Random Walks through Climate Networks: Summer Sea Ice Forecasting with Bayesian Inference

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Introduction

Using a combined approach of Complex Networks and Gaussian Process Regression (GPR), we make skillful predictions of both pan-Arctic and pan-Antarctic monthly averaged summer sea ice extents (SIE) for all years between 1985 and 2019. Predictors are based on monthly averaged sea ice concentration (SIC) data from the preceding 3 months (1 – 3 months lead time). See https://doi.org/10.1175/WAF-D-19-0107.1

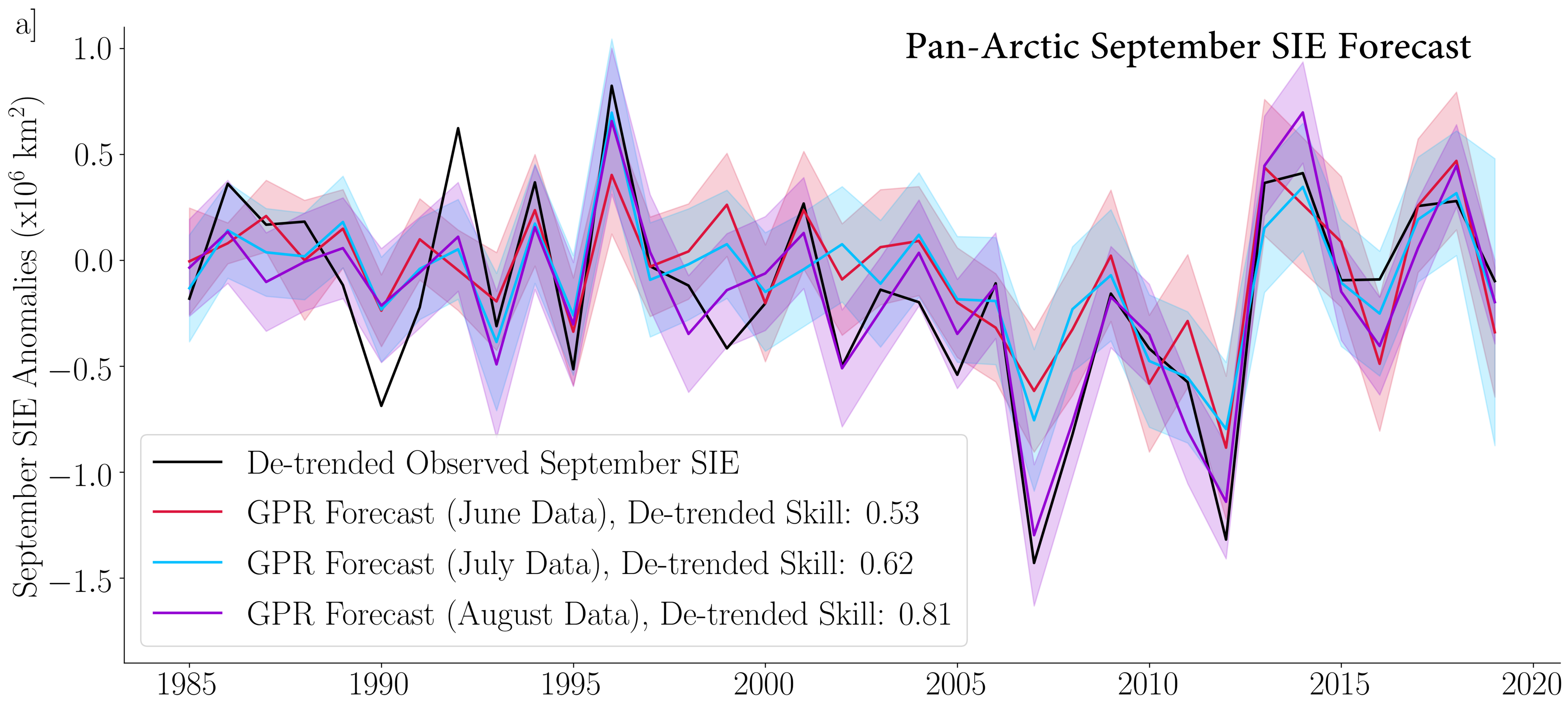
Method

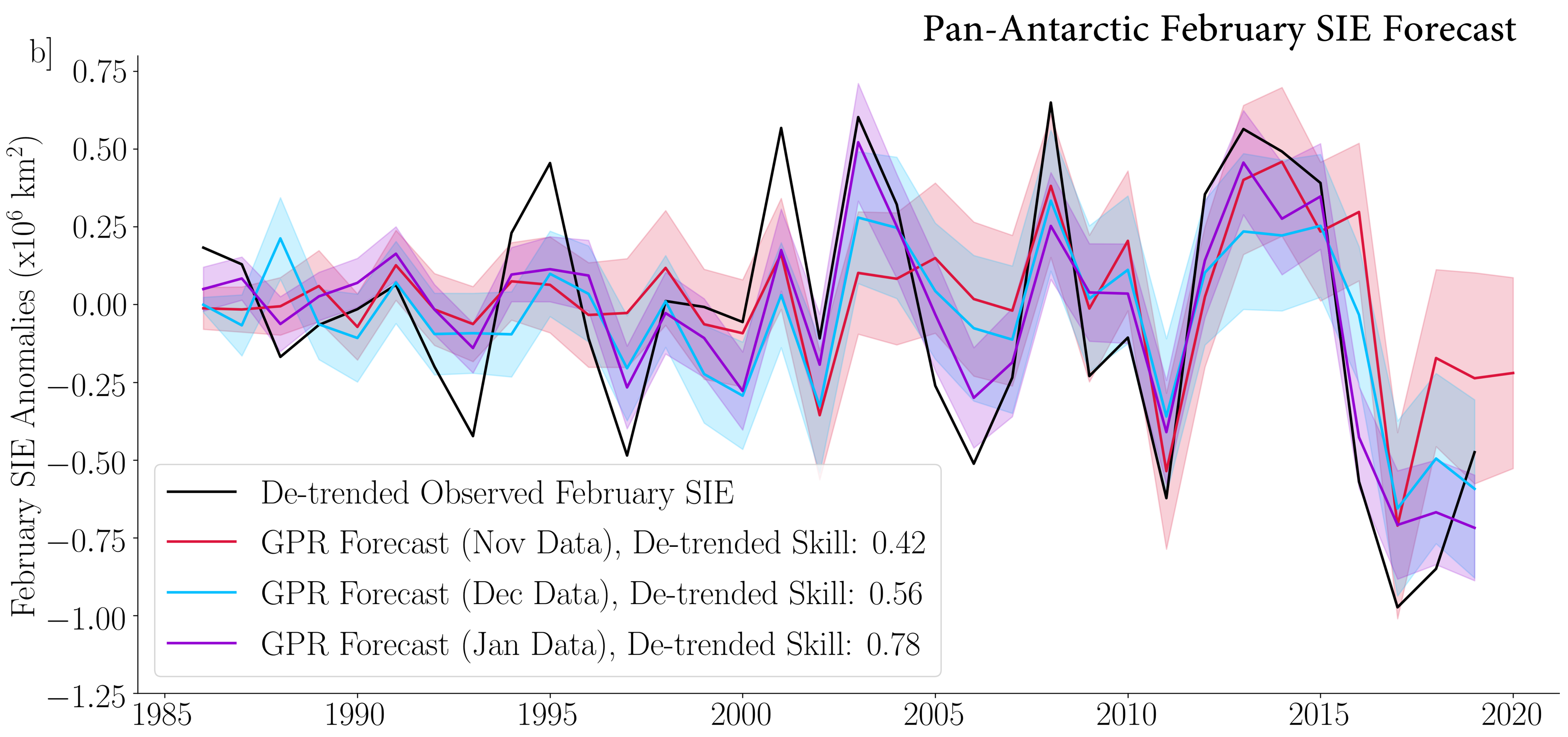
Complex Networks:

- Compute Pearson correlations between all available pairs of SIC grid cells $x_p(t)$ and $x_q(t)$, where each time series t consists of n observations $(t_1, t_2, \dots, t_n)$, with t_n being the year of the forecast.
- Based on Pearson correlations, a community detection (clustering) algorithm groups SIC grid cells into geographic 'areas' $\mathrm{A_i}$ of sea ice homogeneity.
- A single time series is generated for each node $\mathrm{A_i}$ based on the cumulative anomaly of each area-weighted ψ_p grid cell: $\chi_i(t) = \sum_{p \in A_i} x_p(t)\sqrt{\psi_p}$
- Links between nodes are generated as the temporal covariance between nodes $\omega_{ij} = \mathrm{cov}(\chi_i(t), \chi_j(t))$ and are used to create a stochastic matrix of random walk transition rates M for GPR.

Gaussian Process Regression:

- Network nodes $X = \{\chi_i(t)\}_{i=1}^{N}$ become the n x N-dimensional design matrix in a GPR model.
- Priors over functions ($y = \mathrm{f(X)} + \sigma^2 I$) are fitted in the form of a random walk covariance kernel $\Sigma_{\text{prior}} = \alpha\exp(\ell M)$ with hyperparameters $\theta = (\ell, \alpha, \sigma^2)$ determined through type II maximum likelihood.
- The model is trained based on the network inputs X and the summer SIE target y, up to the year t_{n-1}.
- A forecast of Arctic(Antarctic) summer SIE is then computed based on the test inputs as June(November), July(December) or August(January) SIC of the year of the forecast, i.e. t_n.





Spring Barrier

Model studies have shown that a spring predictability barrier exists for coupled model forecasts of Arctic SIE (Bushuk et al 2017; Bonan et al 2019). Our preliminary results show that this barrier also exists in observational data.