A Polar Low Genesis Potential Index and Its Application to Subseasonal Prediction

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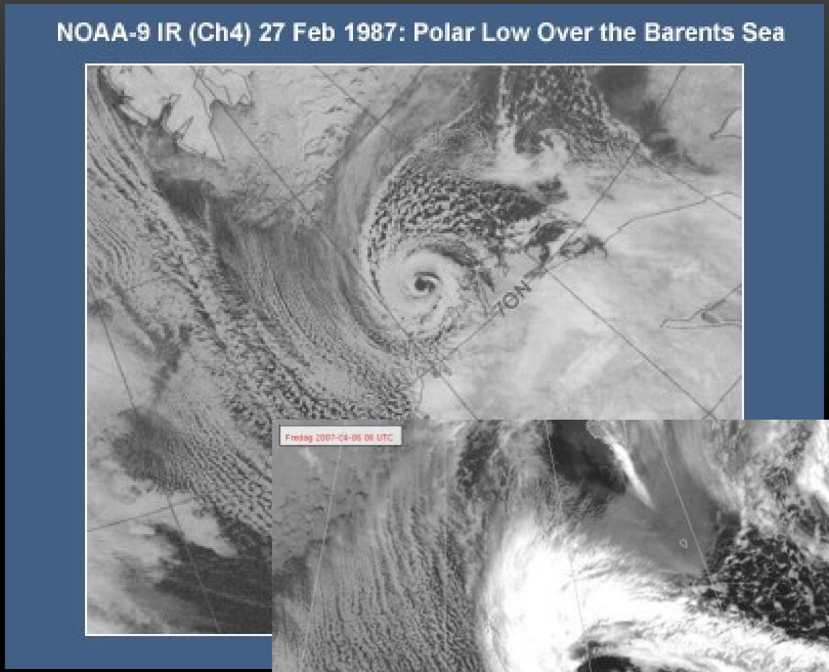
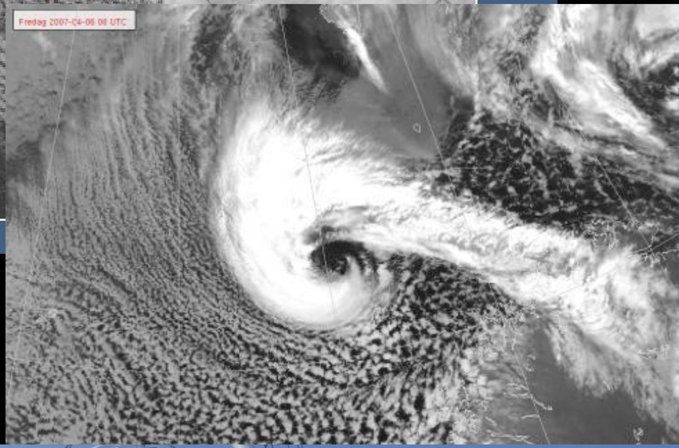
What are Polar Lows?

- Polar lows (PLs) are high-latitude mesoscale (200-600 km in diameter) maritime cyclones, characterized by short lifetimes (typically < two days) and strong surface winds (up to 25-30 m s^{-1}) (e.g., Rasmussen and Turner 2003).
- Some polar lows have an axisymmetric structure, similar to tropical cyclones. They are also known as “Arctic hurricanes” (Emanuel and Rotunno 1989). However, more recent studies suggested that baroclinicity plays an important role in the development of some PLs (e.g., Stolls et al. 2021).
- Severe conditions associated with PLs include large-amplitude ocean waves, heavy snow showers, limited visibility, and strong icing, which can pose hazards to coastal communities and marine operations.
- PLs may affect deep-water formation in the subpolar North Atlantic, and thus the oceanic circulation (AMOC), through strong surface heat fluxes (Condron and Renfrew 2013).
- Skillful PL prediction beyond the synoptic time scale by global climate models remains a challenge due to the coarse model resolution, deficiencies in model physics, and limited observations in the Arctic.





Hypothesis and Objectives

Hypothesis: Variability of PL activity is associated with the changes in some key, large-scale climate variables, which provide predictable information on PL activity beyond the synoptic time scale.

Objective:

- Part I: Develop a polar low genesis potential index (PGI) that links the polar low genesis frequency with the large-scale climate conditions.
- Part II: Application of the PGI to subseasonal prediction

Method

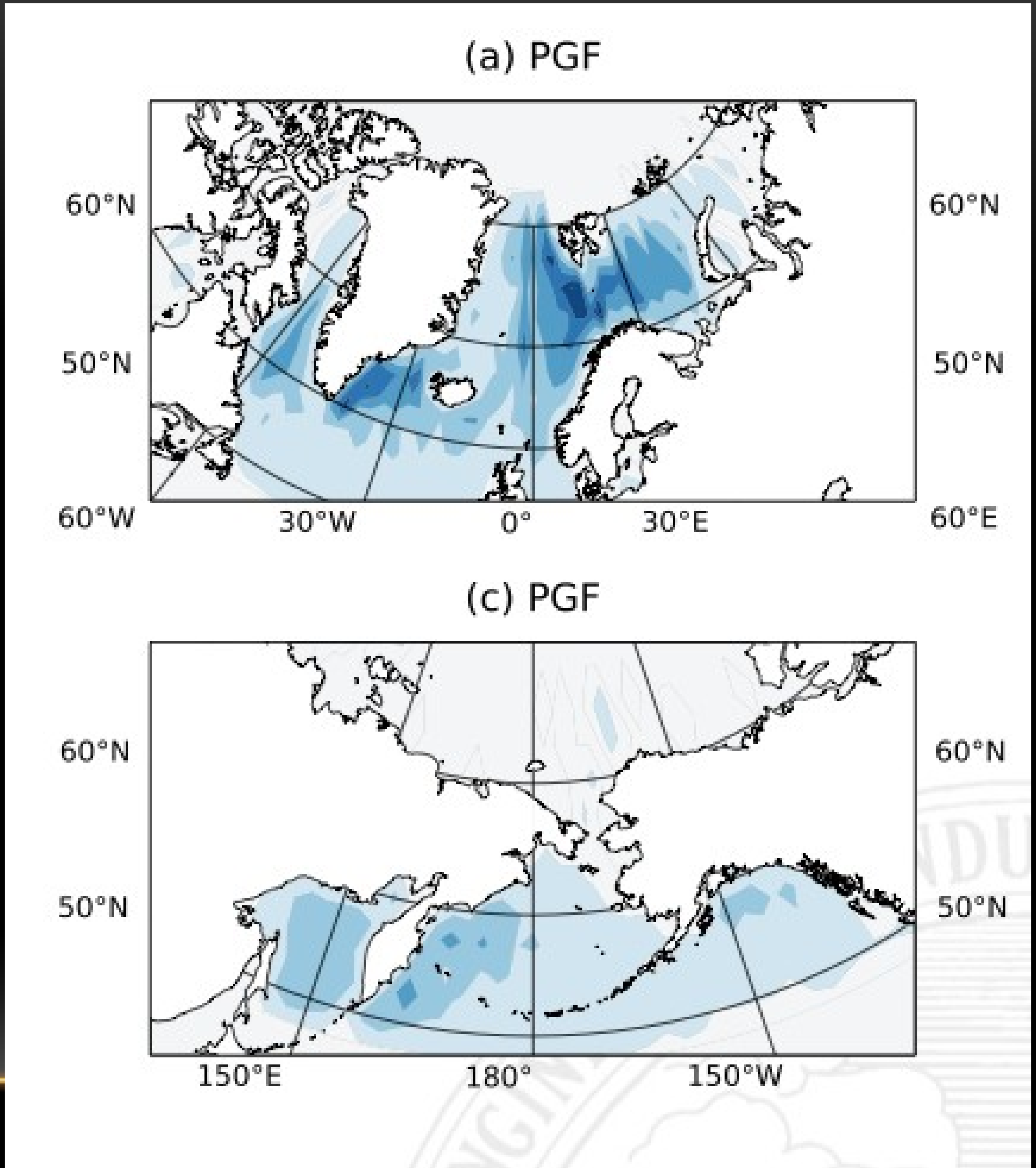
- Assumes a log-linear relationship between PL genesis frequency and climate variables, which can be represented by a Poisson model:

where xi denotes a standardized climate variable (or predictor); the coefficient, *bi,* can effectively be interpreted as the sensitivity of PGI to changes in the climate variable xi.

- This prediction is applied grid-point wise.
- **Assumption**: a stationary relation between PL frequency and climate variables exists across all source regions.

Data

- ERA5 reanalysis data: coarsened to a grid resolution.
- PL track data from Stoll (2021) based on ERA5 reanalysis; a polar low genesis density function (**PGF**) is derived on a grid resolution.
- Analysis is restricted to open oceanic grid points (land or sea-ice fraction < 80%) between 50˚N and 85˚N
- Time period: 1979-2020.



Model Development

- The Poisson regression model is fitted to **long-term** (1979-2020) monthly means of cosine-weighted PGF and climate variables in all calendar months over all open oceanic grid points.
  - Forward selection method is used to choose the best performing predictors from a pool of 29 potential predictors that are physically relevant to PL formation.
- The following climate variables are chosen as model predictors:
  1. A static stability parameter: the difference between the skin potential temperature and the 500-mb potential temperature (associated with MCAO),
  2. An environmental baroclinicity parameter: the magnitude of the horizontal gradient of the 800-hPa equivalent potential temperature

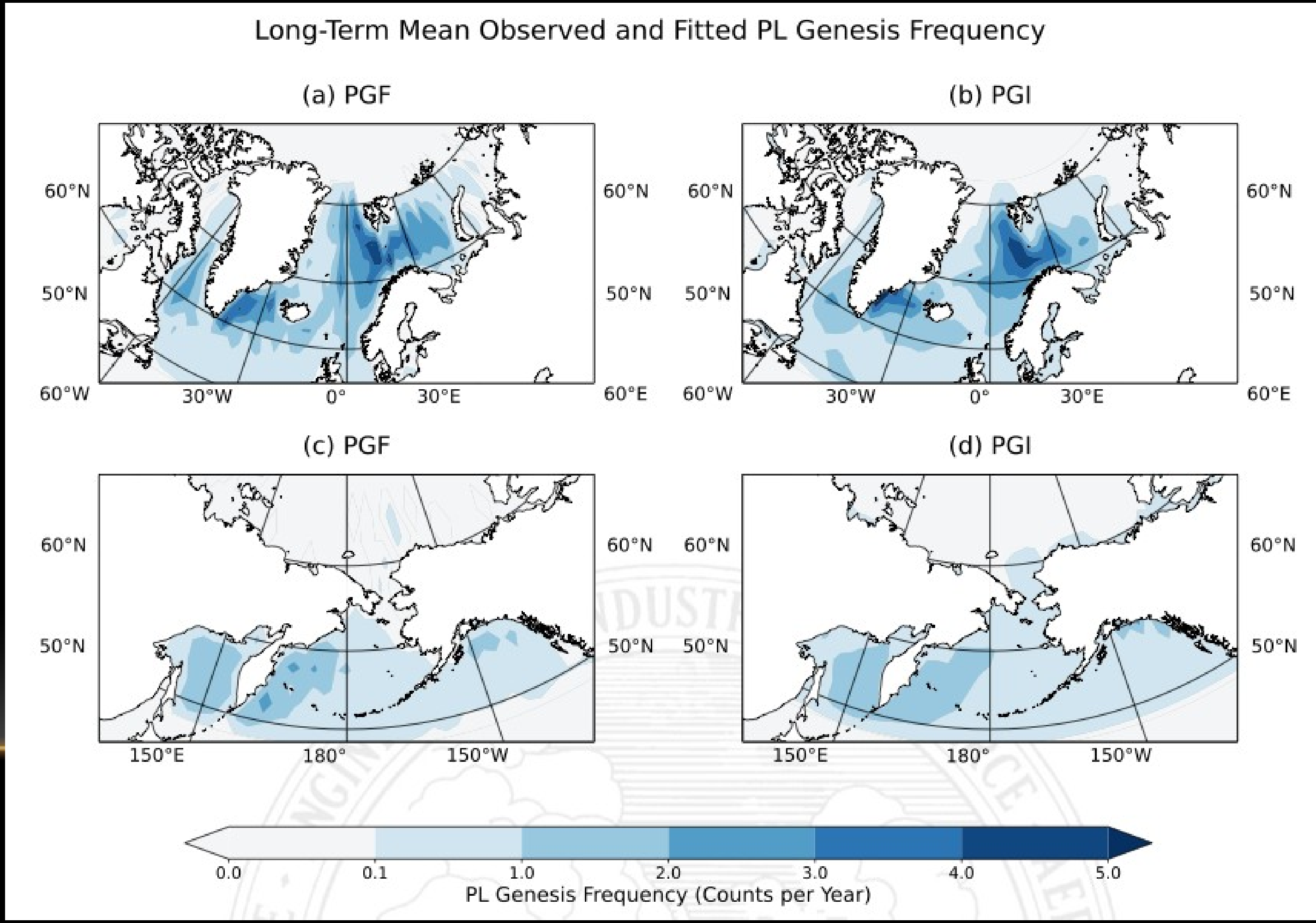
PGI vs. PGF: Spatial Distribution

- There is good agreement between the PGF and PGI.
- In general, the PGI tends to smooth the small-scale features of the PGF.

PL genesis index (**PGI**): statistical fitting
Genesis density function (**PGF**): observations

PGF: Observations

PGI: Fitting

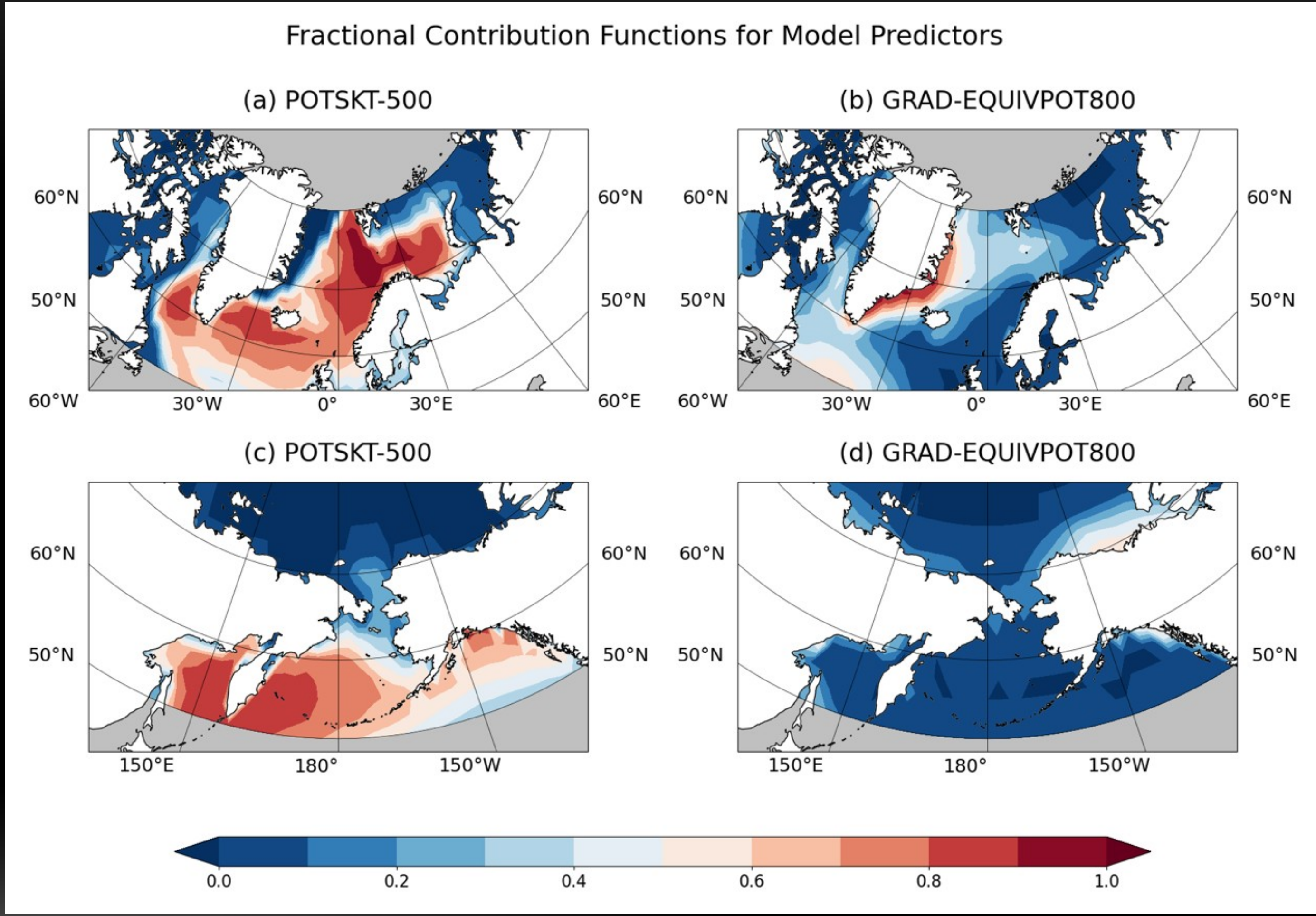


Contributions of Individual Predictors

How do the predictor fields control the spatial distribution of PLs?

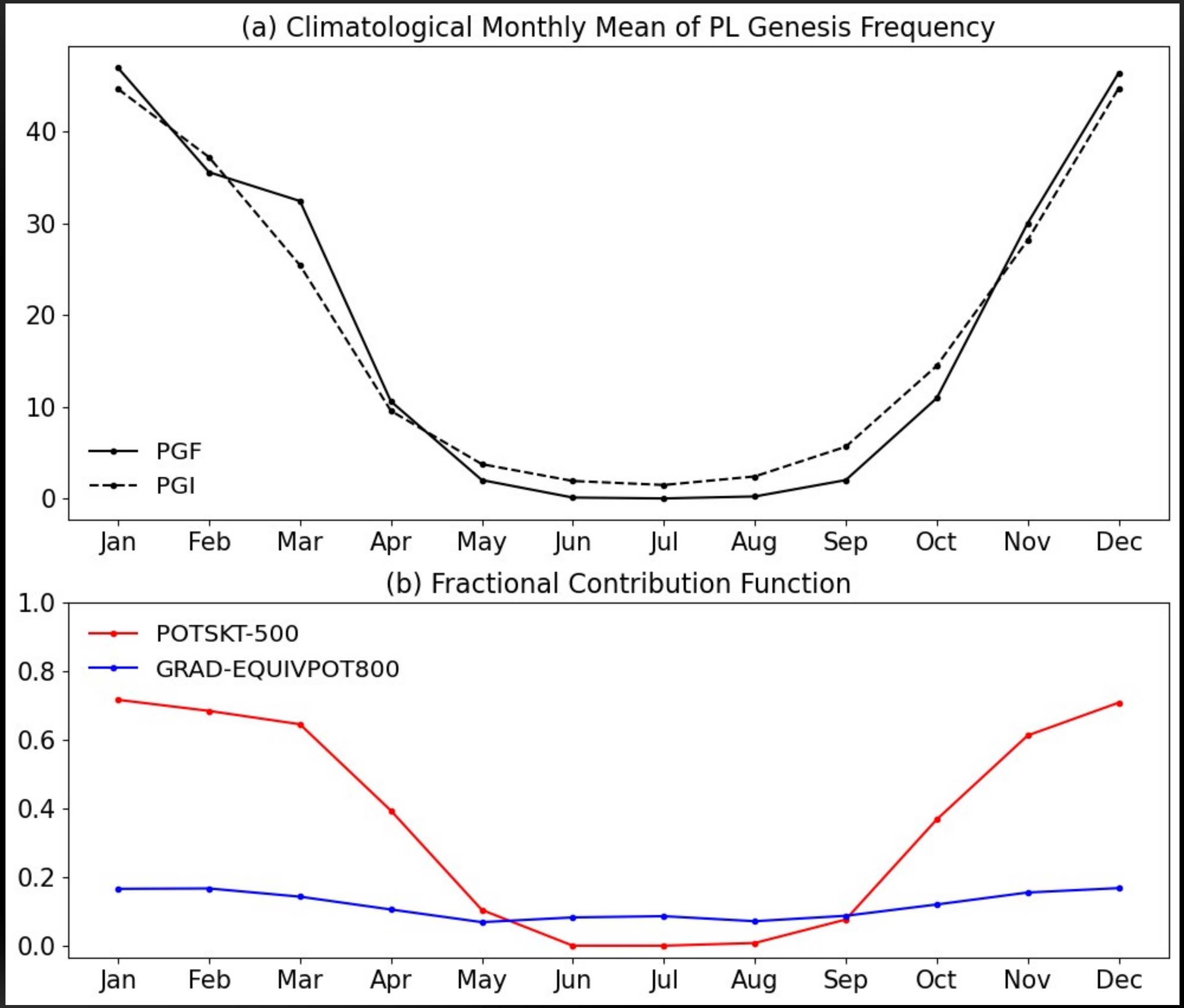
- Fractional Contribution Function:

- Low static stability sets constraints on where PLs *can* form.
- Enhanced values of vertical wind shear amplify pre-existing potential for PL development.
- PLs form in less baroclinic environments in the Pacific compared to the North Atlantic.



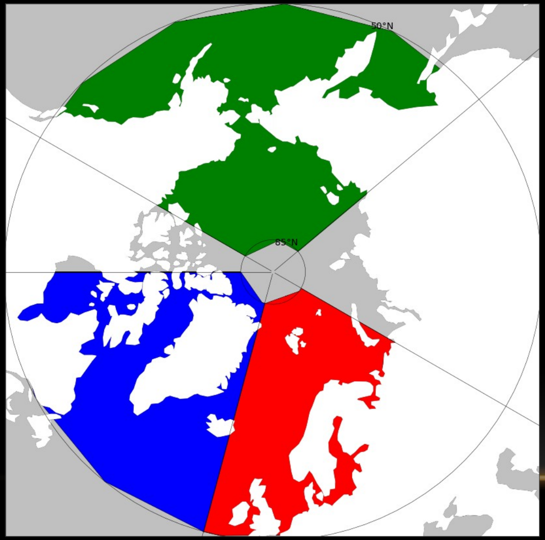
PGI vs. PGF: Seasonality

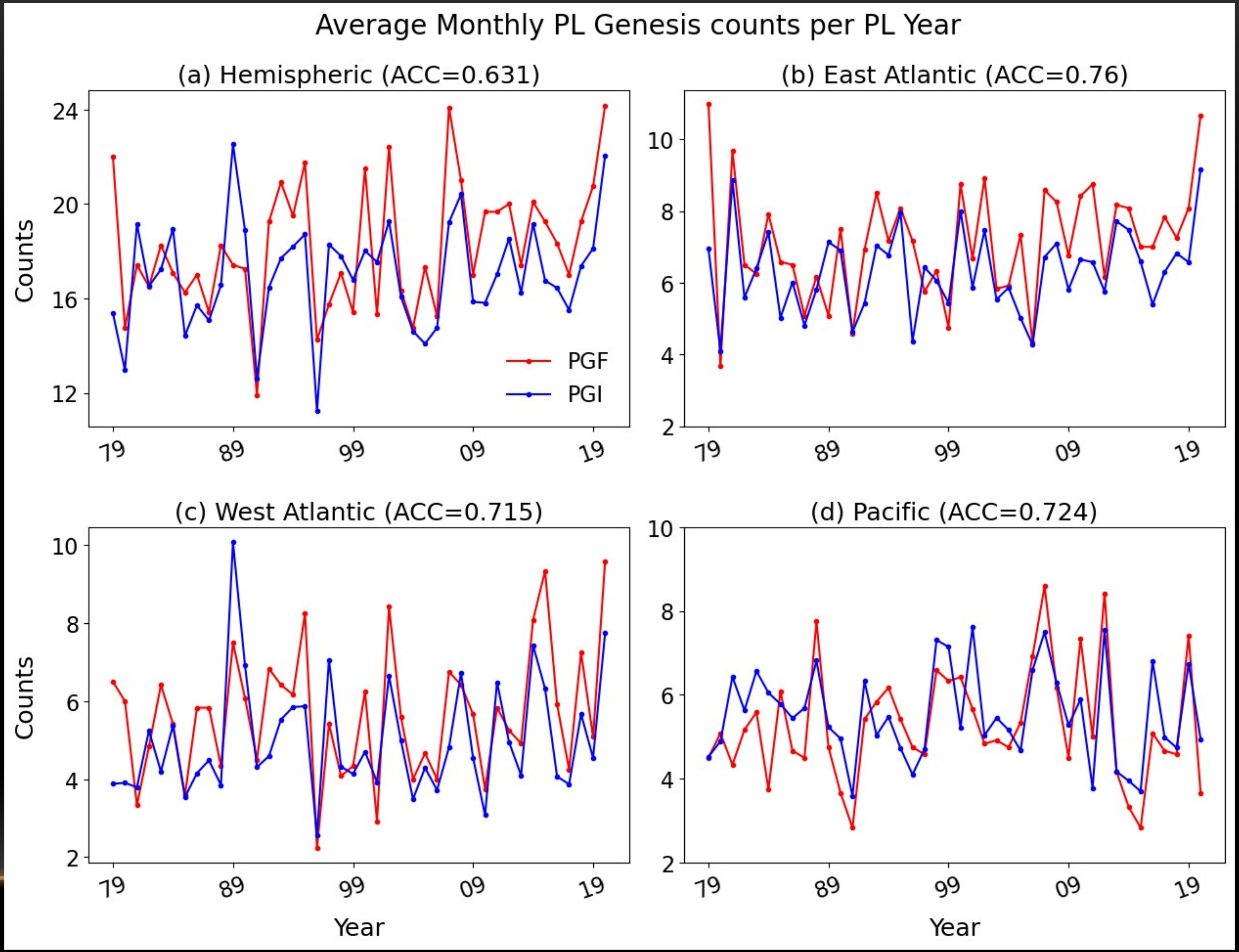
- PGI well represents the seasonal cycle of PL genesis frequency.
- The static stability parameter makes the major contribution to the seasonal cycle of PLs.



PGI vs. PGF: Interannual Variability

- The PGF (obs, red) exhibits great interannual variability.
- PGI (fitting; blue) skillfully represents this variability, at both the hemispheric and regional scales.



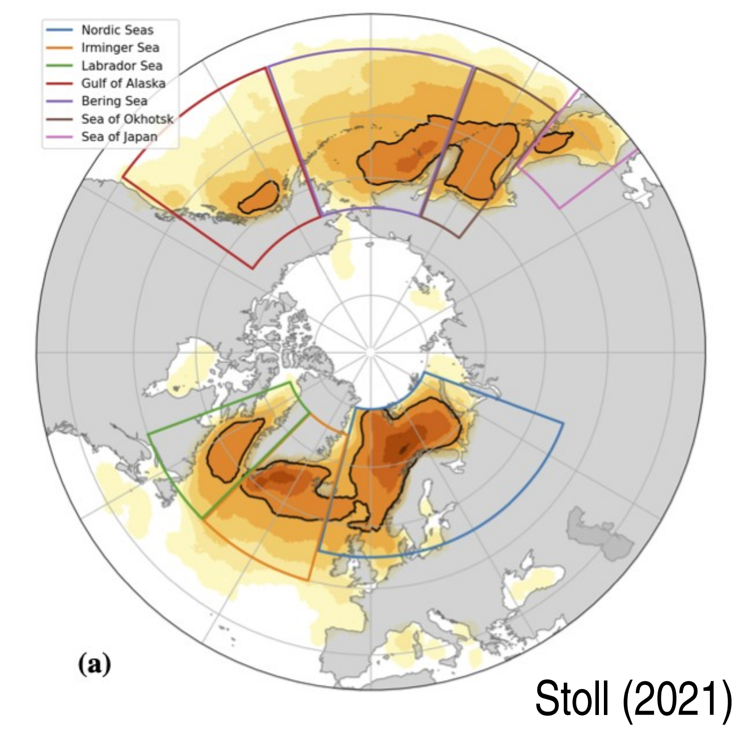


- Part I: PGI development
- Part II: Subseasonal prediction

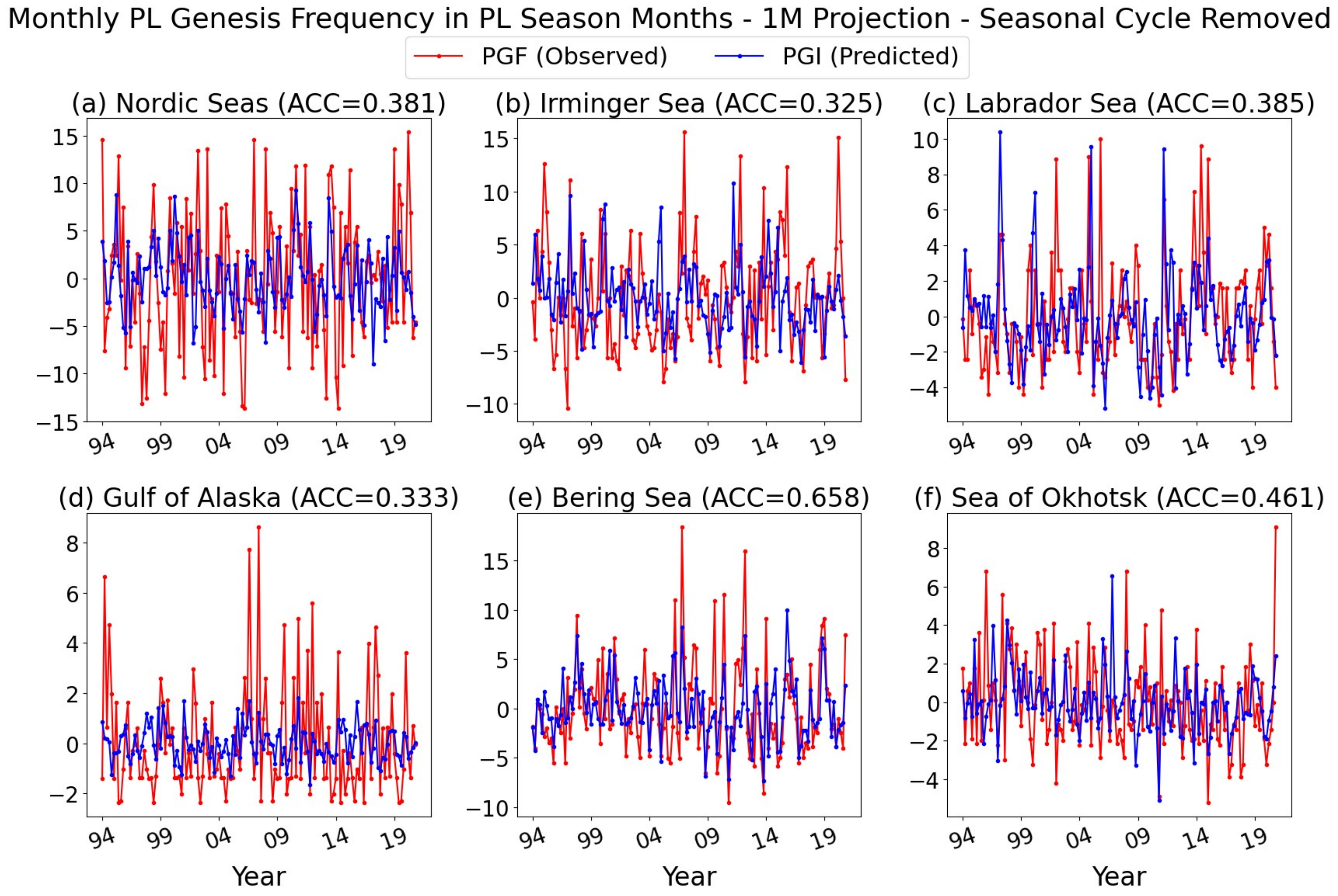
Data and Methodology

- Predictors derived from ECMWF subseasonal and seasonal (re)forecasts are used to predict PGI.
- We focus on the PL season Nov-March.
- The predicted PGI is evaluated against the PGF derived from PL track dataset (Stoll 2021).
- Anomaly correlation coefficients (ACC) and Heidke skill score (HSS) are used to assess the predictions.

Monthly Mean PGF (red, obs) and PGI (blue, prediction)

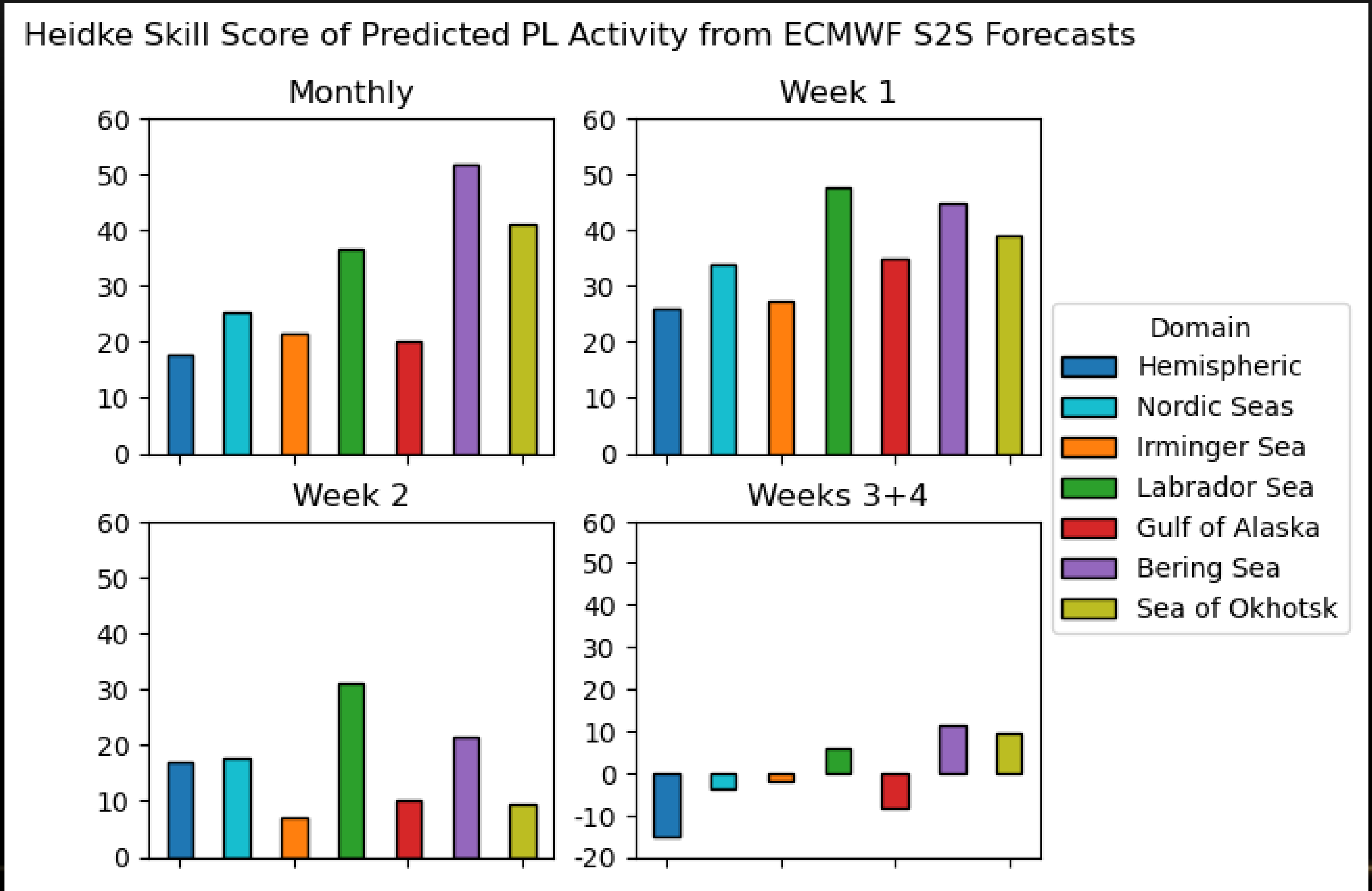


Stoll (2021)



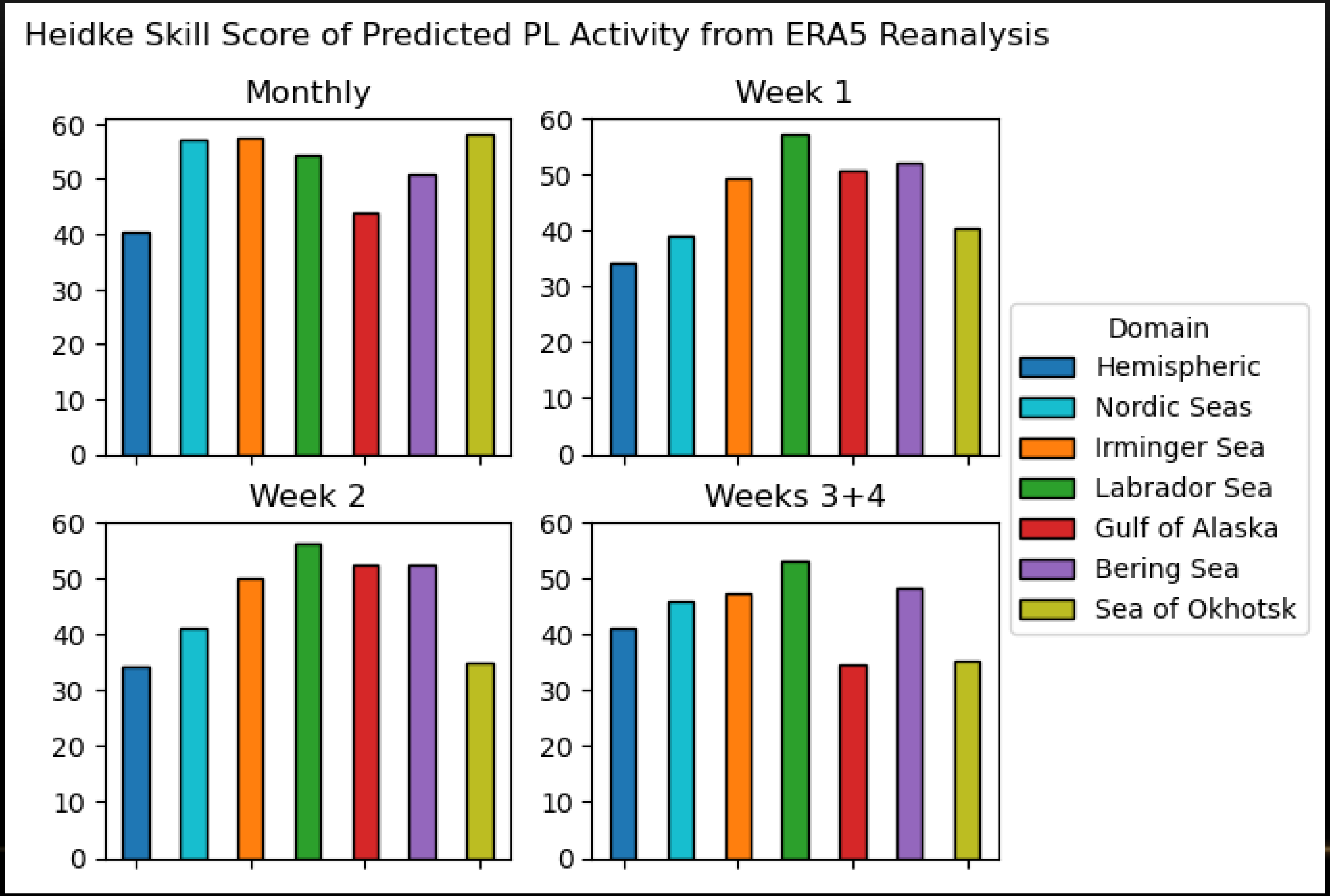
The regional sum of predicted PGI and the observed PGF are computed for each source region. Seasonal cycle is removed before the ACC calculation.

HSS of Two-tier Prediction using ECMWF S2S Forecasts



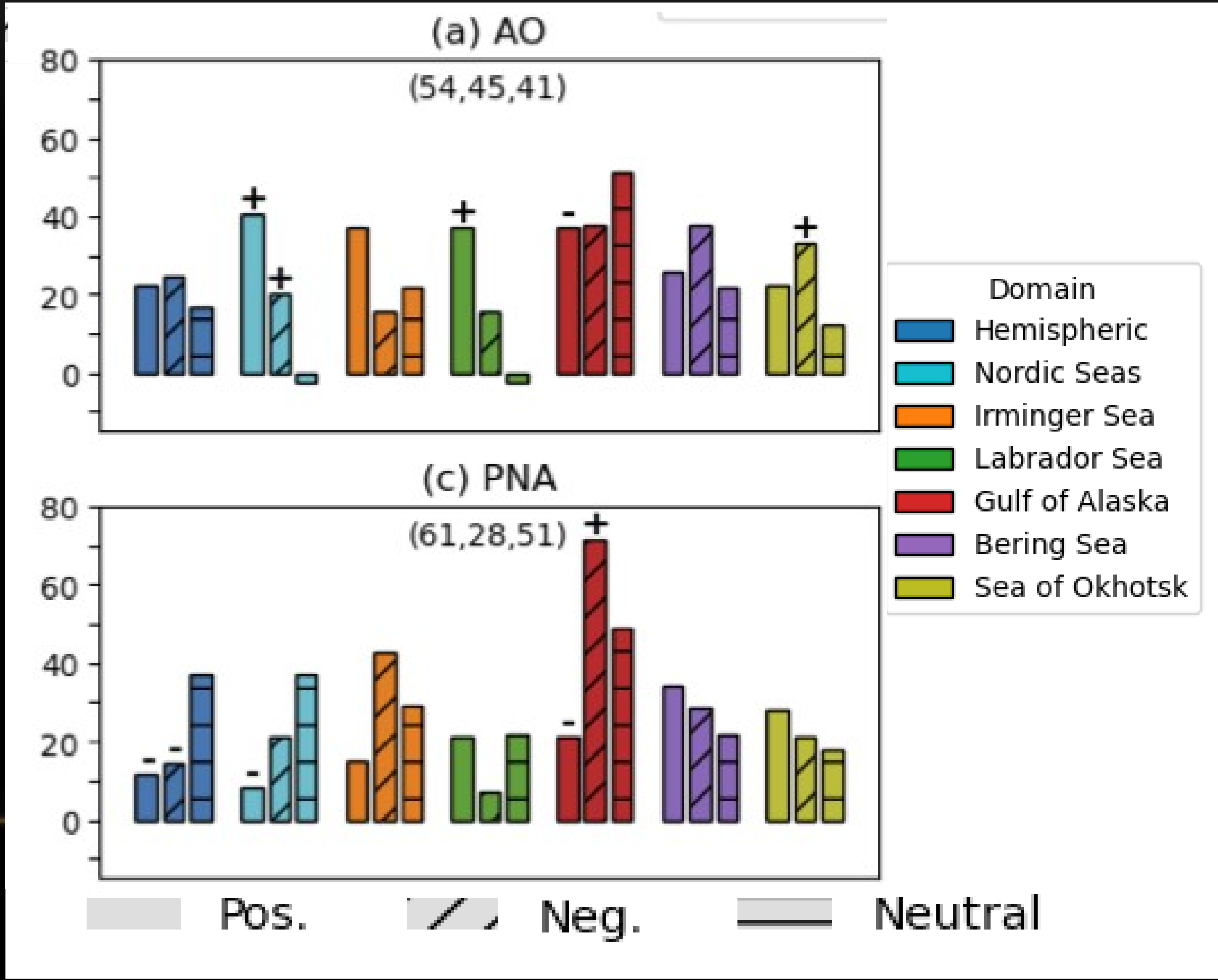
Two-tier prediction: above and below the median

HSS of Two-tier “Perfect” Prediction using ERA5



- Predictors are derived from the ERA5 (”perfect” prediction of predictors)
- An upper bound of the prediction skill using the PGI framework

HSS of Monthly PGI Prediction Modulated by the AO and PNA



Summary

- A PL genesis potential index (PGI) is developed to represent the empirical relationship between key climate variables and PL genesis frequency in a Poisson regression framework.
- PGI well represents the long-term mean seasonal cycle and the spatial distribution of PL genesis frequency climatology, as well as the interannual variability of observations at all scales.
- PGI is a useful diagnostic to understand and quantitatively assess the impacts of environmental conditions on the variability of PL activity and can be used for S2S prediction.
- Dependence on the data sources (not shown): Testing with another PL track dataset and the ERA-Interim data suggests the robustness of the PGI approach.

Future Work

- Future Work:
  - Projection of PL activity in future climates
  - Does the same stationary relationship btw PL genesis freq. and environmental variables exist in the future climate? Will the PGI still work as PLs shift further poleward?

Thanks

Data and Methodology for Hybrid Prediction

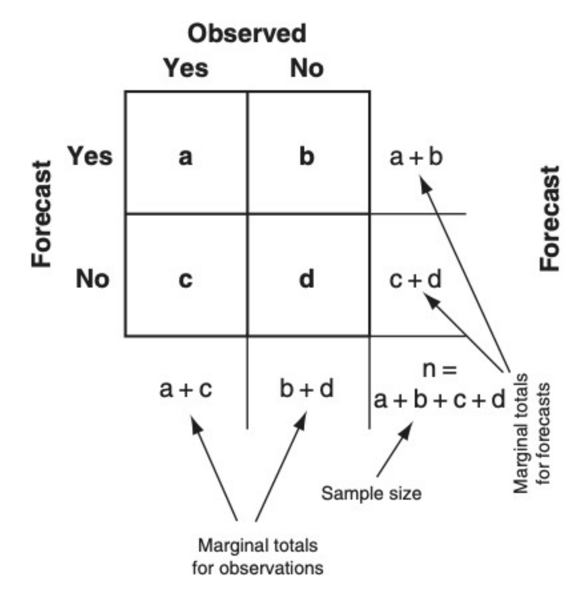
- Monthly Prediction:
  - The ECMWF seasonal hindcasts (1994-2016) and forecasts (2016-2020) are used to develop and test the model.
  - We used the leave-one-year-out cross validation (LOOCV) method for cross validation: there are 27 iterations of the LOOCV in total, which produces a time series of 27*5=135 data points for the predicted PGI.
- Weekly Prediction:
  - The ECMWF subseasonal hindcasts (20 years) from the S2S database are used to train the model for each forecast lead time, and the real-time forecasts during the PL season of 2015-2020 are used to test the model.
  - Forecasts are issued twice a week.
  - There are 240 predictions for each of the three forecast lead times (week-1, week-2, and week 3&4): 6 (years) * 5 (months) * 4 (weeks) *2 = 240

Heidke Skill Score

- The general definition of a skill score

$$SS_{ref} = \frac{A - A_{ref}}{A_{perf} - A_{ref}} \times 100\%,$$

- For HSS, we use the proportion correct (PC) as the metric A. PC is defined as the total number of correct yes and correct no forecasts to the sample size. The reference metric A_ref is set to 50% for two-tier prediction, and A_perf is set to 1.0 for a perfect forecast.



$$PC = \frac{a + d}{n}.$$