

MOTIVATION

- **Arctic Amplification** – greater climate change near the polar regions of Earth as compared to rest of the hemisphere.
- Investigate the **causality** between multiple atmospheric processes and sea ice variations using **data-driven approaches**.
- Pave the way for disentangling the complicated **causal relationships** in the **Earth system**, by taking the advantage of cutting-edge data science and Artificial Intelligence technologies.

PROBLEM STATEMENT

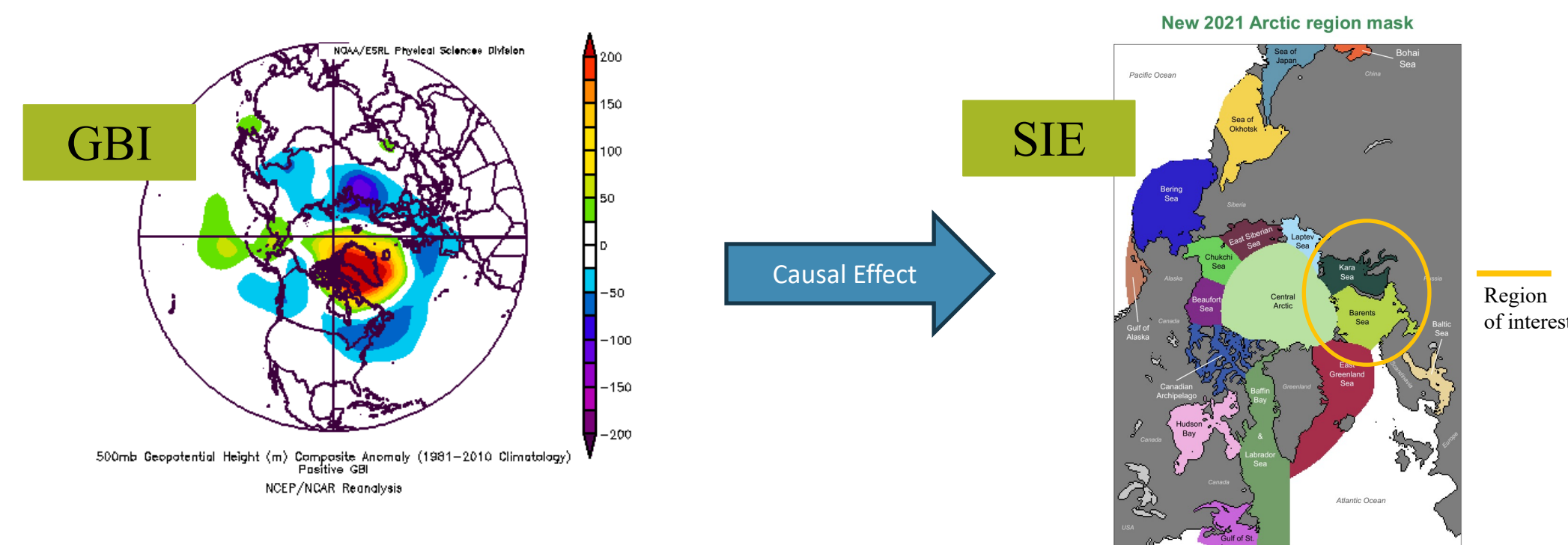
Given the data Z_t (covariates) at timestep t , we want to estimate the lagged causal effect (LATE) by forecasting observed (factual) as well as counterfactual values of sea ice, i.e. potential outcome Y_{t+l} at timestep $t + l$ after intervening on/perturbing on certain atmospheric processes, i.e. time-varying treatment X_t ,

$$Y_{t+l}(X = x_t) = f(Z_t, x_t)$$

$$Y_{t+l}(\hat{X} = \hat{x}_t) = f(Z_t, \hat{x}_t)$$

$$LATE(l) = \frac{1}{N} \sum_{t=1}^N E[Y_{t+l}(\hat{X}_t) - Y_{t+l}(X_t)]$$

CASE STUDY



DATASET

Observational data includes 40 years of NSIDC and ERA5 reanalysis data from 1979 – 2018 in 25km resolution.

Treatment	Covariates	Outcome
Greenland Blocking Index (GBI)	Sea Surface Temperature (SST), Specific Humidity, Longwave Radiation, Shortwave Radiation, Rainfall Rate, 2m Air Temperature	Sea Ice Extent (SIE)

Synthetic data includes 100,000 samples from non-linear time-series:

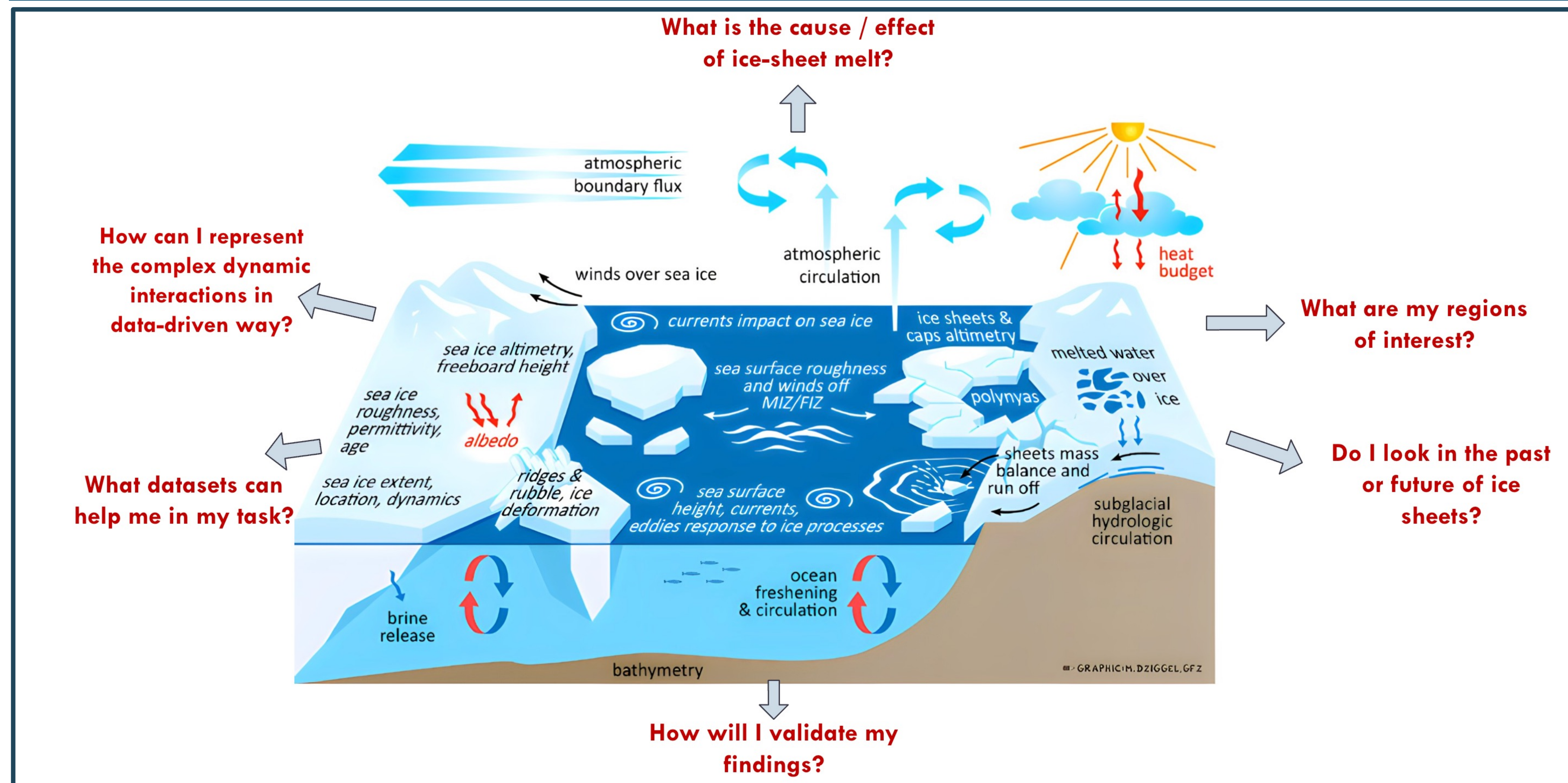
$$S1_t = \cos\left(\frac{t}{10}\right) + \log(|S1_{t-6} - S1_{t-10}| + 1) + 0.1\varepsilon_1$$

$$S2_t = 1.2e^{\frac{S1_t^2 - 1}{2}} + \varepsilon_2$$

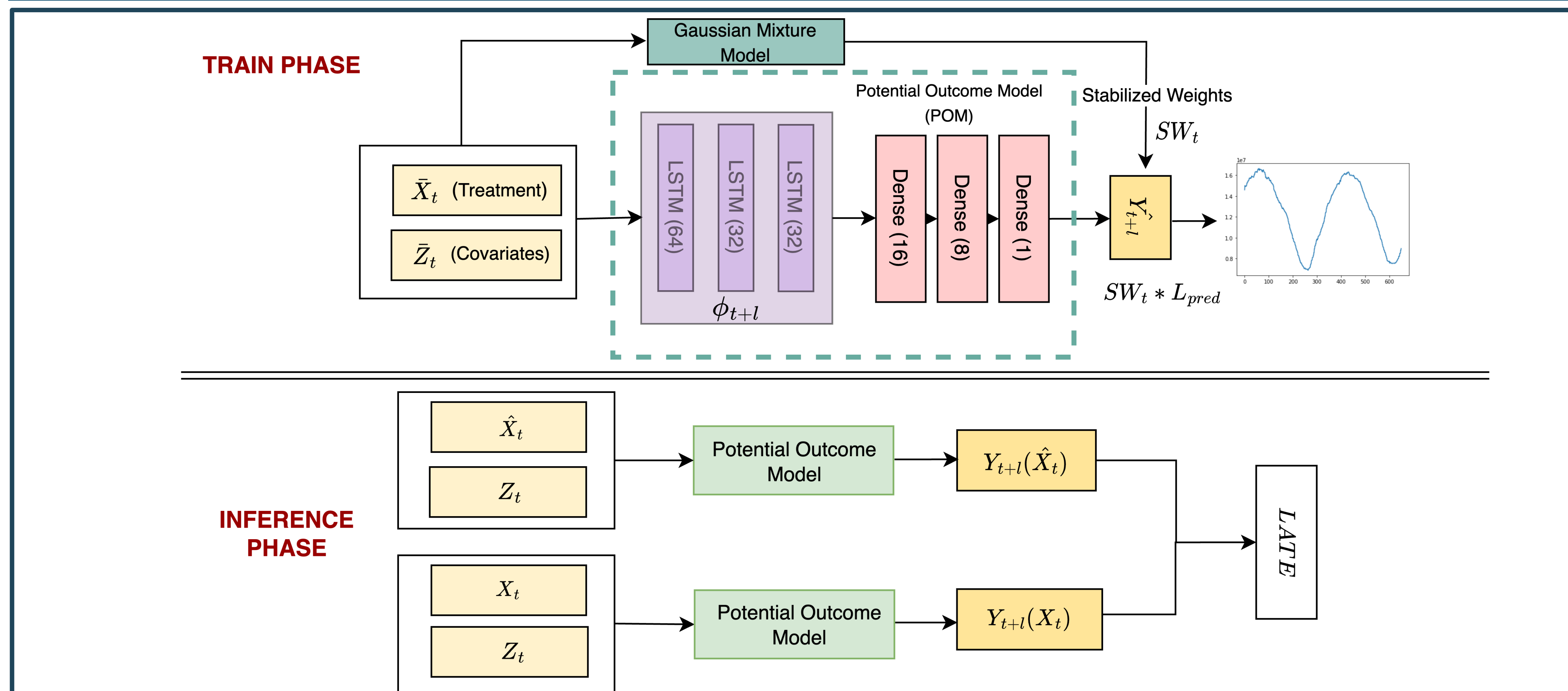
$$S3_t = -1.05e^{\frac{-S1_t^2 - 1}{2}} + \varepsilon_3$$

$$S4_t = -1.15e^{\frac{-S1_t^2 - 1}{2}} + 1.35e^{\frac{-S2_t^2 - 1}{2}} + 0.28e^{\frac{-S4_t^2 - 1}{2}} + \varepsilon_4$$

RESEARCH FOCUS [1]



METHODOLOGY [2]



CONCLUSIONS & FUTURE WORK

- We demonstrate the effectiveness of our model on adjusting bias due to time-series confounding, and continuous treatment effect estimation.
- Our findings align with the literature on "increasing Greenland blocking index leads to decreasing sea ice extent" [3].
- In future, we will extend our work to spatiotemporal causal inference in presence of spatial confounders.

REFERENCES

- [1] Cardellach, Estel et al. (2018). GNSS Transpolar Earth Reflectometry exploriNG system (G-TERN): Mission concept. IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2814072.
- [2] Ali, Sahara et al. (2023). Quantifying Causes of Arctic Amplification via Deep Learning based Time-series Causal Inference. Accepted by IEEE International Conference on Machine Learning and Applications (ICMLA) 2023. Github: <https://github.com/big-data-lab-umbc/sea-ice-prediction>
- [3] Huang, Yiyi, et al. "Summertime low clouds mediate the impact of the large-scale circulation on Arctic sea ice." Communications Earth & Environment 2.1 (2021): 38.

RESULTS - SYNTHETIC DATA

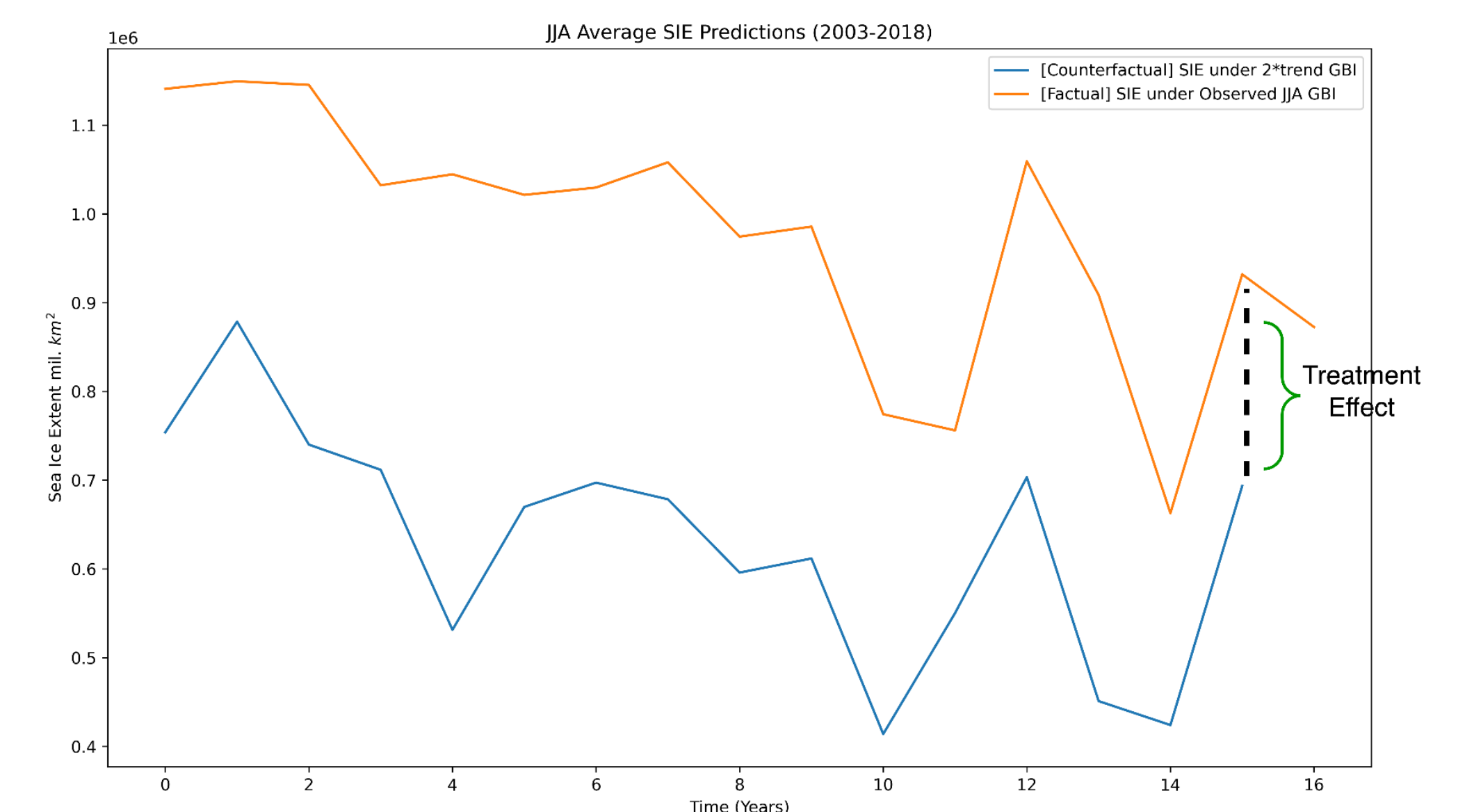
- We compared the performance of our proposed model TCINet-GMM, with multiple SOTA approaches and two baseline variants of TCINet.
- All models are evaluated using Root Mean Squared Error (RMSE), Estimated Lagged Average Treatment Effect (LATE) and Precision Estimation for Heterogeneous Effect (PEHE).

CAUSAL INFERENCE MODELS PERFORMANCE ON SYNTHETIC DATA UNDER FIXED AND CONTINUOUS TREATMENTS FOR ONE-STEP AHEAD PREDICTION (TRUE ATE = -0.0514)

MODEL	TEST RMSE	ESTIMATED LATE	PEHE
FIXED TREATMENT			
TCINet	1.079	-0.040	1.132
TCINet-LR	1.142	-0.037	1.227
TCINet-GMM	1.023	-0.051	1.004
CIV	N/A	-0.219	N/A
CAUSAL IMPACT	N/A	-0.060	1.110
CONTINUOUS TREATMENT			
TCINet	1.026	-0.036	1.221
TCINet-LR	1.000	-0.049	1.143
TCINet-GMM	0.998	-0.050	1.102
CIV	N/A	0.515	N/A
CAUSAL IMPACT	N/A	-0.040	1.112

RESULTS - OBSERVATIONAL DATA

How does increased Greenland Blocking index affect JJA Arctic sea ice melt after 8 days given atmospheric and oceanic data in the Barents and Kara Sea?



CAUSAL EFFECT ESTIMATION BY TCINET-GMM (IN million km²) ON OBSERVATIONAL ARCTIC DATA UNDER CONTINUOUS TREATMENTS.

TREATMENT	ESTIMATED LATE (TCINET-GMM)
40YR-AVG-GBI	-0.60 million km ²
GBI (2× TREND)	-0.64 million km ²
GBI (3× TREND)	-0.65 million km ²
GBI (4× TREND)	-0.69 million km ²

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