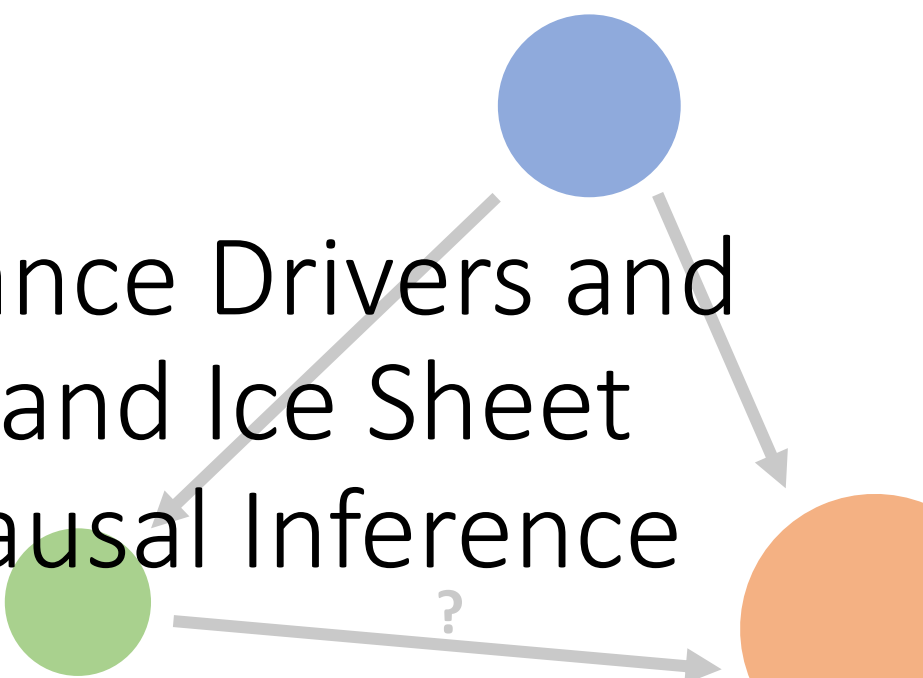


Identifying Energy Balance Drivers and Feedbacks of Greenland Ice Sheet Surface Melt Using Causal Inference



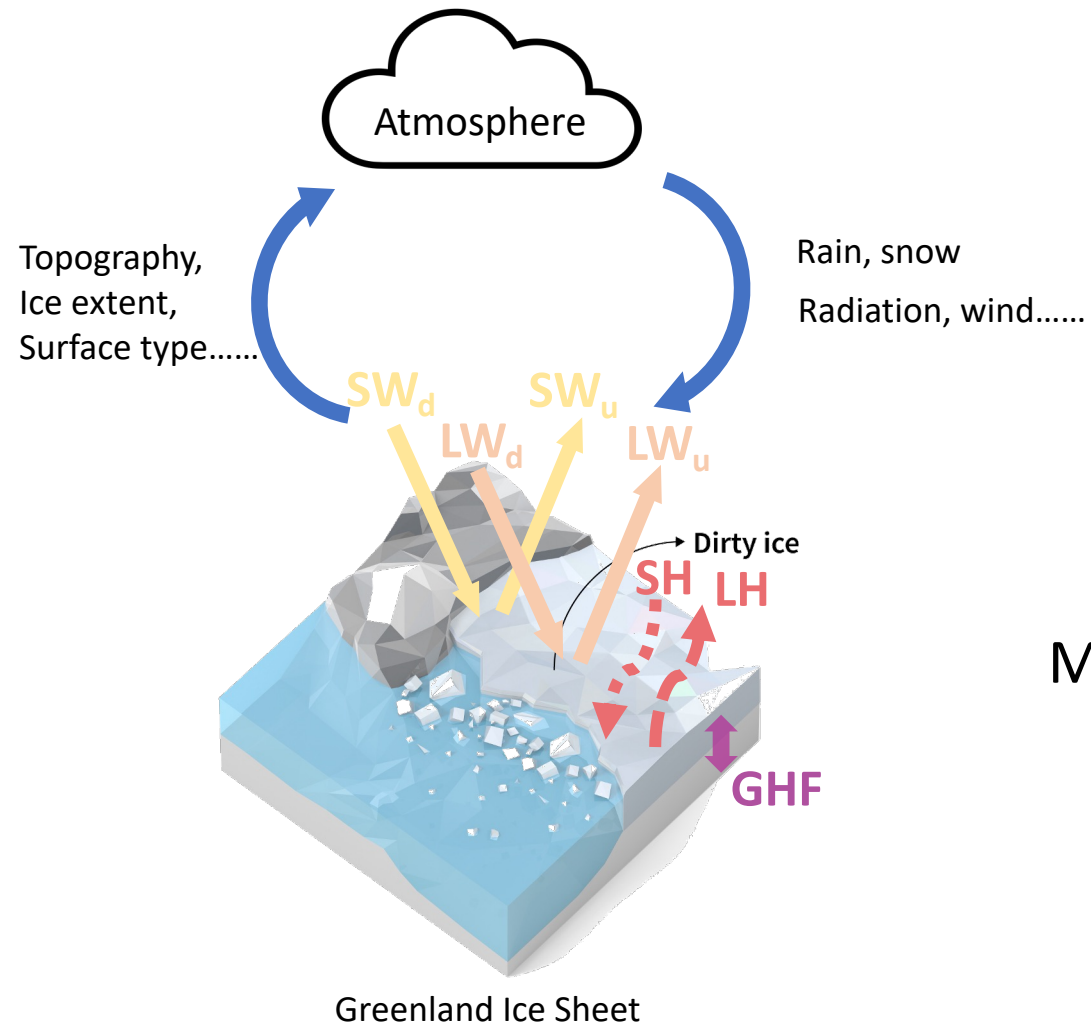
Ziqi Yin¹, Aneesh Subramanian¹, Rajashree Tri Datta¹, Adam R Herrington² and Danni Du¹

¹University of Colorado, Boulder, Department of Atmospheric and Oceanic Sciences, Boulder

²National Center for Atmospheric Research, Climate and Global Dynamics Laboratory, Boulder



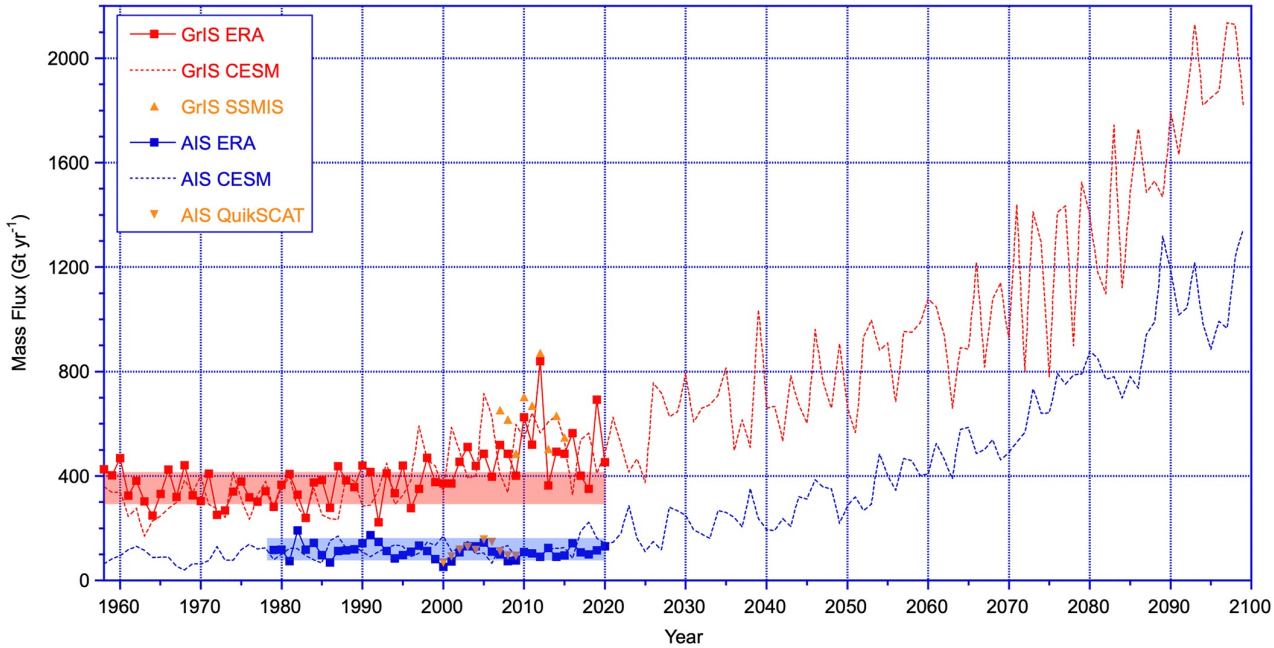
Interactions & feedbacks between the GrIS & atmosphere



- Albedo/melt feedback
- Geometry/SMB feedbacks
- Melt & accumulation/discharge feedbacks

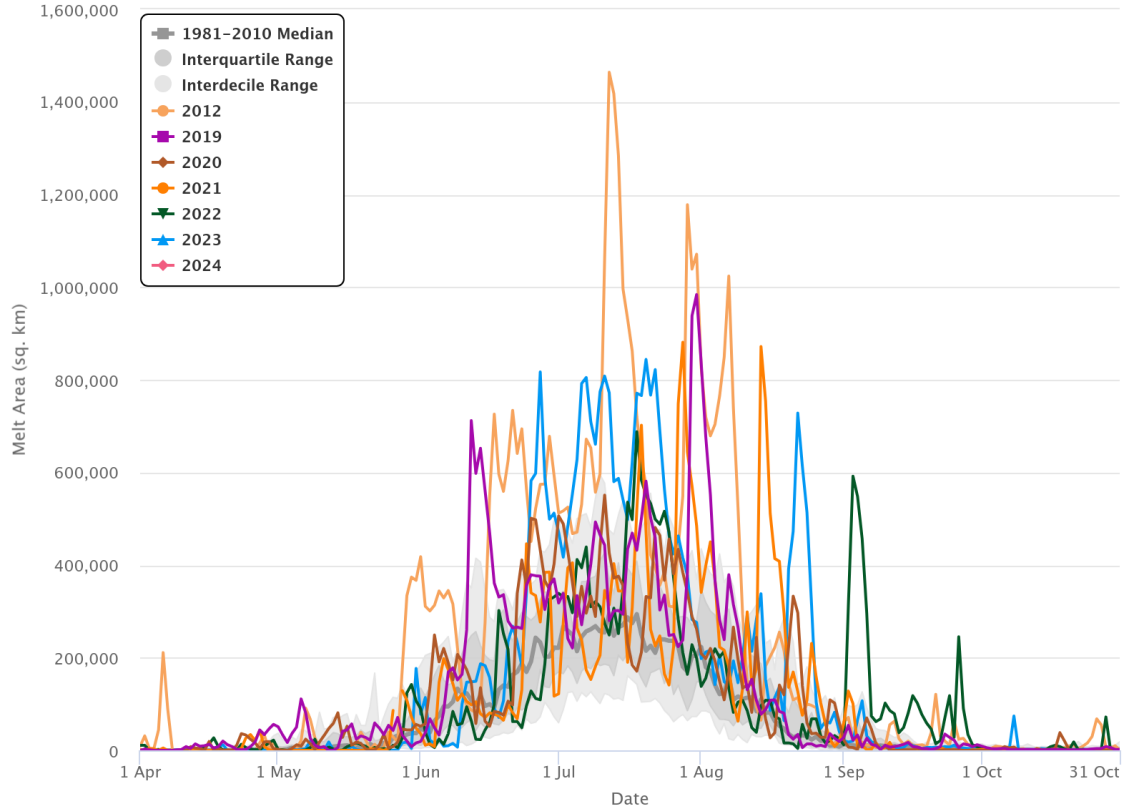
$$\text{Melt energy} = LW_{\text{net}} + SW_{\text{net}} + \text{Latent heat} + \text{Sensible heat} + \text{Ground heat}$$

GrIS Surface Melt change & variability



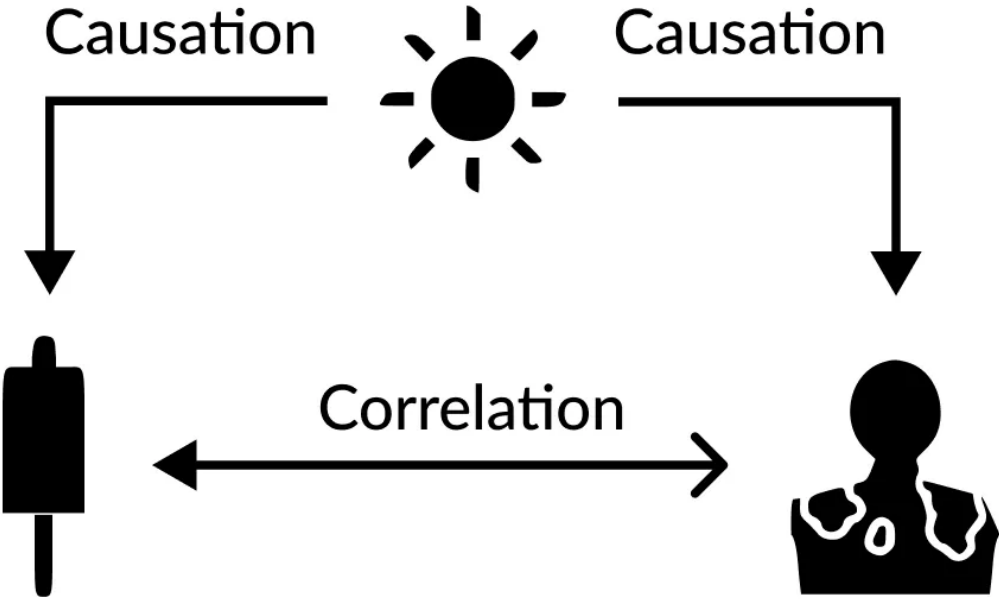
(van den Broeke et al. 2023)

Greenland Surface Melt Extent

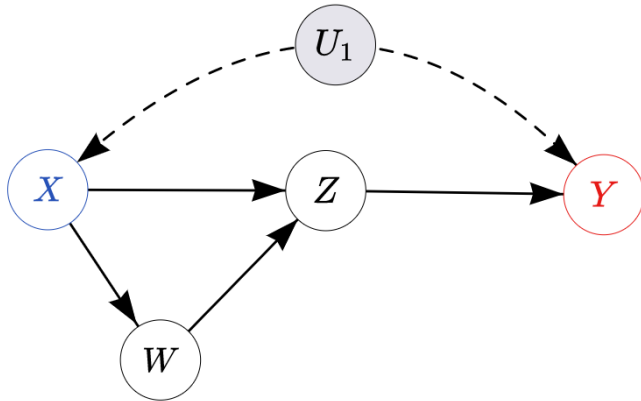


National Snow and Ice Data Center, University of Colorado Boulder
(credit: NSIDC)

Causation vs Correlation



Causal inference

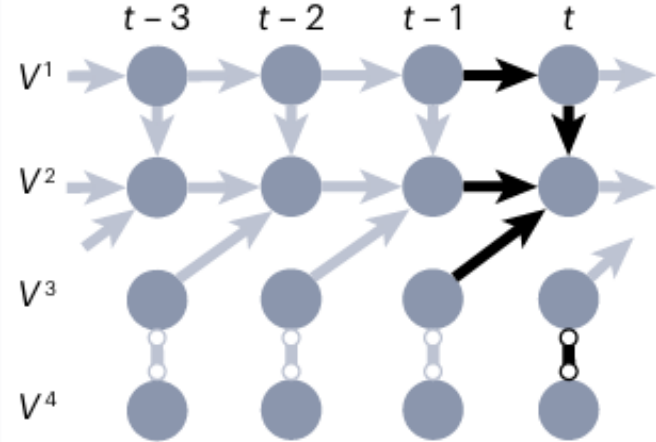


Causal inference is a discipline to formalize the pursuit of identifying, modeling, and quantifying causal relationships.

Two pillars of current causal learning:

a Causal discovery

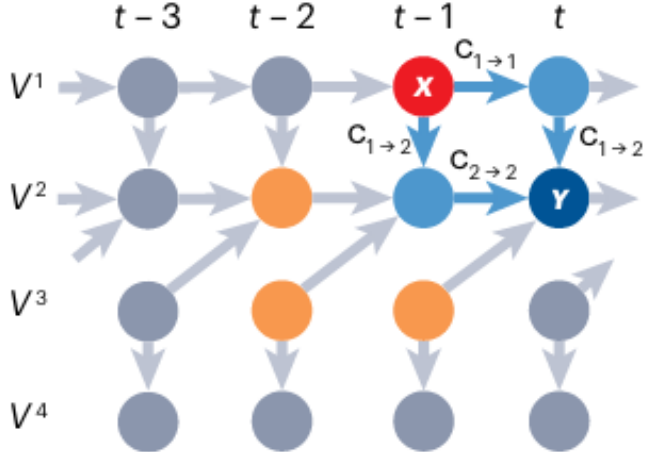
Assuming no hidden confounding



- Learning qualitative causal relationships

b Causal effect estimation

Graph without hidden variables



- Quantifying causal effects given qualitative relationships

Research questions

1. What is the relative importance of the SEB components and processes for GrIS summer surface melt?
2. Under global warming, will there be a regime shift?

The causal inference method

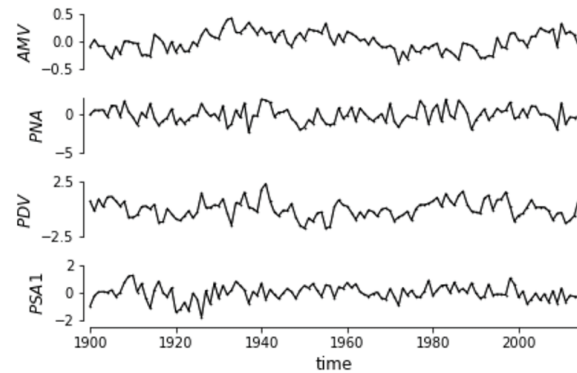
① **PCMCI** (Peter Clark Momentary Conditional Independence) is a causal discovery framework developed by Runge et al. (2019).

Suitable for time series with

- high dimensionality (number of variables, time lags, autocorrelation)
- nonlinear dependencies

② **Wright's path method** is a method to assess the effects of a set of variables acting on a specified outcome via multiple causal pathways developed by Sewall Wright (1918).

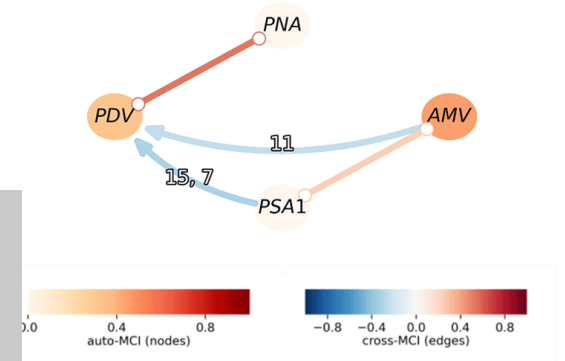
Example: application of the **PCMCI+** algorithm to modes of climate variability



Detrended timeseries



An extended version that can also detect contemporaneous causal links (Runge, 2020)



Causal network

(Karmouche et al. 2023)

Assumptions:

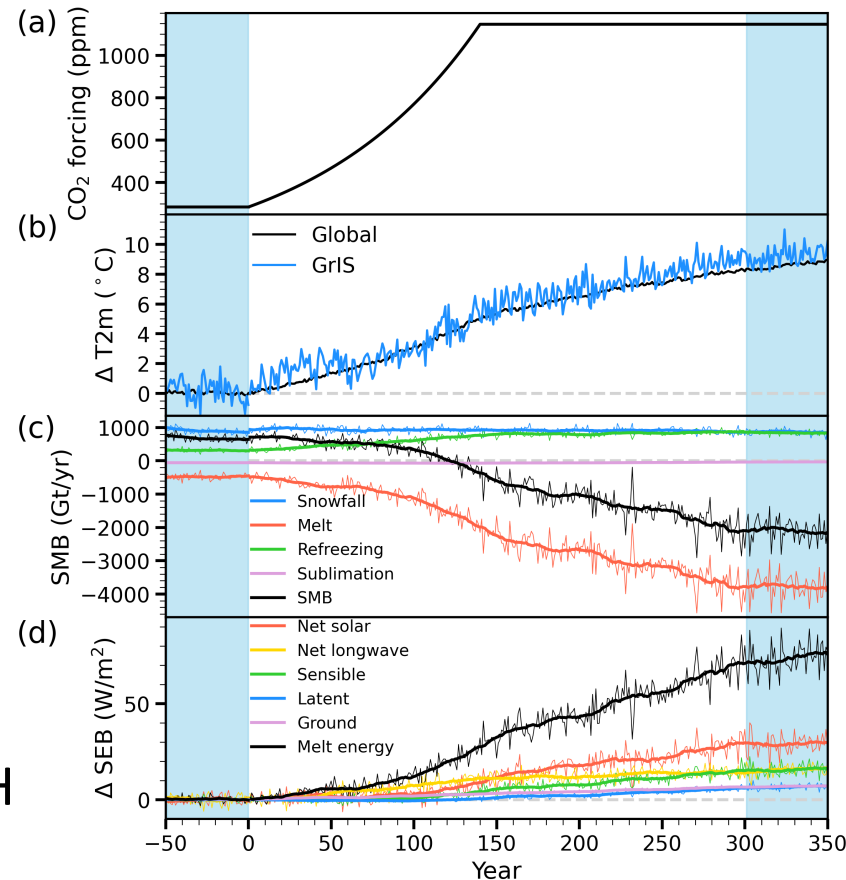
- Causal Markov condition
- Causal faithfulness
- Causal sufficiency
- Stationarity (through preprocessing)
- Linear dependencies (relatively short sample size)
- Acyclicity
- Gaussian noise distribution

Data– Fully coupled CESM2.2-CISW2.1 simulation (Yin et al. in prep)

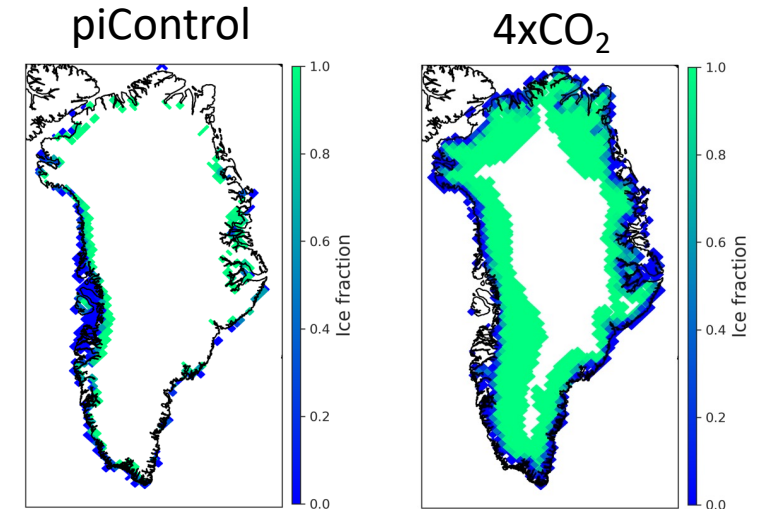
- Variable-resolution grid for atmosphere & land ($1/4^\circ$ over the Arctic and 1° elsewhere)
- 180yrs preindustrial control + 350yrs idealized warming scenario
- Monthly time resolution

Variables selection:

$$\text{Melt energy} = \text{SW}_n + \text{LW}_n + \text{SH} + \text{LH}$$

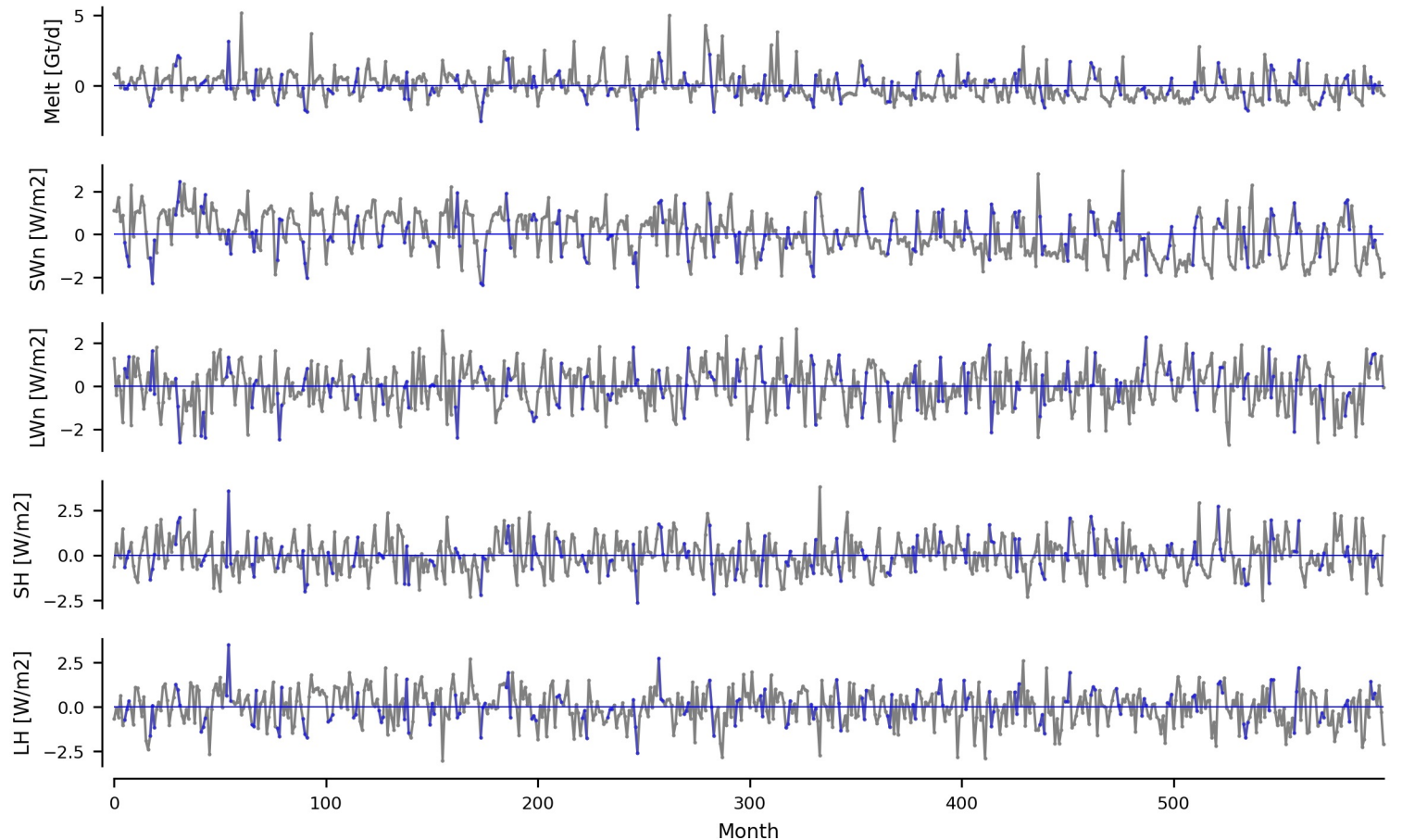


Averaged over the ablation zone

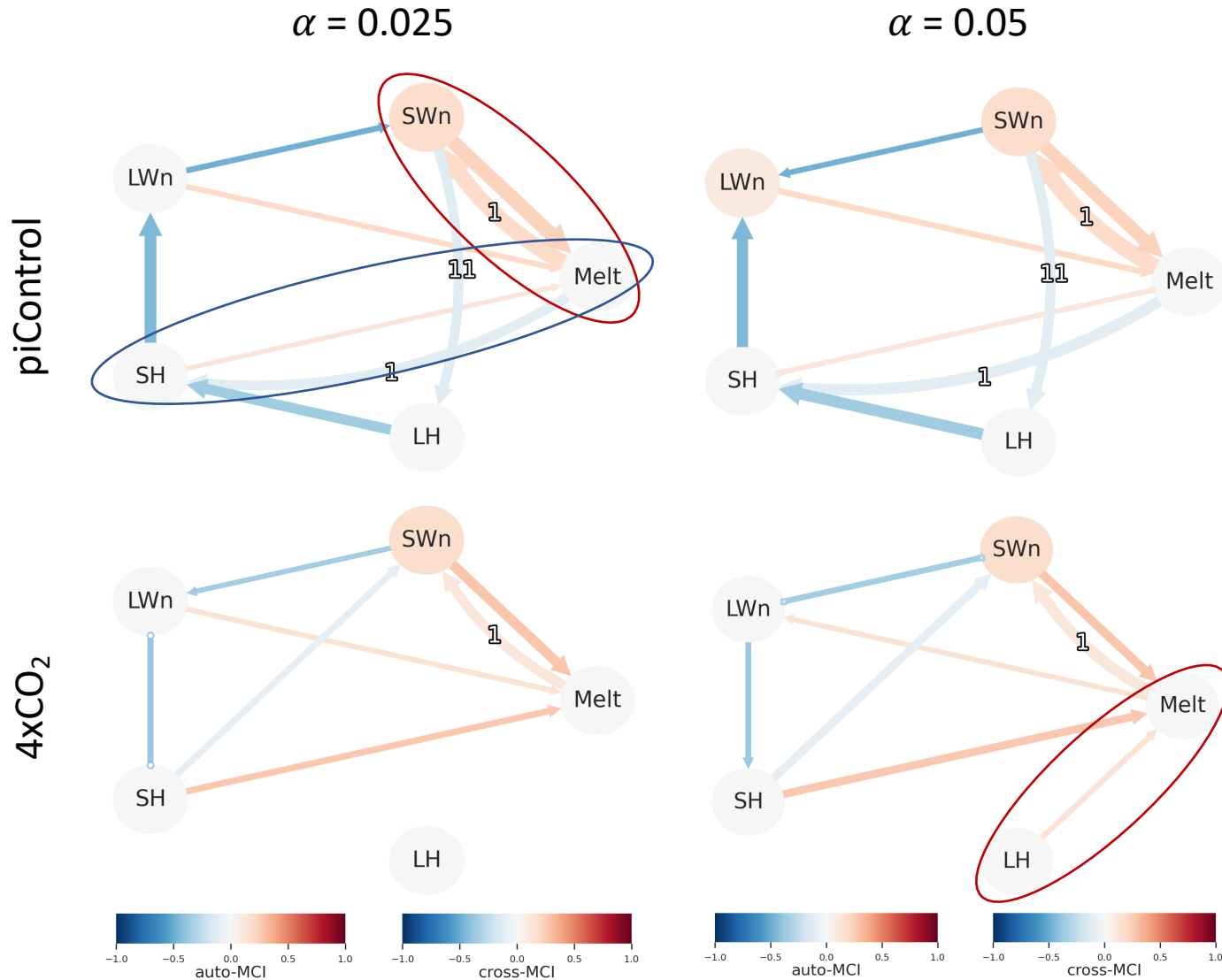


Data preprocessing

- **Detrending:** remove long term trends (decadal Gaussian kernel (15 years))
- **Normalization:** remove seasonal mean, divide by seasonal standard deviation
- **Masking:** samples at time t can only come from Jun-Aug

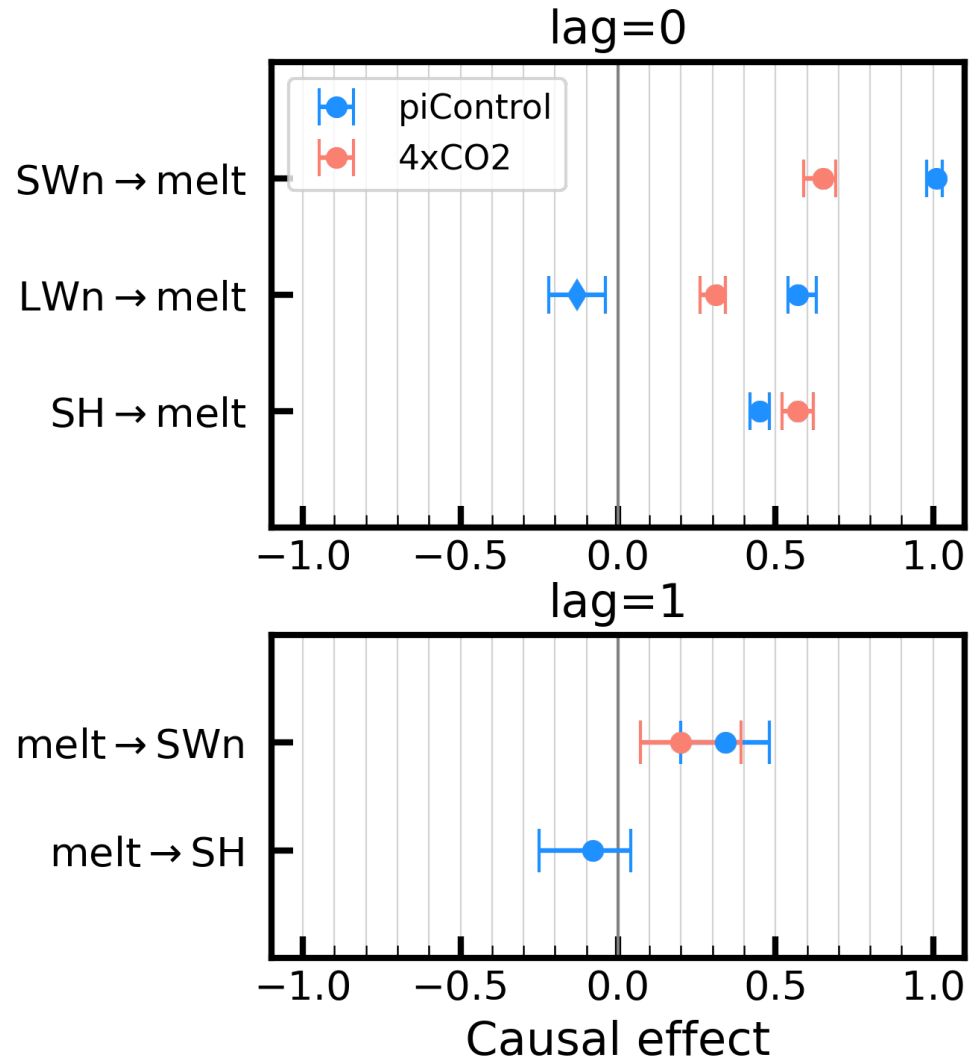


Causal discovery



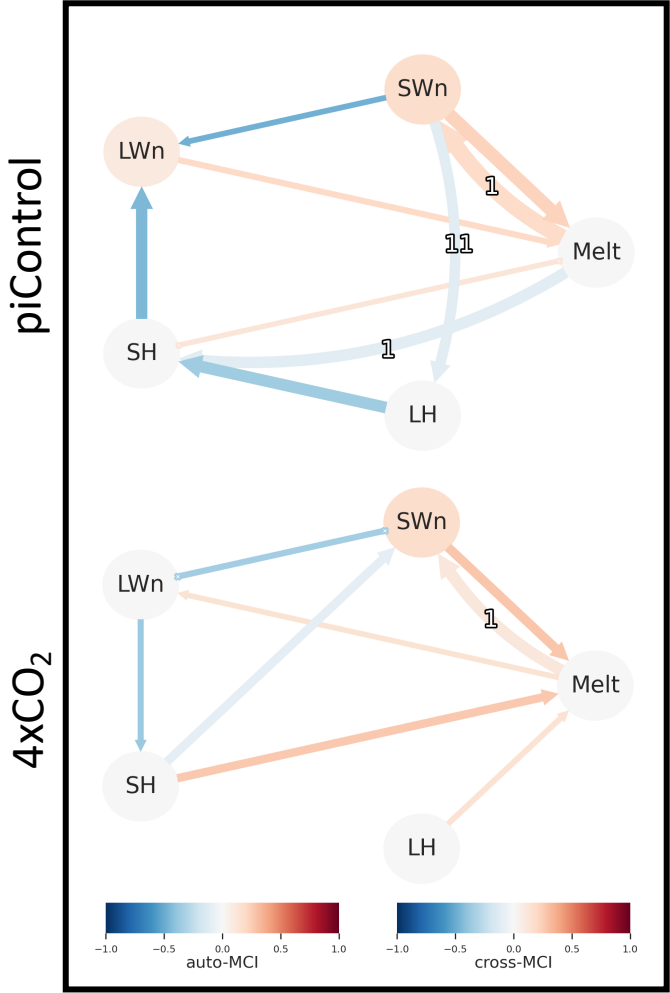
- SW_n, LW_n and SH have contemporaneous positive direct effect on melt; with significance level of 5%, LH→Melt is also detected for the 4xCO₂ period.
- Melt/albedo feedback is detected for both periods, with one-month lagged Melt→SW_n; for piControl, there is a negative feedback loop between SH & Melt, which is not detected during 4xCO₂.

Causal effect estimation



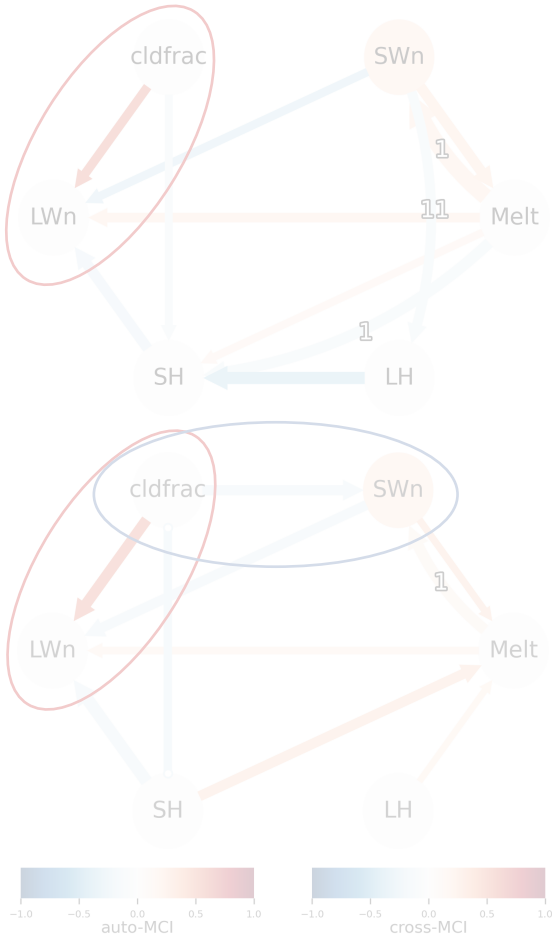
- For direct causal effect, the relative importance of SH increases compared to the radiative fluxes in a warmer climate, but SW_n remains dominant.
- Estimating total causal effect (direct + indirect) requires a complete and more robust causal graphs.

Towards a complete graph...

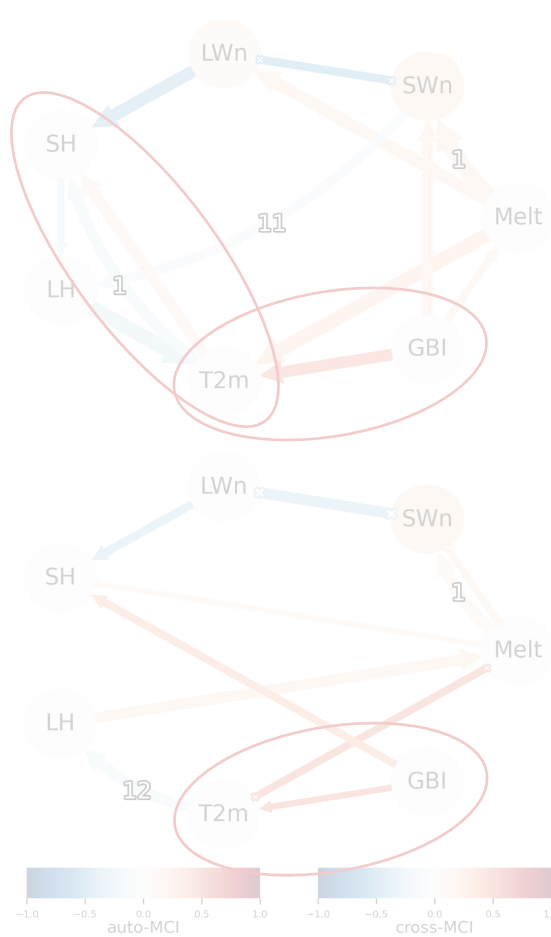


($\alpha = 0.05$)

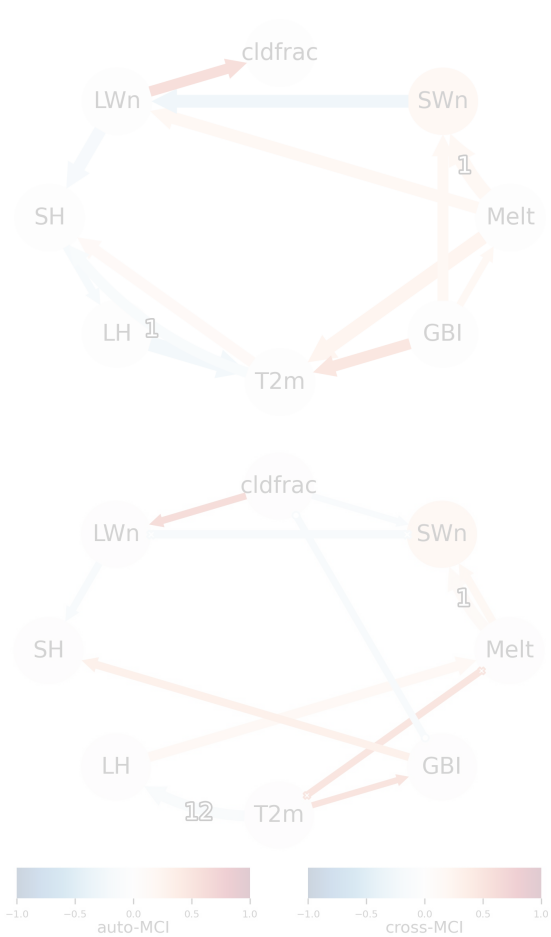
Add cldfrac



Add GBI, T2m

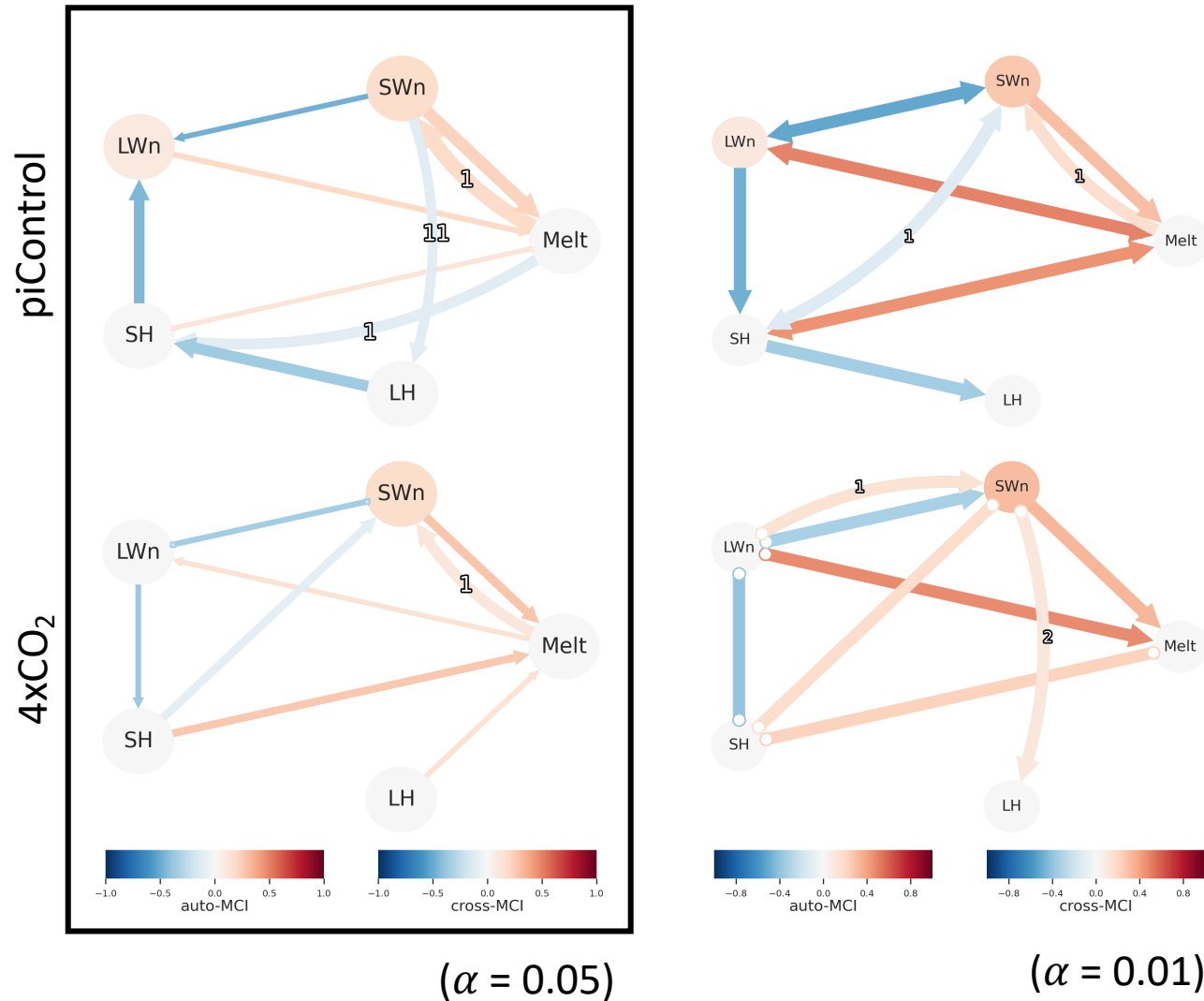


All



Latent-PCMCI: version allowing unobserved variables

(Gerhardus and Runge, 2020)

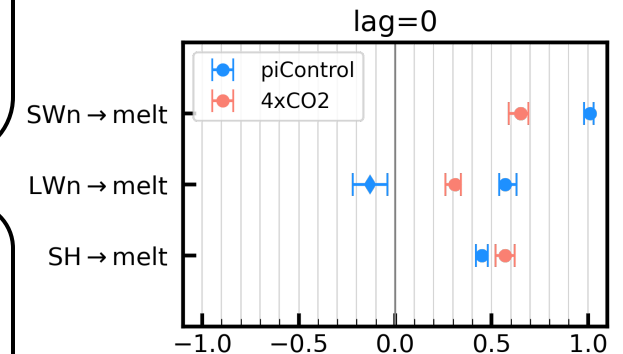
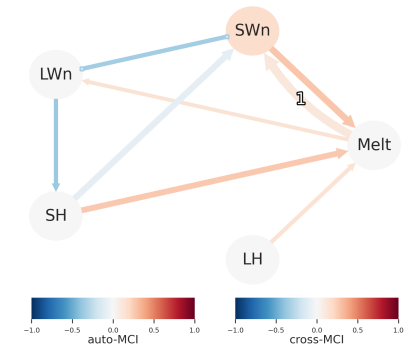


Similar problem as PCMCI+, but there is a way to implement physical knowledge.

Summary & next steps

- Causal inference let us focus on few important drivers and can detect lagged feedback loop for Greenland summer melt
- Net shortwave radiation acts as the dominant direct melt driver
- In a warmer climate, there is a regime shift of the direct effects of SEB terms on Greenland summer melt, with increasing role of turbulent heat fluxes

- Experiment with more variables and model parameters, then summarize a robust graph, based on which the total causal effect can be estimated
- Implement physical knowledge
- Compare with results detected from observation/reanalysis



References

- Van den Broeke, M. R., Kuipers Munneke, P., Noel, B., et al. (2023) Contrasting current and future surface melt rates on the ice sheets of Greenland and Antarctica: Lessons from in-situ observations and climate models. PLOS Clim2(5): e0000203.
- Runge, J., Nowack, P., Kretschmer, M., et al. (2019): Detecting and quantifying causal associations in large nonlinear time series datasets, Sci. Adv., 5, eaau4996
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- Gerhardus, A. & Runge, J. (2020): High-recall causal discovery for autocorrelated time series with latent confounders Advances in Neural Information Processing Systems

Interactions & feedbacks between the GrIS & atmosphere

