employed:

Multiple linear regression (MLR)

The most commonly applied form of regression, simple and easy to interpret, but only capable of capturing linear relationships

Generalized additive model (GAM)

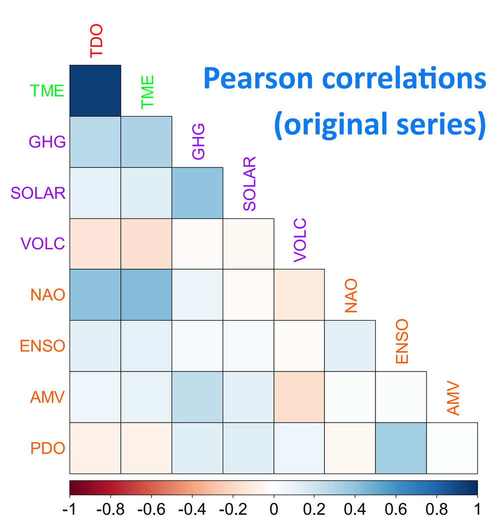
A more general model, simulating the predictor-predictand relationships through flexible nonlinear transformation functions applied to individual predictors, thus capable of revealing and approximating even nonlinear links

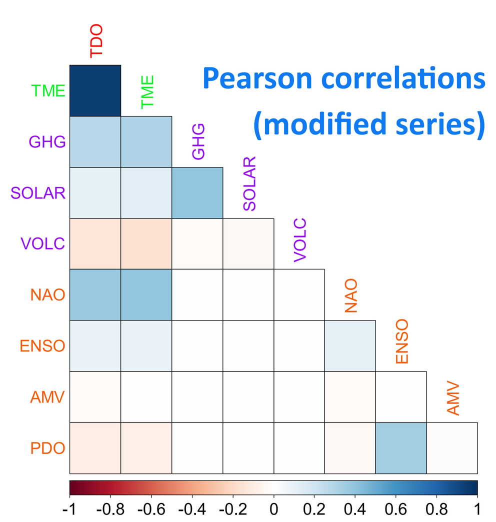
Analysis period

1500-2000 CE

Mutual correlations of the time series

To limit the potential influence of external forcings in the predictors pertaining to internal climate variability, linear regression was used to remove components related to radiative, solar and volcanic forcing from the rest of the predictors.

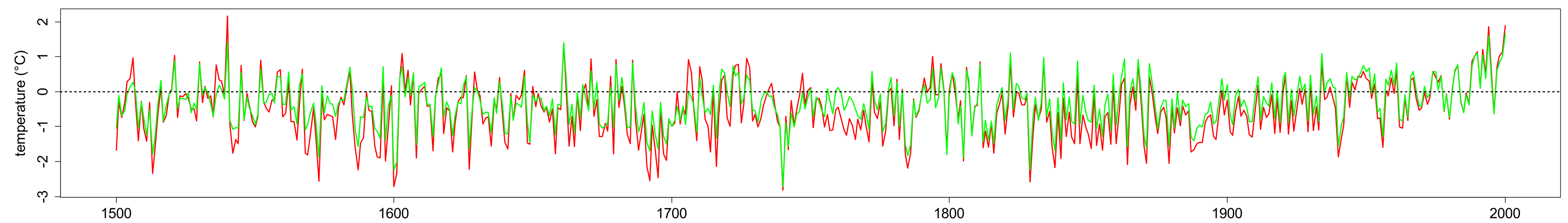




Temperature data

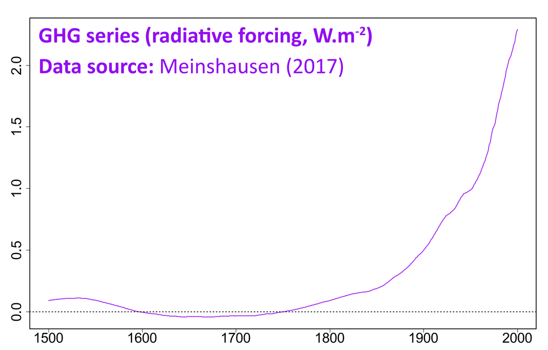
TDO: Central European temperature reconstruction by Dobrovolný et al. (2010), using documentary and instrumental data from Austria, Czechia, Germany & Switzerland

TME: Central European temperature series generated from the ModE-RA paleo-reanalysis (Valler et al. 2024) as a mean of all 20 ensemble members over the area between 7-19°E, 45-52°N



Regression-estimated influence of external and internal temperature variability drivers

Greenhouse gases radiative forcing (GHG)

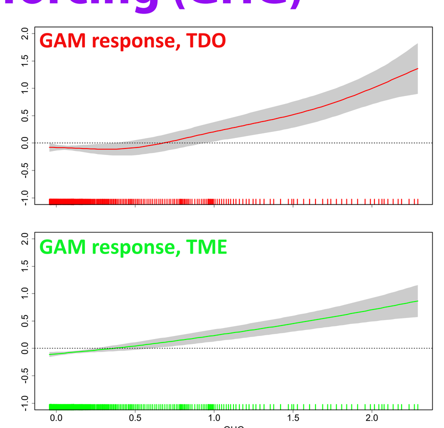


MLR: coefficient
0.44 | 0.39

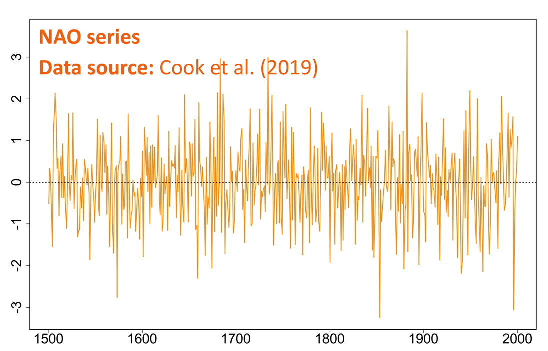
MLR: p-value
1.7e-10 | 2.6e-12

GAM: EDF
3.0 | 1.8

GAM: p-value
< 2e-16 | < 2e-16



North Atlantic Oscillation (NAO)



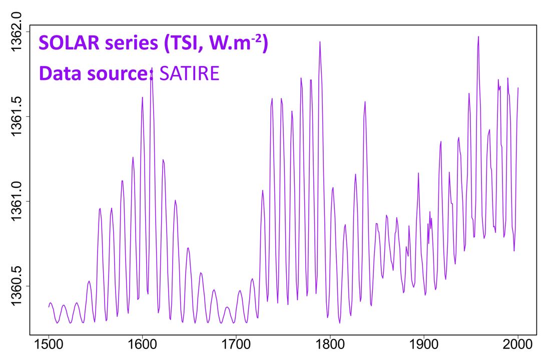
MLR: coefficient
0.30 | 0.26

MLR: p-value
< 2e-16 | < 2e-16

GAM: EDF
2.2 | 1.9

GAM: p-value
< 2e-16 | < 2e-16

Solar activity (SOLAR)

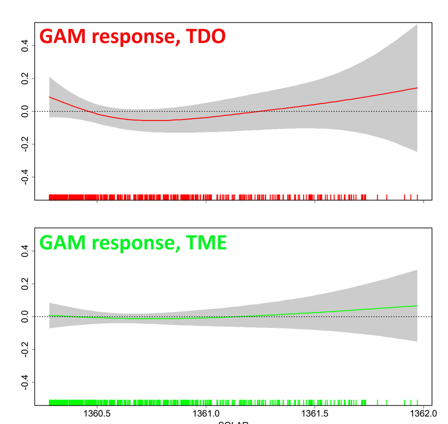


MLR: coefficient
-0.01 | 0.01

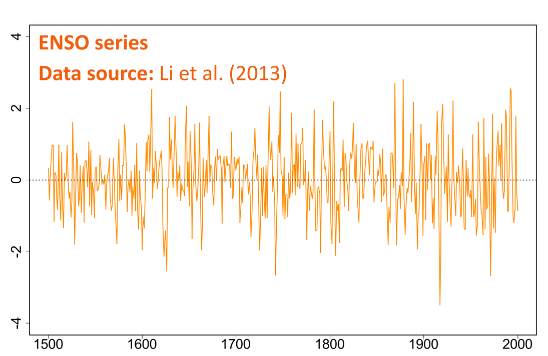
MLR: p-value
0.905 | 0.882

GAM: EDF
2.3 | 1.4

GAM: p-value
0.368 | 0.739



El Niño / Southern Oscillation (ENSO)

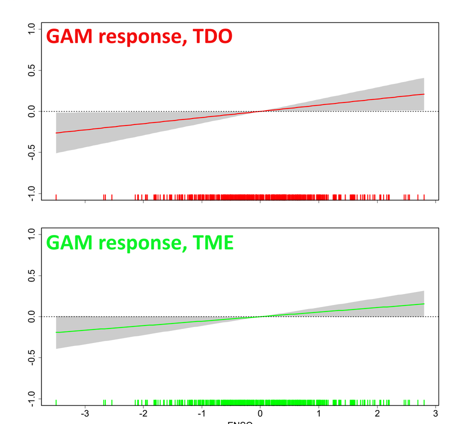


MLR: coefficient
0.08 | 0.06

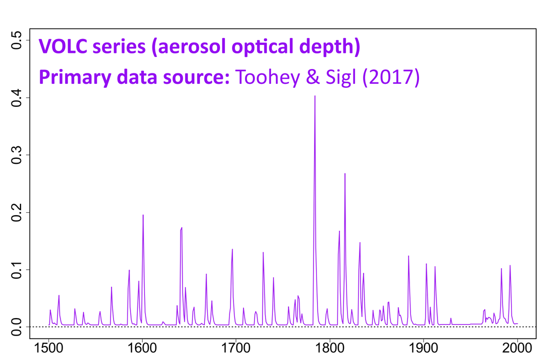
MLR: p-value
0.021 | 0.045

GAM: EDF
1.0 | 1.0

GAM: p-value
0.034 | 0.053



Volcanic activity (VOLC)

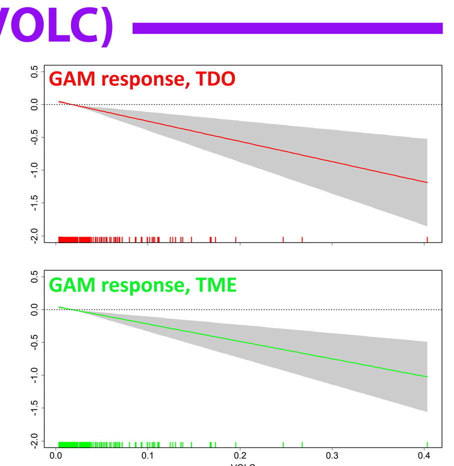


MLR: coefficient
-2.89 | -2.59

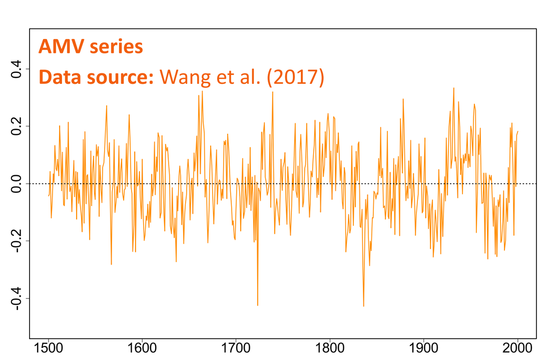
MLR: p-value
0.001 | 2e-4

GAM: EDF
1.0 | 1.0

GAM: p-value
4e-4 | 2e-4



Atlantic Multidecadal Variability (AMV)

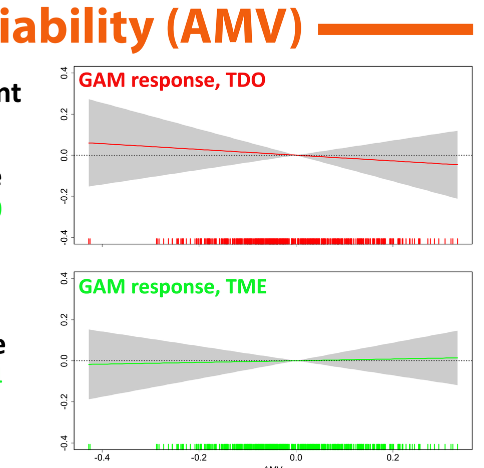


MLR: coefficient
-0.13 | 0.03

MLR: p-value
0.601 | 0.879

GAM: EDF
1.0 | 1.0

GAM: p-value
0.574 | 0.834



Interpretation of the regression outcomes

p-values

Estimated by the t-test and F-test for the MLR and GAM models, respectively

Effective degrees of freedom (EDF)

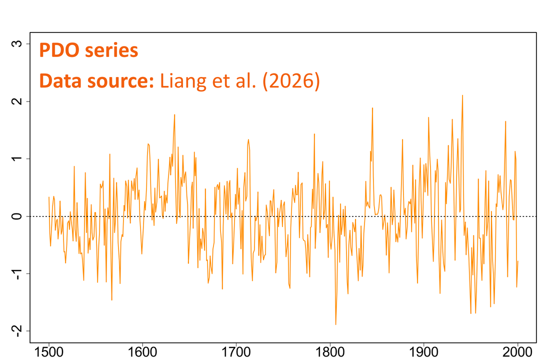
Characterize complexity of the GAM response:
close to 1: Linear response
1 to 2: Weakly nonlinear
over 2: Substantial nonlinearity

GAM response graphs

Response functions approximated by thin plate splines; straight lines indicate linear relationship between the temperature values and the predictor

Estimated uncertainty shown by shading (95% Bayesian credible interval)

Pacific Decadal Oscillation (PDO)

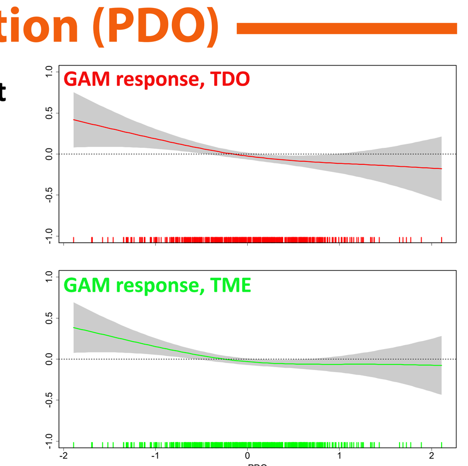


MLR: coefficient
-0.15 | -0.11

MLR: p-value
0.005 | 0.011

GAM: EDF
1.8 | 2.2

GAM: p-value
0.012 | 0.018



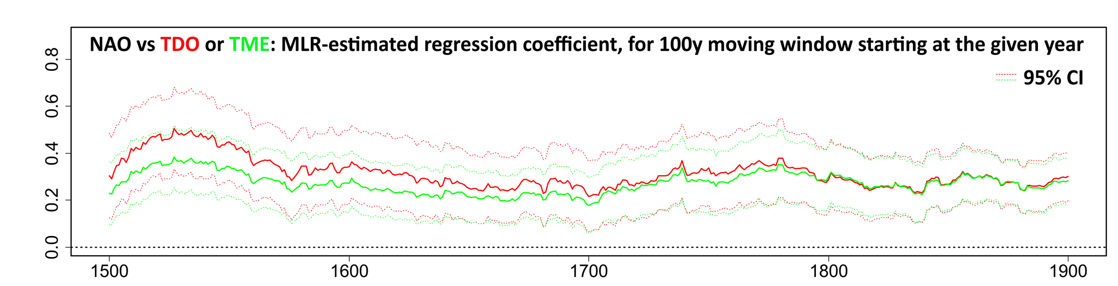
Main results & conclusions

Our results confirm strong resemblance between the ModE-RA reanalysis data and the documentary-based temperature reconstruction. This similarity applies not only to the overall temperature signal, but also to its individual components attributable to various climate variability drivers.

Aside from factors with well-established influence on central European temperature (radiative forcing, NAO), our analysis provides a clearer representation of local temperature responses less evident from instrumental-only data (especially temperature components related to volcanic forcing or PDO). Curiously, no significant link was found in case of AMV (however, noteworthy correlations can be found when multi-year time-delayed links are also considered). No discernible temperature signal was found in response to solar forcing, linear or otherwise.

Presence of distinctly nonlinear responses has been established for some of the temperature drivers, including those with the strongest statistical significance (such as NAO). For others (including volcanic forcing), the linear model seems sufficient.

Although not addressed in detail here, one of the crucial aspects of proxy-based time series analysis concerns temporal stability and homogeneity of individual signals and their links. For predictors dominated by persistent, higher-frequency variability, this issue can be investigated by analysis applied over shorter time segments: E.g., for NAO-related temperature component, a largely stable link throughout our analysis period exists, suggesting considerable level of mutual consistency between the proxy-based NAO reconstruction and the temperature series:



Future directions:

Transition to seasonal and monthly time scales

Inclusion of more variants of the proxy-based predictors

Investigation of time-delayed responses and inter-predictor interactions, at both monthly and multiannual time scales

References & acknowledgements

This analysis would not be possible without the various reconstructions of temperature and climate variability drivers:

Cook et al. (2019): https://doi.org/10.1007/s00382-019-04696-2
Dobrovolný et al. (2010): https://doi.org/10.1007/s10584-009-9724-x
Li et al. (2013): https://doi.org/10.1038/nclimate1936
Liang et al. (2026): https://doi.org/10.1016/j.gloplacha.2026.105333
Meinshausen et al. (2017): https://doi.org/10.5194/gmd-10-2057-2017
SATIRE: https://www2.mps.mpg.de/projects/sun-climate/data.html
Toohey & Sigl (2017): https://doi.org/10.5194/essd-9-809-2017
Valler et al. (2024): https://doi.org/10.1038/s41597-023-02733-8
Wang et al. (2017): https://doi.org/10.1038/ngeo2962

R library *mgcv* was used for implementation of GAM regression

Sharing is encouraged

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