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:	**Dr. Jakob Runge**
Report period:	**2019-07-01 to 2020-06-30**

Overview of Work During the Reporting Period

During the last year, we made progress in several aspects. Firstly, we developed new data-driven tools for causal discovery and deep learning. Secondly, we used these to evaluate the CMIP ensemble of climate models, constrain climate projections, and in general to test hypotheses on interactions among climate teleconnections. These topics are detailed in the following.

Report for Task (i) Development and Applications of Causal Discovery Methodology for CMIP Model Evaluation

In the CMIP project more than 40 modeling centers distributed over the globe are developing climate models (Eyring et al., 2016). While the models share common physical principles, differences in their implementation lead to significantly different model behavior. These contribute to persistent discrepancies between models and observations, as well as among model projections. Hence, a broad range of tools to evaluate and compare models and observations regarding a wide variety of evaluation metrics are needed to cover different aspects of model behavior. In a recent publication in *Nature Communications* (Nowack et al., 2020), we introduce a causal discovery based framework for process-oriented model evaluation. We demonstrated how the resulting causal networks (fingerprints) offer an objective pathway for process-oriented model evaluation. Models with fingerprints closer to observations better reproduced important precipitation patterns. We further identified expected model interdependencies due to shared development backgrounds (see Fig. 1). Finally, our network metrics provided stronger relationships for constraining precipitation projections under climate change as compared to previous evaluation metrics for storm tracks or precipitation itself. Such emergent relationships highlight the potential of causal networks to constrain longstanding uncertainties in climate change projections. This publication builds on the PCMCI causal discovery method that was published last November in *Science Advances* (Runge et al., 2019). PCMCI in particular addresses several main challenges for causal discovery in climate data: strong autocorrelation, high-dimensionality, and nonlinearity. However, PCMCI is currently limited to identifying time-lagged causal relationships. Our analyses of climate data brought up the frequent problem that relevant relationships occur at the same time scale as the time resolution typically used in climate analyses, *e.g.,* , daily or monthly data. To also be able to identify *contemporaneous* causal relations, we are currently developing a modification called PCMCI$^+$ that shares the same advantages of PCMCI (challenges above), but also identifies contemporaneous causal links. This new method is currently under review. An important part of PCMCI and PCMCI$^+$ are conditional independence tests. We found that these need to be improved to better account for nonlinearity and complex variable types and we will address this in the next funding period.

Building on PCMCI (Runge et al., 2019), in his master's thesis Soufiane Karmouche considered reanalysis data and CMIP6 data. He analyzed how CMIP6 models reproduce causal networks between major modes of climate variability such as El Niño-Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), the Pacific North American pattern (PNA), the Indian Ocean Dipole (IOD), and the North Atlantic Oscillation (NAO). To calculate the indices related to these major modes of climate variability, he used the NCAR Climate Variability Diagnostics Package (CVDP) from ESMValTool.

Moreover, we started the application of the PCMCI method to identify causal precursors that contribute to climate change with a major focus on the Arctic region. Since the 1990s, the increase of Arctic surface temperatures was reported to be twice as fast as the global average (known as Arctic amplification). Although some parts of the variability of Arctic amplification are understood, the potential causes and their relative importance are still under debate (Kretschmer et al., 2016). To better understand their causal relationships, as well as their relationship with midlatitude winter circulation, we reproduced the study of Kretschmer et al. (2016) using PCMCI and expanded the analysis to improved reanalysis ERA5 data from the European Centre for Medium-Range Weather Forecasts (ECMWF) as well as CMIP6 data to evaluate how CMIP models simulate these processes.

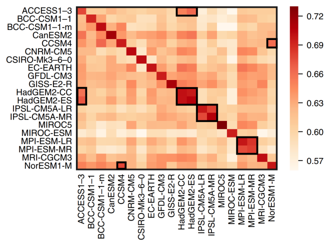

Figure 1: Matrix of average F1-scores for pair-wise network comparisons between ensemble members (20 models, January 1948 to December 2017).

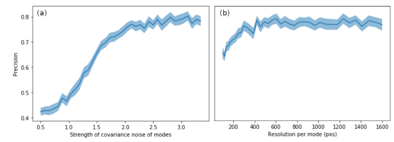

Figure 2: Precision of the causal graph with 95% confidence interval versus (a) strength of covariance noise in modes, and (b) resolution of modes.

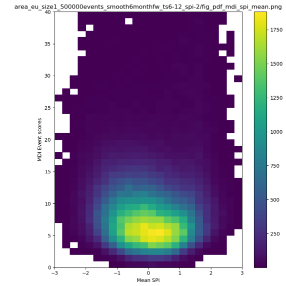

Figure 3: 2D histogram of the number of anomalous intervals showing their MDI score and their mean SPI.

Report for Task (ii) Application of Causal Discovery to Systematically Find Emergent Constraints

Emergent constraints are a promising novel tool that can shed light on climate change uncertainties. In this task we evaluate how the causal discovery method PCMCI can be used to systematically find emergent constraints. Here PCMCI needs to be complemented by methods of dimensionality reduction (*e.g.,* PCA or Varimax) as also done in, *e.g.,* (Runge et al., 2015; Nowack et al., 2020) in order to reconstruct modes of climate variability. A major difficulty in developing and evaluating methods for dimension-reduction and causal discovery is that there is no ground-truth for causal networks. This makes it hard to evaluate assumptions and performance of algorithms. For example, modes or teleconnections are emergent properties of models, while emergent constraints are properties of model ensembles.
To approach this difficulty, we developed a spatio-temporal model to evaluate causal discovery algorithms in conjunction with dimensionality reduction. The so-called Spatially Averaged Vector Autoregressive Model (SAVAR) is a spatio-temporal version of vector auto-regressive models. In the past funding period (and still currently) we developed and intensively tested emergent constraints methods on this model. In Fig. 2 it is shown how the precision of a standard method (varimax + PCMCI) for estimating causal networks changes as a function of (a) the strength of covariance noise of modes, and (b) the spatial resolution of the modes and the model.

Report for Task (iii) Development and Application of Promising Machine Learning Techniques for CMIP Model Analysis

The work comprised under this task was done at the University of Bremen. The Maximally Divergent Intervals (MDI) algorithm (Barz et al., 2019) was tested in comparison to classical methods for detecting extreme events. For the detection of droughts we worked with the Standardized Precipitation Index (SPI), based purely on precipitation and the Standardized Precipitation Evapotranspiration Index (SPEI), which additionally includes potential evapotranspiration (PET). A master's thesis was written by Kemisola Adeniyi in this context. The goal was to analyze droughts based on the SPI and SPEI data for CMIP6 reanalysis data, historical model runs, as well as future scenarios produced to prepare the MDI analysis. We only prepared small samples of MDI results up to now, because the characteristics between the MDI events and the droughts detected through SPI need further analyses and tests since no clear connection was currently found (see Fig. 3). The MDI tool was also used for the analysis of hurricane data in a master's thesis by Simon Zitzmann.

Report for Task (iv) Development and Application of Deep Learning Techniques for CMIP Model Output

In this subproject we originally envisioned to utilize Variational Autoencoder Decoders (VAE, Hinton and Salakhutdinov, 2006) as an alternative to classical dimension reduction techniques used in climate research such as principal component analysis. Due to a change in the scope of a project, we switched to investigating the highly relevant problem of emulating modules of climate models with VAEs. The DKRZ GPU nodes were used for these particular Deep Learning experiments involving a tensorflow-gpu environment in combination with extensive hyperparameter tuning. The training data consisted of preprocessed aquaplanet simulations of the Community Atmosphere Model Version 3 with active superparameterisation (SP). VAEs were used with different architectures (depth of the network, node size, latent space size, *etc.*) to emulate SP. This project is very promising and will be further pursued in another DKRZ grant application, while this task will not be further continued in this DKRZ grant.

References

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