Report for Project 1083 "Climate Informatics: New Machine Learning Methods for Climate Data and Climate Model Evaluation"

Project: **1083**
Project title: **Climate Informatics: New Machine Learning Methods for Climate Data and Climate Model Evaluation**
Project leader: **Prof. Dr. Jakob Runge**
Report period: **2024-07-01 to 2025-04-30**

Overview

In the last reporting period, we have worked on developing improved parameterizations for earth system models with machine learning, new causal discovery algorithms for high-dimensional data sets and different regimes as well as methods to infer causally meaningful representations from data. We have applied existing causal inference algorithms to better understand the causal drivers for specific cloud regimes, atmospheric chemical-dynamical processes and air-sea interactions based on observations and climate model data. We used variational autoencoders to characterize and analyze heatwaves and to detect and analyze droughts in climate model projections.

Task (i) Application of state-of-the-art causal discovery methods for observations and earth system model evaluation

For the Eddy Rich Earth System Models (EERIE) Horizon 2020 project we used PCMCI+ to analyze causal networks for variables related to air-sea interactions from reanalysis and Earth System Model (ESM) data. High-resolution native climate model data were preprocessed to prepare for the application of causal discovery methods. To showcase the pivotal role causal inference can play in disentangling complex chemical-dynamical influences on tropical stratospheric ozone we analyzed different causal discovery algorithms for satellite observations and the chemistry-transport model simulations (Gülletutan, 2025). Dimension reduction, causal network estimation and evaluation together with a causal weighting scheme were used to constrain climate model precipitation projections based on historical performance Debeire et al. (2025).

Task (ii) Development and application of improved parameterizations for earth system models with causal informed neural networks and equation discovery

In our hybrid ESM simulations we conducted experiments with machine learning stochastic and deterministic multi-member convection parameterizations using GPU nodes on Levante to compute the model spread of distinct convective variables, resulting in a spread that it strongly related to drivers of convective processes such as ocean currents, topography or the atmospheric general circulation. This proved that machine-learning multi-member parameterizations are able to capture not only the magnitude of the spread of convective processes but rather collocate the spread with the observed variability that we expect to see in hybrid simulations (Behrens et al., 2025). In addition, an improved sea-ice albedo parameterization was developed with data driven equation discovery using symbolic regression on satellite and reanalysis data.

Task (iii) Development and application of methods for regime-dependent and mixed-type causal discovery

A mixed-type independence test was developed in (Popescu et al., 2025) and accepted for publication at CLeaR 2025. As part of the European Space Agency (ESA) CMUG (Climate Modelling User Group) project, we used causal inference to better understand the causal drivers for cloud properties. We applied the causal discovery algorithm LPCMCI on the ESA Climate Change Initiative (CCI) and ERA5 data to estimate causal links from cloud-controlling factors to cloud properties and quantified them using causal effect estimation focused on the marine stratocumulus region in western South America. Appenheimer (2024) used different causal discovery methods to test the robustness of their results for precipitation anomalies and related variables in Southeastern Africa.

Task (iv) Development and application of methods for causal inference with high-dimensional spatio-temporal data sets

Gamella et al. (2025) studied the practical performance of causal representation learning methods in a controlled real-world setting. Herman et al. (2025) proposed a more realistic sampling approach to simulate data better resembling real-world conditions. Herman and Runge (2024) proposed using multi-variate climate indices to improve causal effect estimation without losing information, shown via ENSO–NAO analysis.

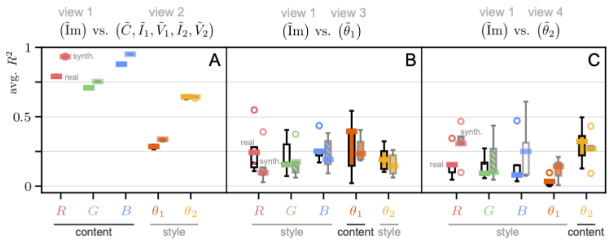

Figure 1: From Gamella et al. (2025): experimental results of applying the CRL method of Yao et al. (2024) to a real-world dataset with known ground truth latent causal variables. (A, B, C): Average R^2-score of predicting ground truth factors from the learned representation. Variables in the highlighted content blocks are expected to obtain a score close to one, while variables in the score block should have a lower score.

Task (v) Application of extreme event and tipping points detection machine learning techniques.

Lanson and Runge (2025) estimate the autocorrelation of a tipping element to detect tipping points more reliably. The standardized precipitation evapotranspiration index (SPEI) was computed to detect droughts in climate model projections (Lindenlaub et al., 2025). Additionally, we used variational autoencoder (VAE) to characterize and analyze heatwaves in multivariate data.

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