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Supplement of

Summer Greenland Blocking in reanalysis and in SEAS5.1 seasonal forecasts: robust trend or natural variability?

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S1 – Snow cover

Snow cover is calculated following the following Kouki et al. (2023). The instructions can be found on the ECMWF website, under "Computation of snow cover" (https://confluence.ecmwf.int/display/CKB/ERA5%3A+data+documentation):

For ERA5, the **snow cover** (SC) is computed using **snow water equivalent** (SD, parameter 141.128) as follows:

$$SC = min\left(1, \frac{\frac{RW * SD}{RSN}}{0.1}\right)$$

where RW is **density of water** equal to 1000 and RSN is **density of snow** (parameter 33.128).

SEAS5.1 snow cover is calculated in the same way.

S2 – TIGRAMITE parameters

The PCMCI algorithm is implemented in the Tigramite package, which can be found on GitHub: https://github.com/jakobrunge/tigramite.

Here, we use version 5.2, and the PCMCIplus, which allows to detect directed lagged links, and directed and undirected contemporaneous links. The list of parameters used for each dataset and in both discovery and inference mode is shown below. The FDR correction is applied in causal discovery mode, unless otherwise stated.

Tigramite packages:

```
from tigramite import data_processing as pp
from tigramite import plotting as tp
from tigramite.pcmci import PCMCI
#from tigramite.independence_tests import ParCorr, GPDC, CMIknn, CMIsymb # tig4.1
from tigramite.independence_tests.parcorr import ParCorr
from tigramite.models import LinearMediation, Prediction
from tigramite.toymodels import structural_causal_processes as toys
from tigramite.models import Models
```

Function used in discovery mode:

```
dataframe = pp.DataFrame(data, datatime = np.arange(len(data)), var_names=var_names,mask=data_mask)
parcorr = ParCorr(significance='analytic', mask_type='y', verbosity=4)
pcmci = PCMCI(    dataframe=dataframe,     cond_ind_test=parcorr,     verbosity=4)
results = pcmci.run_pcmciplus(tau_min=tau_min, tau_max=tau_max, pc_alpha=None)
q_matrix=pcmci.get_corrected_pvalues(p_matrix=results['p_matrix'],tau_max=tau_max,fdr_method='fdr_bh', exclude_contemporaneous=False)
graph=pcmci.get_graph_from_pmatrix(p_matrix=results['p_matrix'],alpha_level=alpha_level_v, tau_min=tau_min, tau_max=tau_max)
```

```
results['graph'] = graph
all_parents=pcmci.return_parents_dict(graph,val_matrix=results['val_matrix'],include_lagzero_parents=True)
```

<u>Function used in inference mode:</u>

```
dataframe = pp.DataFrame(data, datatime = np.arange(len(data)), var_names=var_names,mask=data_mask)
parcorr = ParCorr(significance='analytic', mask_type='y', verbosity=4)
pcmci = PCMCI(    dataframe=dataframe,     cond_ind_test=parcorr,     verbosity=4)
med = Models(dataframe=dataframe, model = sklearn.linear_model.LinearRegression(), mask_type = 'y', data_transform = None)
med.fit_full_model(all_parents = all_parents, tau_max=tau_max)
Links = med.get_val_matrix()
```

<u>ERA5 – Causal discovery (Fig. 6, S9):</u>

```
tau_min = 0
tau_max = 1
alpha_level_v = 0.1
```

No FDR correction applied.

<u>SEAS5.1 – Causal discovery (Fig. 6, S9):</u>

```
tau_min = 0
tau_max = 1
alpha_level_v = 0.05
```

<u>ERA5, SEAS5.1 – Causal inference (Fig. 7):</u>

```
tau_min = 0
tau_max = 1
all_parents = {0: [(0, −1),(1, 0),(2, −1), (3, 0),  (3, −1),(4, 0)], 1: [(0, 0), (1, −1), (2, −1), (4, 0)], 2: [ (2, −1), (3, −1),(1, −1)], 3: [(0, 0), (3, −1), (2, −1)],
4: [(0, 0),(1, 0), (4, −1)]}
```

S3 – Atlantic multidecadal variability (AMV) index

AMV (Atlantic Multidecadal Variability) index: area average of sea surface temperature (SST) anomalies over the North Atlantic (80°W-0°, 0°-60°N). To calculate SST anomalies and remove the external forced component, we follow the method described by Zhang et al. (2019) which allows to "remove the local component regressed on the global mean SST".

The global mean SST is the area average of SST (0°-360°E,60°S-60°N). The average is stopped at 60°S/N to exclude temperatures over the sea ice.

To calculate the monthly AMV index, the following steps are taken:

1. Remove the climatological mean month by month
2. Calculate annual average (centered over the season of interest)
3. Compute the global mean SST anomalies (GMSSTA time series)
4. For each grid point, regress the SST anomalies on the GMSSA → regCOEF(lon,lat)
5. Residual SSTA_r = SSTA - regCOEF*GMSSTA
6. Calculate AMV averaging over the North Atlantic box (80°W-0°, 0°-60°N) using the residual SSTA_r.

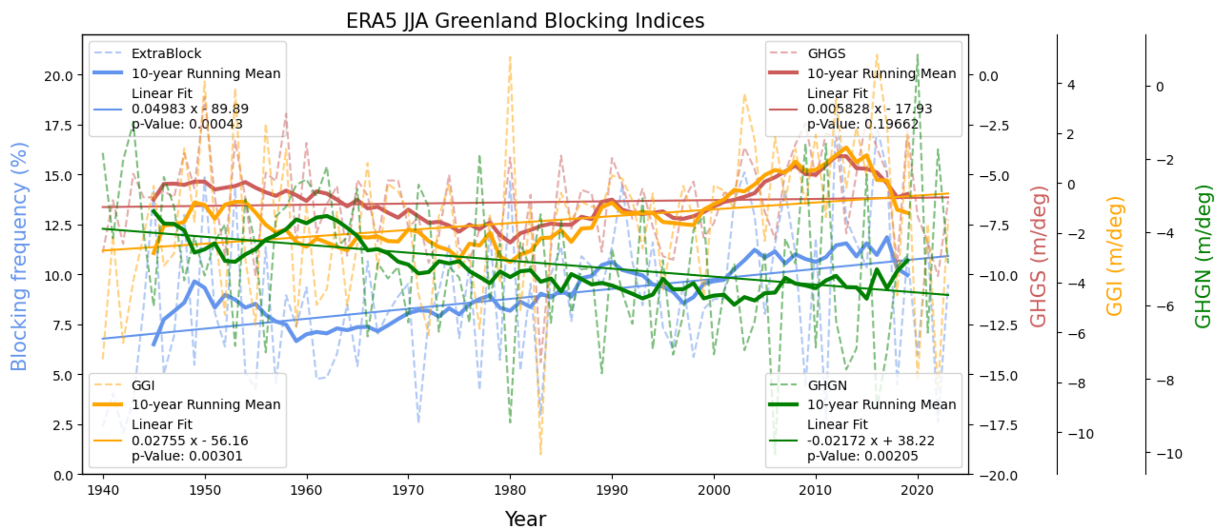

Figure S1: Greenland blocking index observed trends from 1981-2023. Figure shows JJA Greenland Blocking Index (blue) and Greenland Gradient Index (yellow) GHGS(red) and GHGN (green) for ERA5-81. Dashed lines show the season average, bold lines the 10-year running mean and the thin solid lines the linear trend. Values for the trend and their p-values (estimated with a Mann-Kendall test) are shown in the legend for all indices. Significance at 99% level is achieved by all the indices but by GHGS, which shows a decreasing trend/variability since 2010.

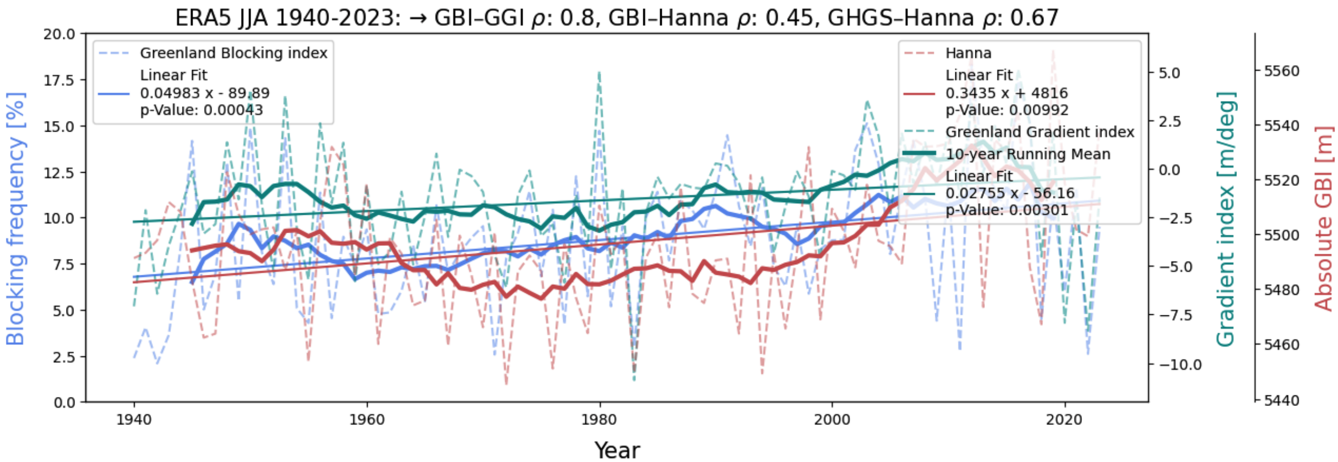

Figure S2. **HA16 index**. Same for Fig. 1c but reporting also the HA16 index (reported in red as Absolute GBI). This is the area-weighted average of the geopotential height between 60N-80N, 80W-20W. Pearson's correlation with the Greenland Blocking Index used in this study is 0.45 (significant at the 99% level) and reported in the title.

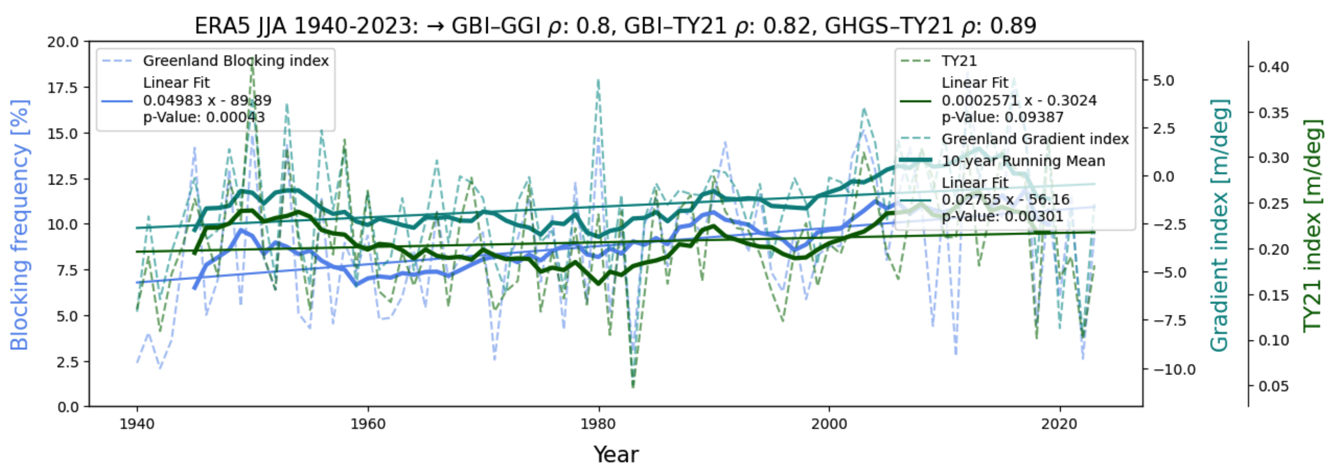

Figure S3. TY21 index. Same for Fig. 1c but reporting also the TY21 index (reported in green, as TY21 index). This index loosen the constraint on the GHGN gradient from -10 to 0 deg/m Being substantially similar to the one used in the current study, Pearson's correlation with the Greenland Blocking Index used in this study is 0.82 (significant at the 99% level) and reported in the title.

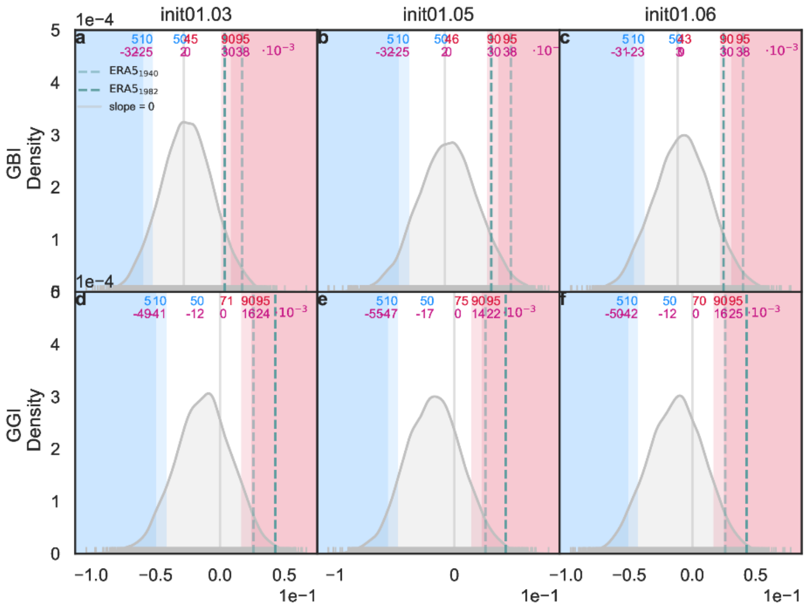

Figure S4: Greenland blocking index (GBI) and Greenland Gradient index (GGI) trends in SEAS5.1-03, SEAS5.1-05 and SEAS5.1-06. Upper row: as Figure 2a but for SEAS5.1-03 (a), SEAS5.1-05 (b), SEAS5.1-06 (c). Bottom row: as Figure 2b, but but for SEAS5.1-03 (d), SEAS5.1-05 (e), SEAS5.1-06 (f)

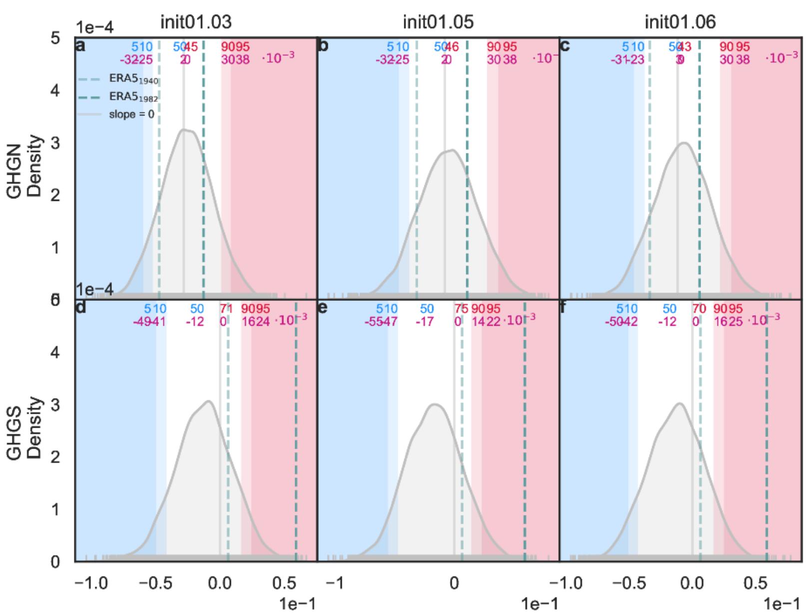

Figure S5: GHGN and GHGS trends in SEAS5.1-03, SEAS5.1-05 and SEAS5.1-06. Same as Figure S4 but for GHGN (top row) and GHGS (bottom row) .

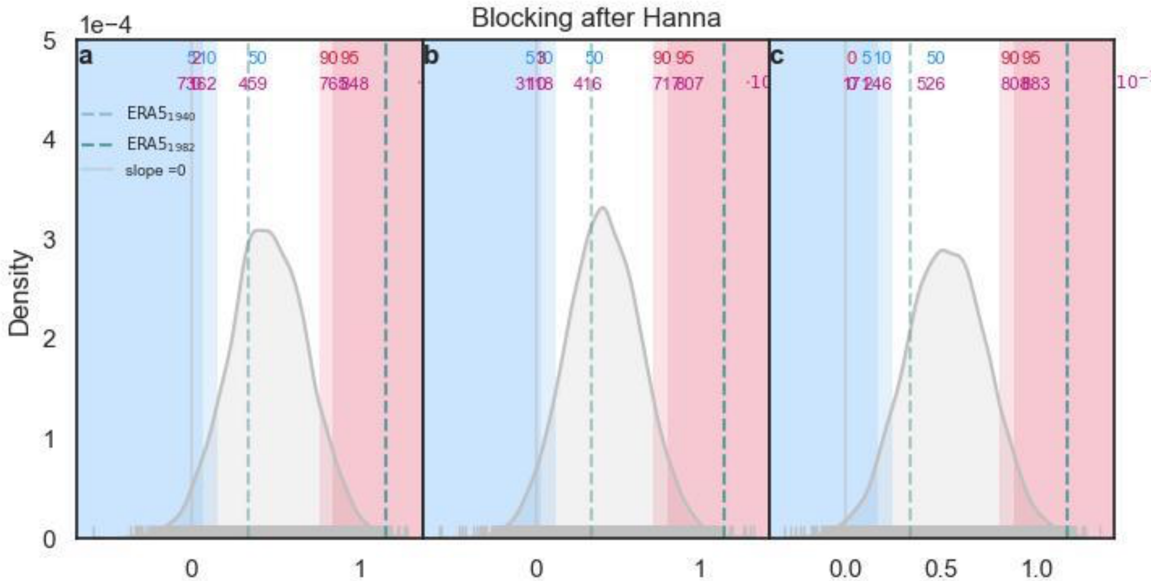

Figure S6. HA16 index trends in SEAS5.1-03, SEAS5.1-05 and SEAS5.1-06: Same for Figure S4 but for the HA16 index.

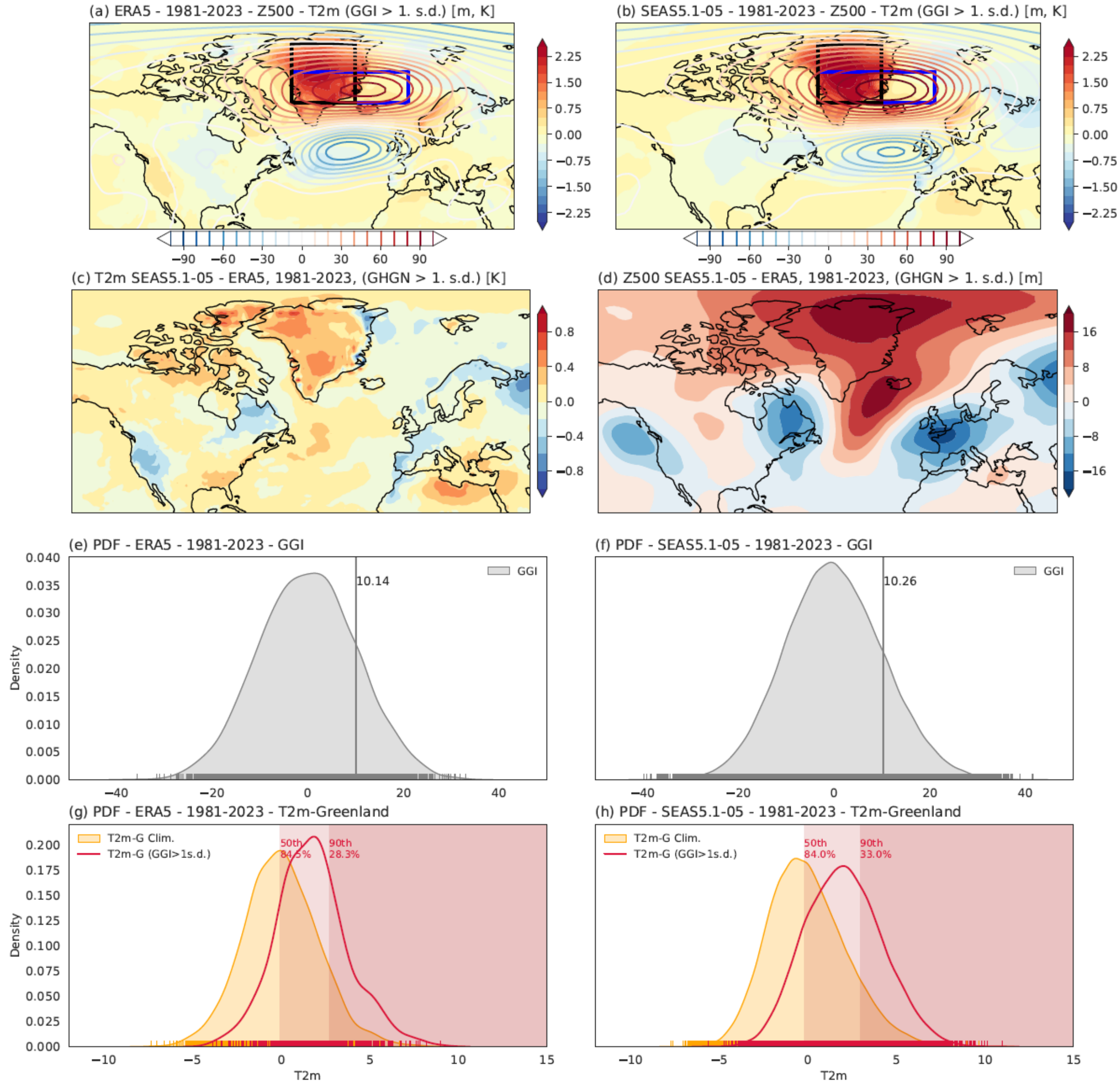

Figure S7. Same as for Fig. 3 but for SEAS5.1 init. 1st of May.

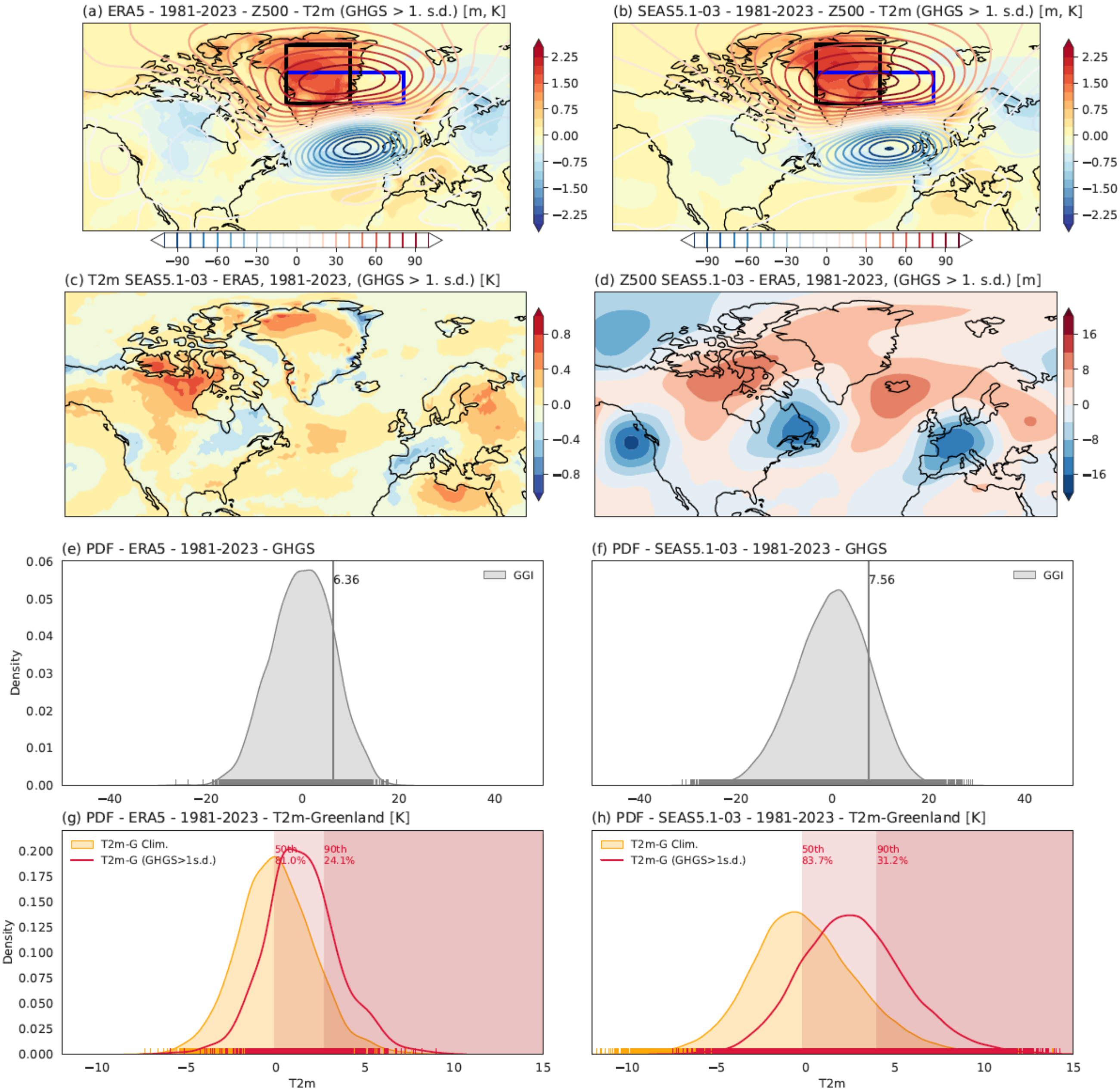

Figure S8. Same as for Fig. 3 but for GHGS.

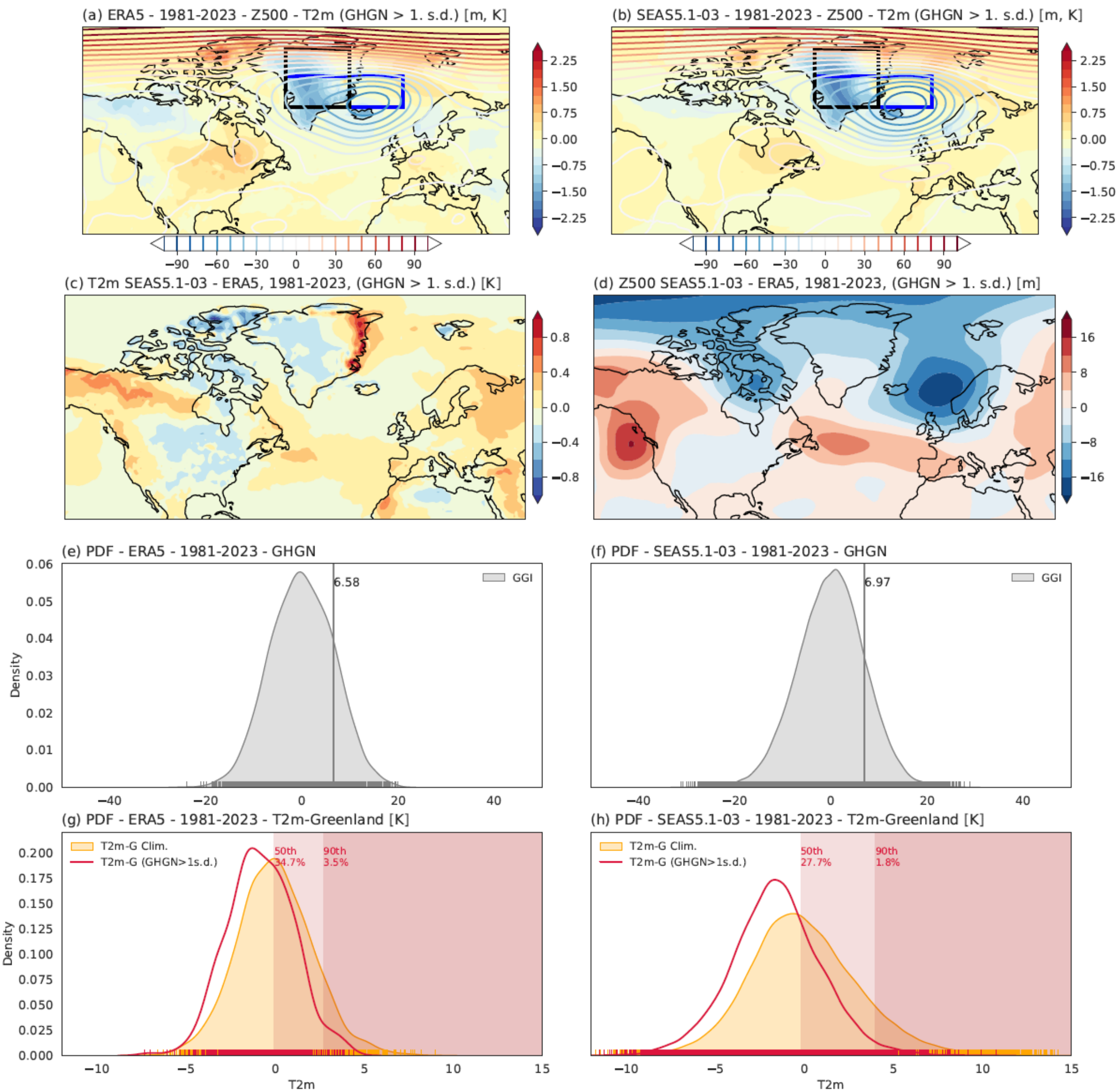

Figure S9. Same as for Fig. 3 but for GHGN.

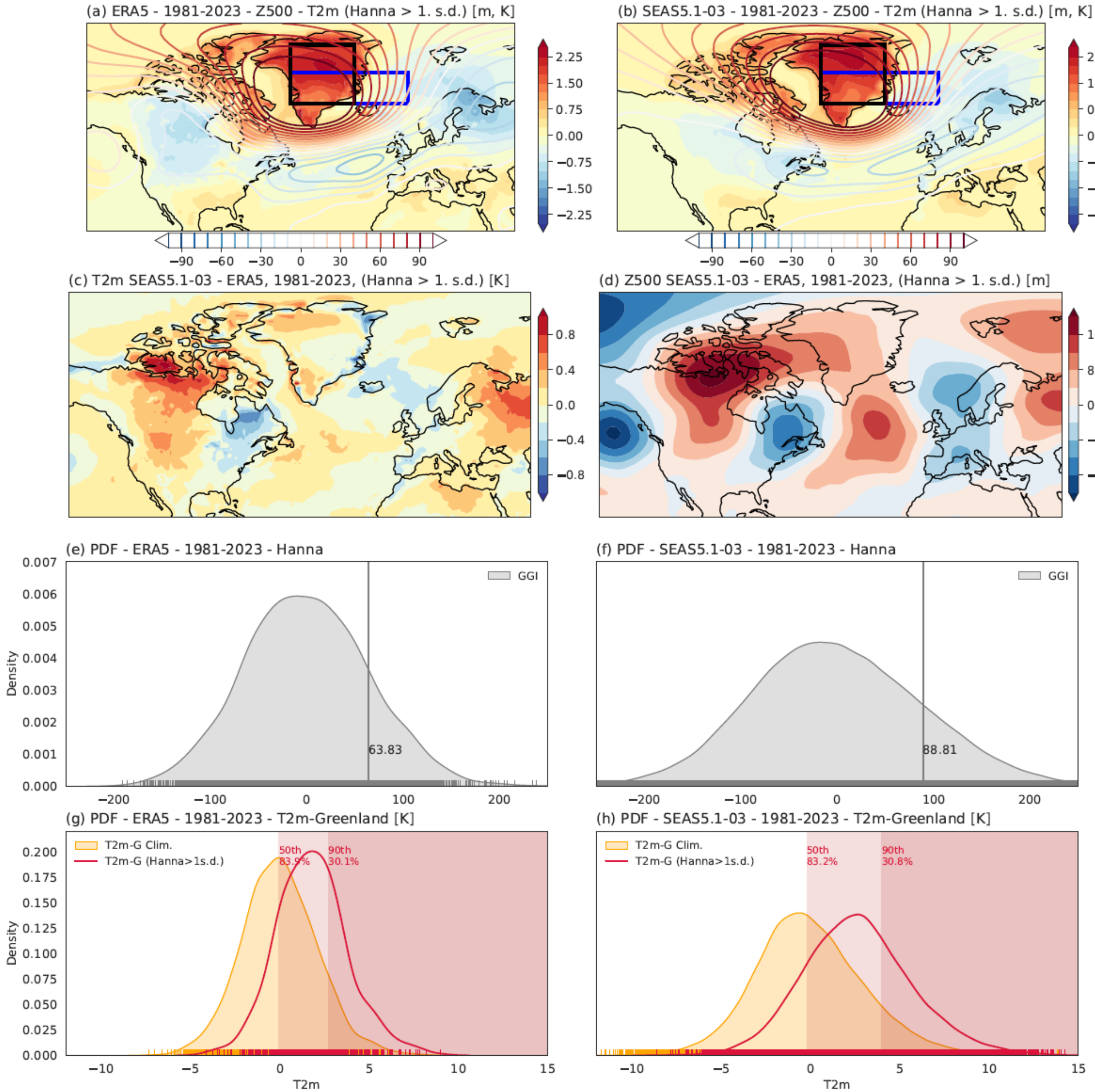

Figure S10. Same as for Fig. 3 but for the HA16 index.

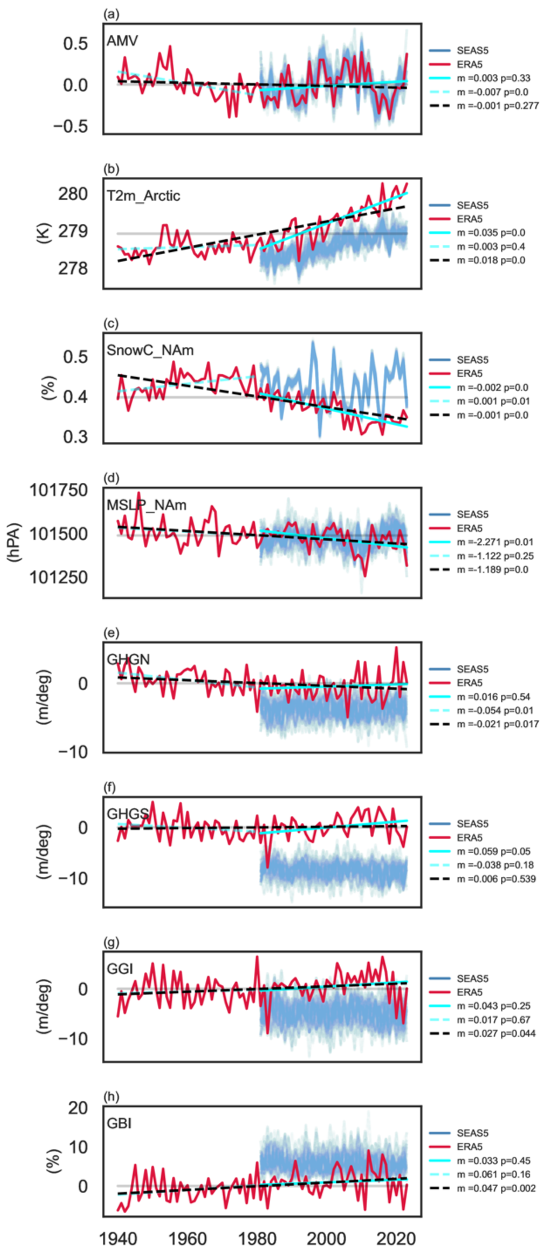

Figure S11: Monthly drivers and Blocking indices in ERA5 and SEAS5.1-03. Shown are the monthly drivers AMV (a) T2m-Arctic (b), Snow-NAm(c), MSLP-NAm (d), and Blocking indices GHGN (e), GHGS (f), GGI (g), GBI (h) for ERA5 (red) and the SEAS5.1-05 members(blue). For ERA5 the trends over the whole timeseries in 1941-2023,(black dashed)as well as for the timeseries 1940-1980,(cyan dashed) and 1981-2023(cyan, solid) are depicted with their slope and p-values listed in the legend to the right. The light grey line indicates the mean values of the whole timeseries.

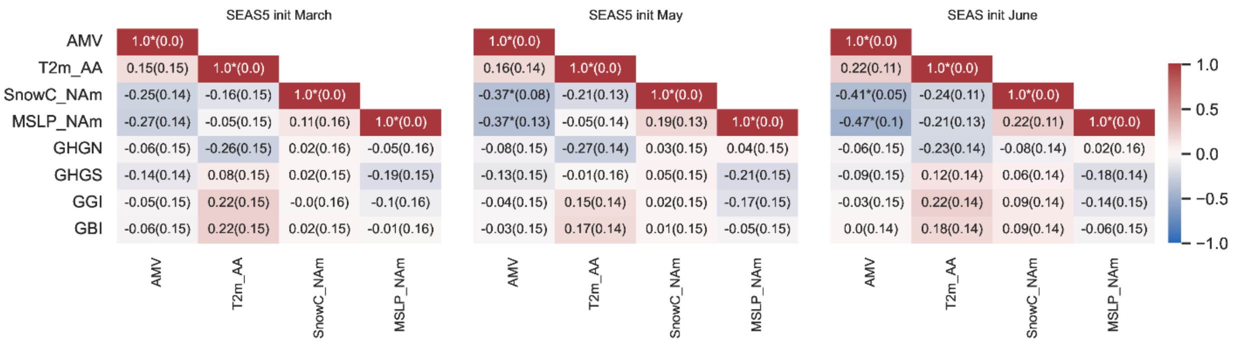

Figure S12: Same as for Fig. 5but with SEAS5.1-03, -05, and -06. Correlation heat maps. -Correlation plot of different variables in and SEAS5 initialized in March, May and June for the detrended data.`. Statistically significant values are indicated with an asterix. The correlation values of SEAS5 are the median correlation values of the 1e5 random SEAS5 runs and the p-values of the corresponding timeseries combination. SnowC NAm in SEAS5.1-06 was replaced by the ERA_1981 timeseries to calculate the correlation values.

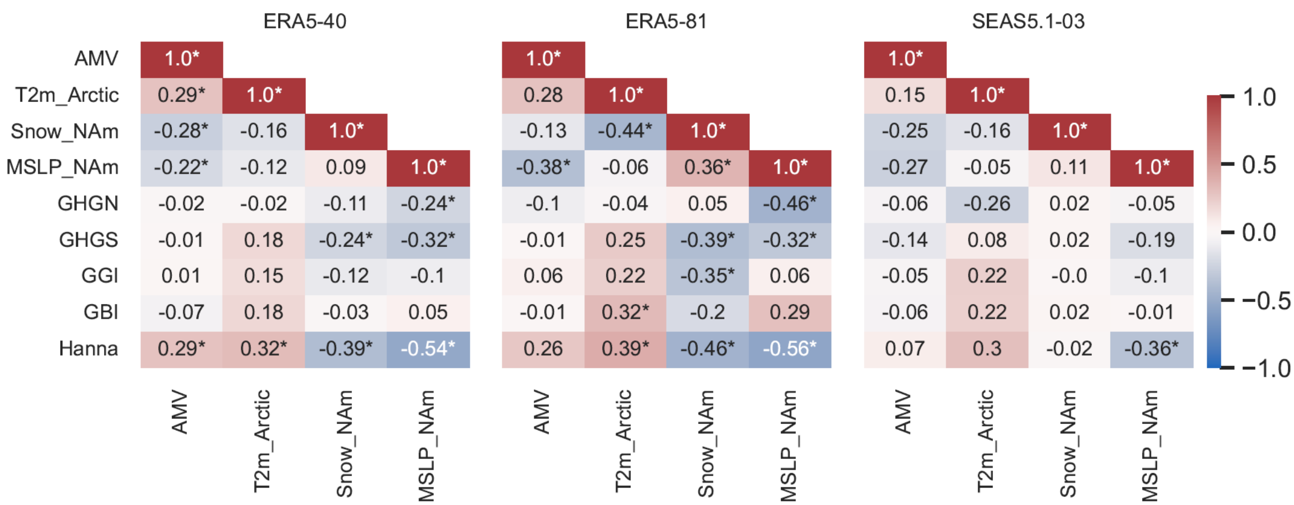

Figure S13. Same as for Fig. 5 but for the HA16 index.

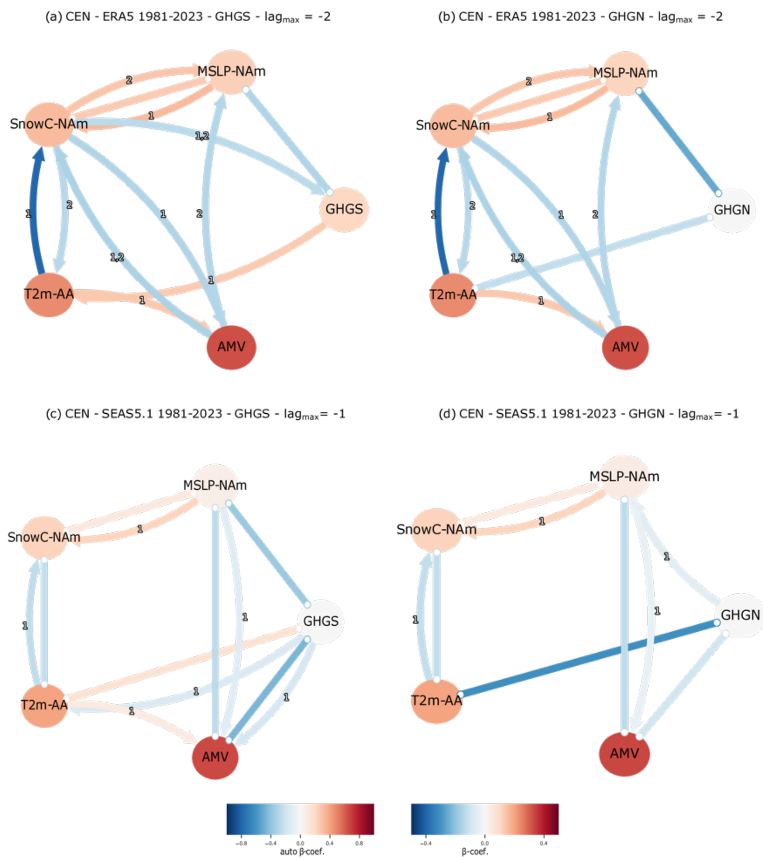

Figure S14: Same as for Fig. 8 but for GHGS and GHGN.

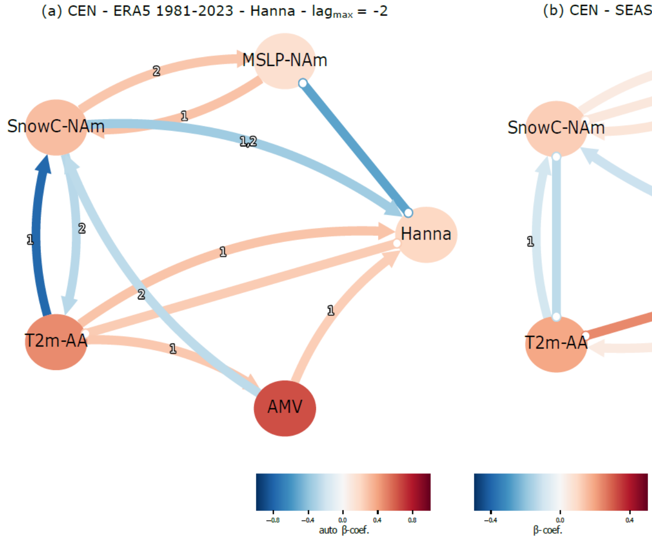

Figure S15. Same as for Fig. 5 but for the HA16 index.

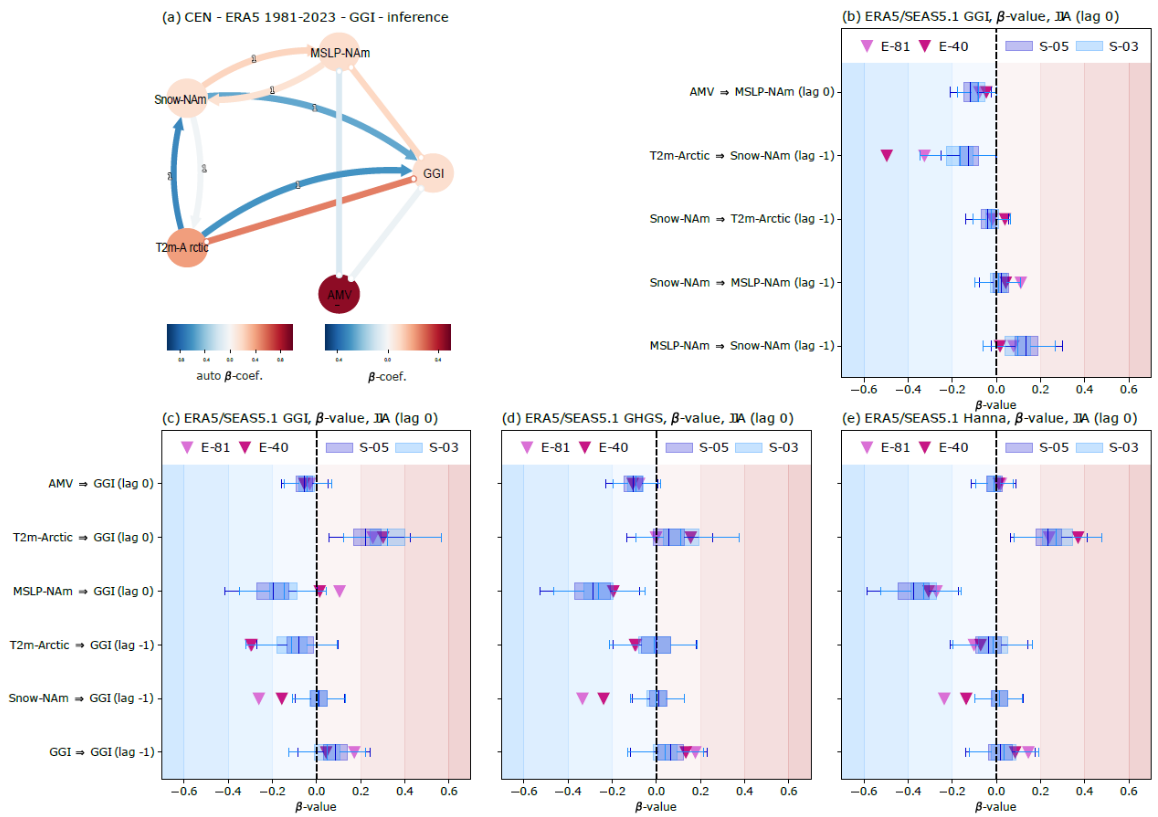

Figure S16. Same as for Fig. 5 but for the HA16 index.

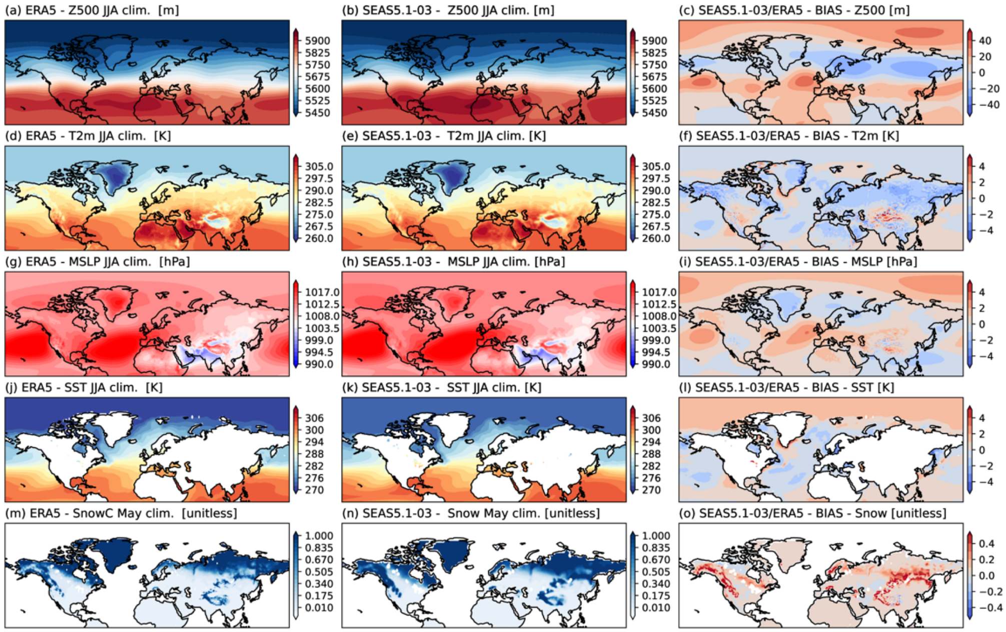

Figure S17. JJA climatology for Z500, T2m, MSLP, SST and snow cover for ERA5 and SEAS5.1-03.

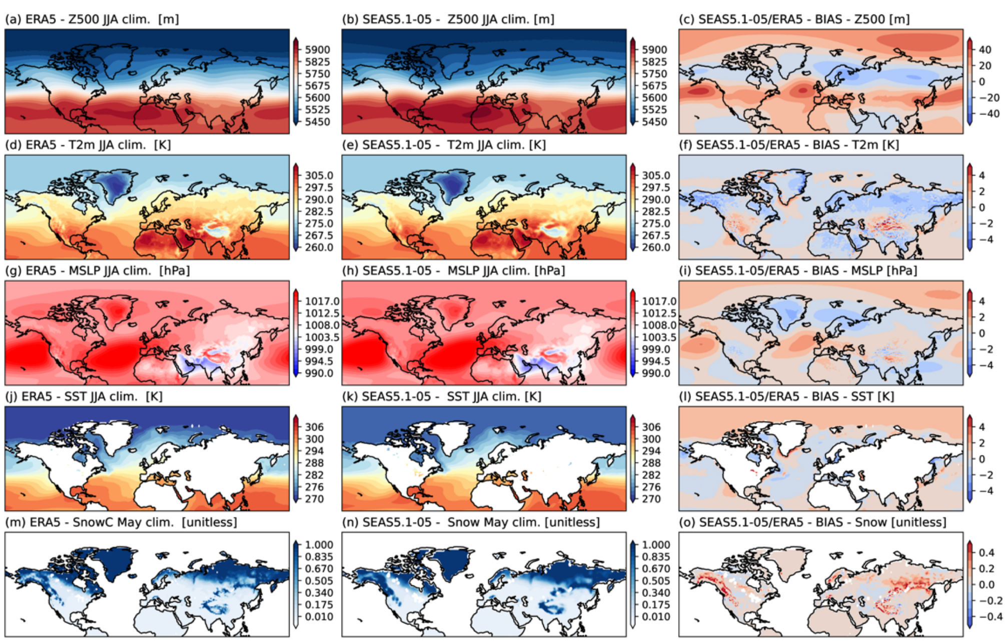

Figure S18. JJA climatology for Z500, T2m, MSLP, SST and snow cover for ERA5 and SEAS5.1-0**5**.