Supporting Information – Summer Greenland Blocking in observations and in SEAS5.1 seasonal forecasts: robust trend or natural variability?

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Abstract. Given its impact on enhanced melting of the Greenland ice sheet, it is crucial to assess changes in frequency and characteristics of summer Greenland blocking. Indeed, the occurrence of such atmospheric pattern has seen a marked increase in recent decades: however, the observed trend is not captured by any simulation from state-of-the-art global climate models. It is therefore paramount to determine whether the lack of trend is caused by a misrepresentation of key physical mechanisms in climate models or whether such trend is mainly attributable to decadal variability, or both. Here we investigate Greenland blocking characteristics in reanalysis (ERA5) and ECMWF seasonal forecasts (SEAS5.1), showing that about 10% of the 1000 permutations of SEAS5.1 runs can simulate a 43-year trend equal or larger to the ERA5 one: this suggests that the initialization and the higher model resolution contribute to a more realistic representation of the blocking dynamics than in freely-evolving climate runs. To further investigate these aspects, we apply the Peter and Clark momentary conditional independence (PCMCI) algorithm to assess monthly causal pathways. Results show that while the relationship among Arctic temperature, snow cover, Atlantic multidecadal variability and Greenland blocking is consistent both in ERA5 and SEAS5.1, the effect of early snow melt over North America on Greenland blocking is mostly absent in SEAS5.1. Therefore, while it is possible that the observed trend is due to internal decadal variability, the misrepresentation of the snow cover processes may explain the difficulty that SEAS5.1 has in reproducing the observed trend. This deficit in representing the snow impact on the atmospheric circulation might also be the culprit of the missing trend in climate models, raising the question whether long-term projections underestimate a future increase in Greenland blocking and ice melt.

Text 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:

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

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.

Text 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.

<u>Tigramite packages:</u>

```
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
```

<u>Function used in discovery 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)
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=Tru
e)
```

<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)]}
```

Text 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.

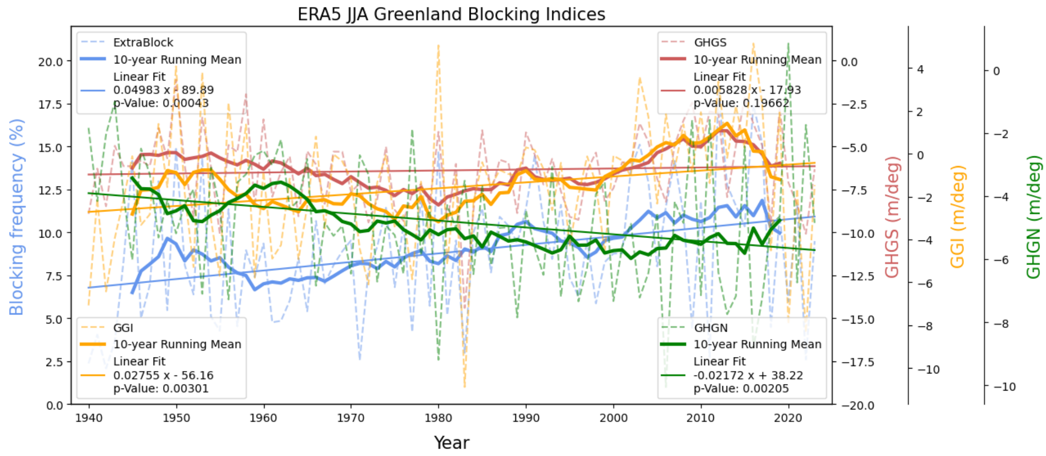

Figure S1: Greenland blocking index observed trends from 1981-2023. Figure shows JJA Greenland Blocking Index (blue) and Greenland Gradient Index (yellow) GHGS(red)and GHGN(green) for ERA5-81. Dashed lines shows the season average, bold lines the 10-year running mean and the thin solid lines the linear trend. Values for the trend and their p-values (estimated with a Mann-Kendall test) are shown in the legend for all for indices.

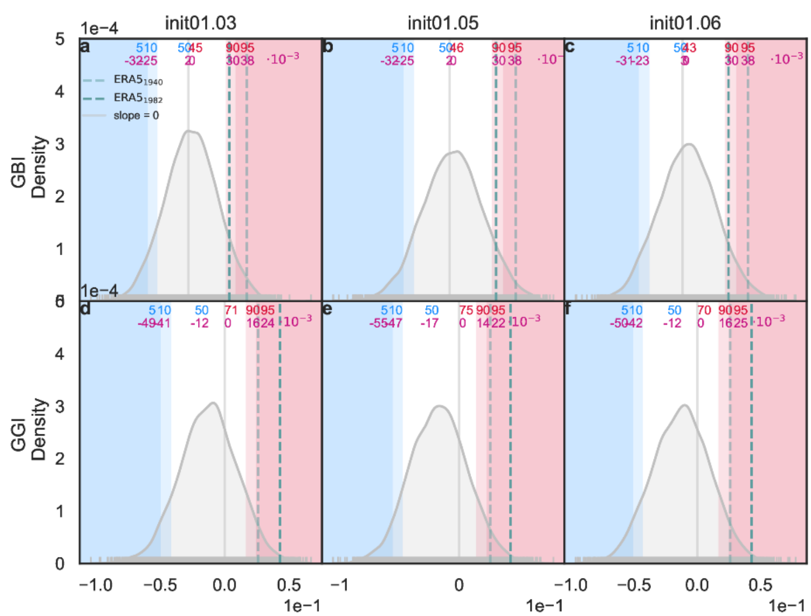

Figure S2: Greenland blocking and Greenland Gradient index trends in SEAS5.1 initialized March till June SEAS5.1-06 and ERA5. Panel (a-c) shows the Probability density function of JJA trends in GBI and panel (d-f) for GGI and for the 10^4 different member combinations of each SEAS5.1 with different initialization date: Panel (a,d) for of SEAS5.1-03, Panel (b,e) for of SEAS5.1-05, Panel (c,f) for of SEAS5.1-06. Shaded vertical lines show values 5^{th},10^{th}, 90^{th} and 95^{th} percentiles. Percentile are shown in blue (5^{th},$10^{th,}$ 50^{th}) and red (90^{th} and 95^{th}) and the corresponding trend values in magenta. Percentile of the distribution of a slope of 0 is also given in red and indicated with the grey vertical line. Green dashed verticals indicate linear slope of ERA5-40 (light green) and ERA5-81 (solid green). Panel (c) shows the the 11-year running trend of ERA5 (red) and the SEAS5.1-03 trend distribution (blue shadings) for the GBI. Panel (d) same as for panel (c) but for the GGI index. The dark blue line indicates the median 11-year running mean of the SEAS5.1-03 distribution.

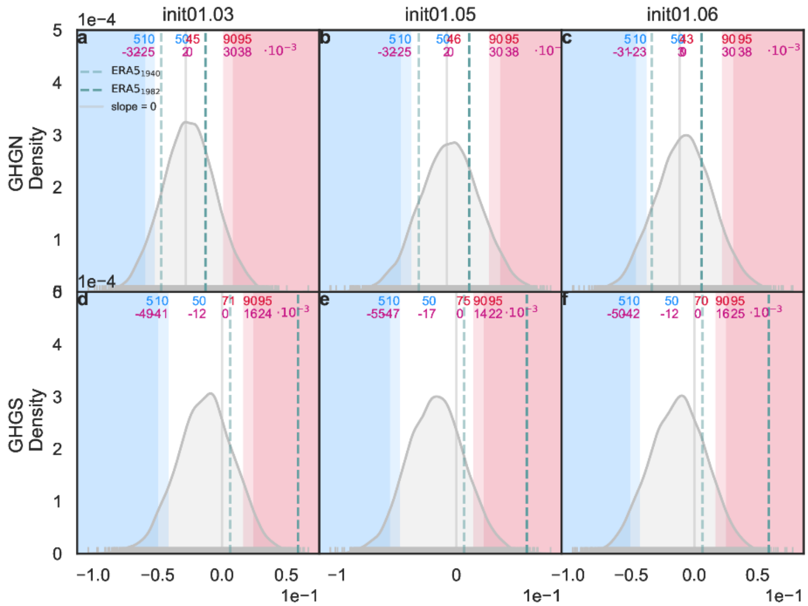

Figure S3: GHGSN and GHGS in SEAS5.1 initialized March till June SEAS5.1-06 and ERA5. Same as Figure S2.

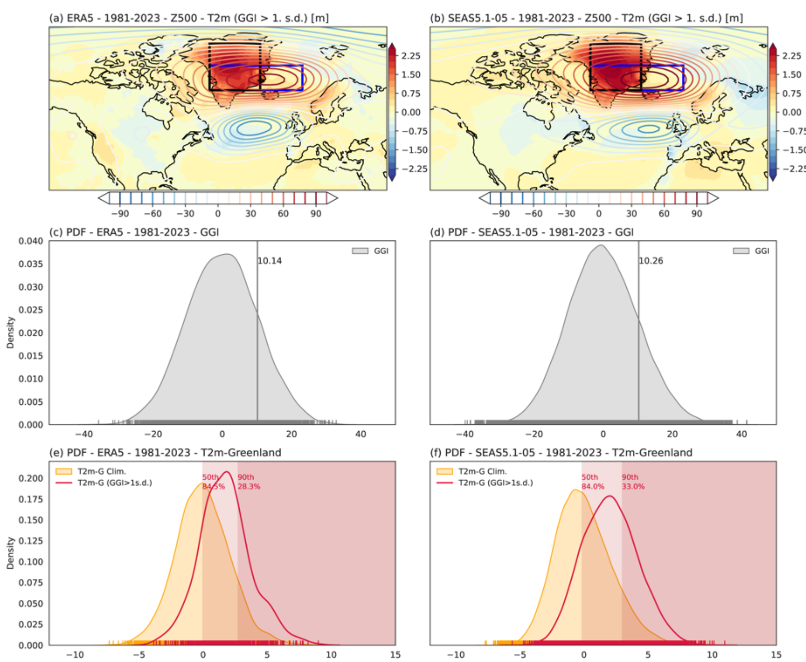

Figure S4. Same as for Fig. 3 but for SEAS5.1 init. 1st of May.

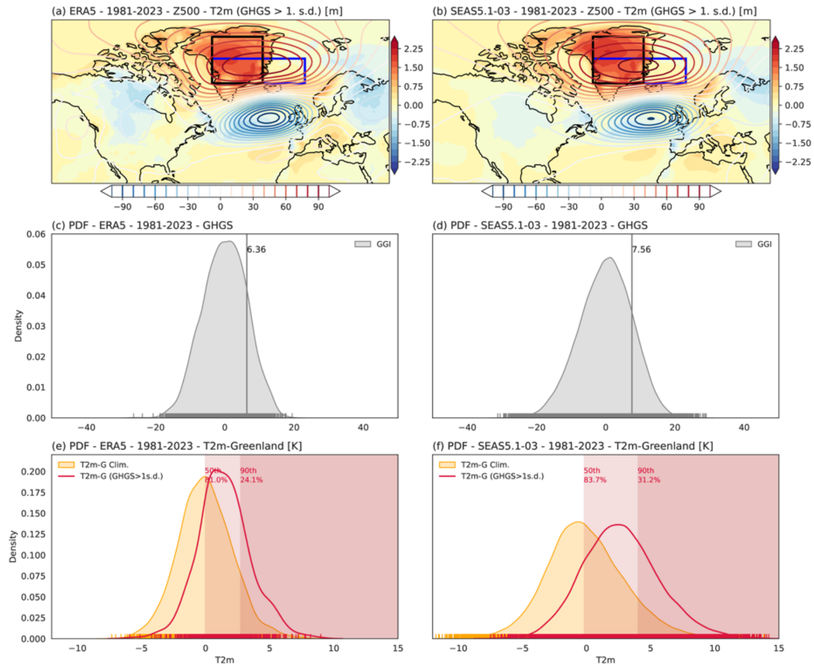

Figure S5. Same as for Fig. 3 but for GHGS.

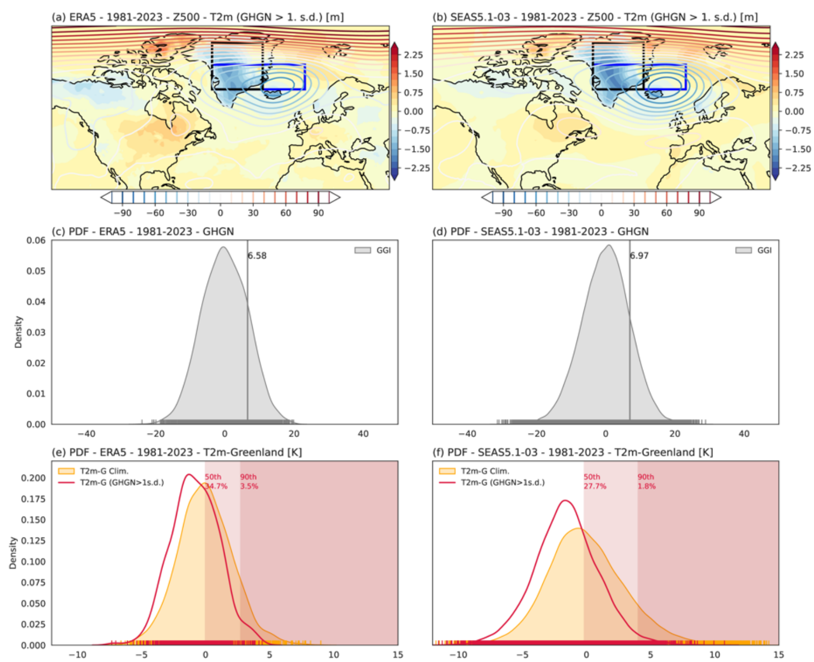

Figure S6. Same as for Fig. 3 but for GHGN.

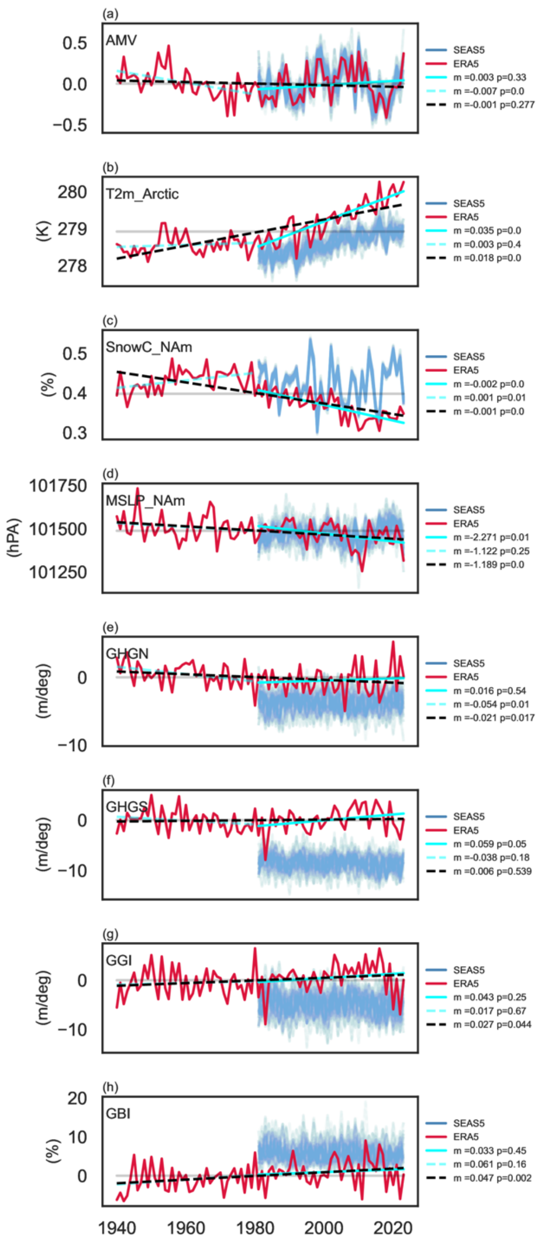

Figure S7: Monthly drivers and Blocking indices in ERA5 and SEAS5.1-03. Shown are the monthly drivers AMV (a) T2m-Arctic (b), Snow-NAm(c), MSLP-NAm (d), and Blocking indices GHGN (e), GHGS (f), GGI (g), GBI (h) for ERA5 (red) and the SEAS5.1-05 members(blue). For ERA5 the trends over the whole timeseries 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.

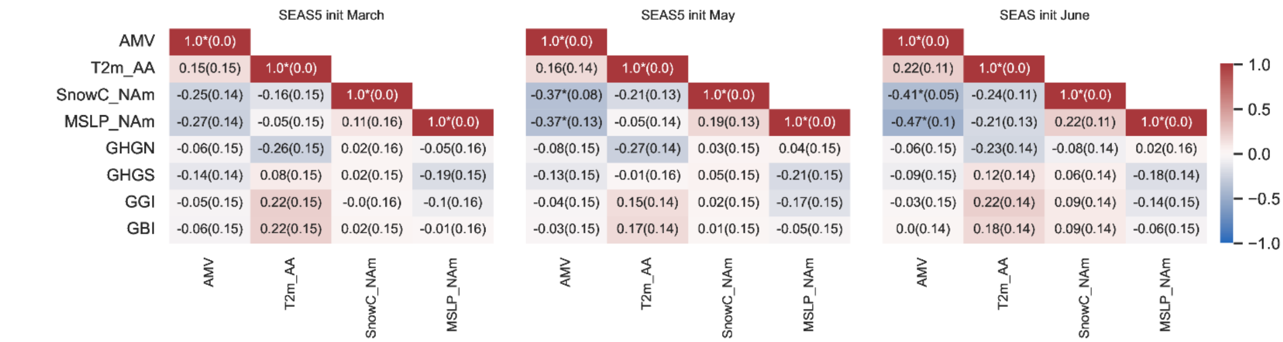

Figure S8: Same as for Fig. 5but with SEAS5.1-03, -05, and -06. Correlation heat maps. -Correlation plot of different variables in and SEAS5 initialized in March, May and June for the detrended data.`. Statistically significant values are indicated with an asterix. The correlation values of SEAS5 are 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.

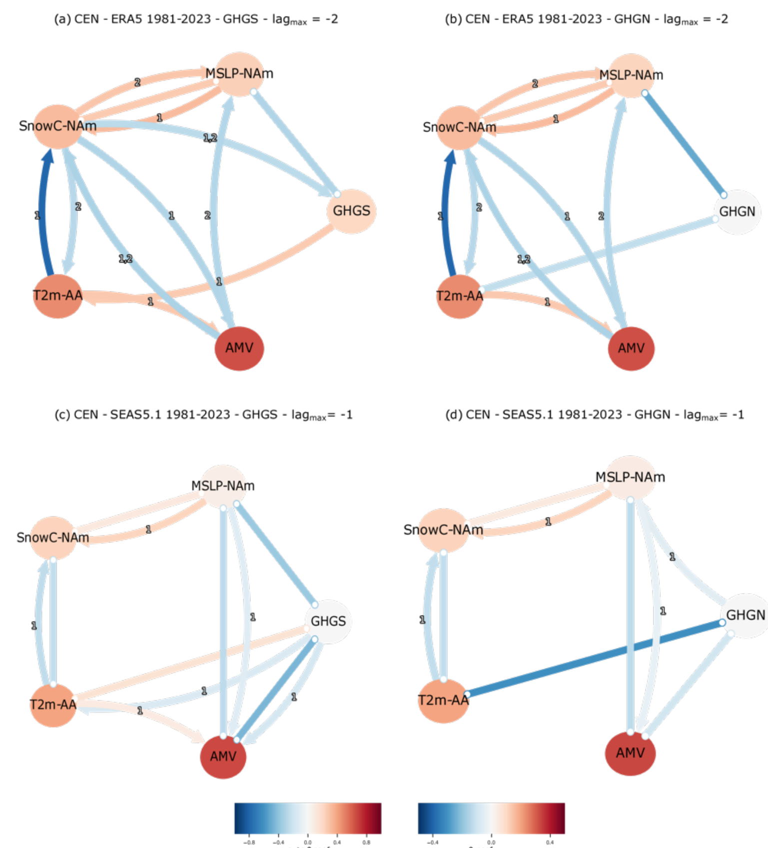

Figure S9: Same as for Fig. 8 but for GHGS and GHGN.

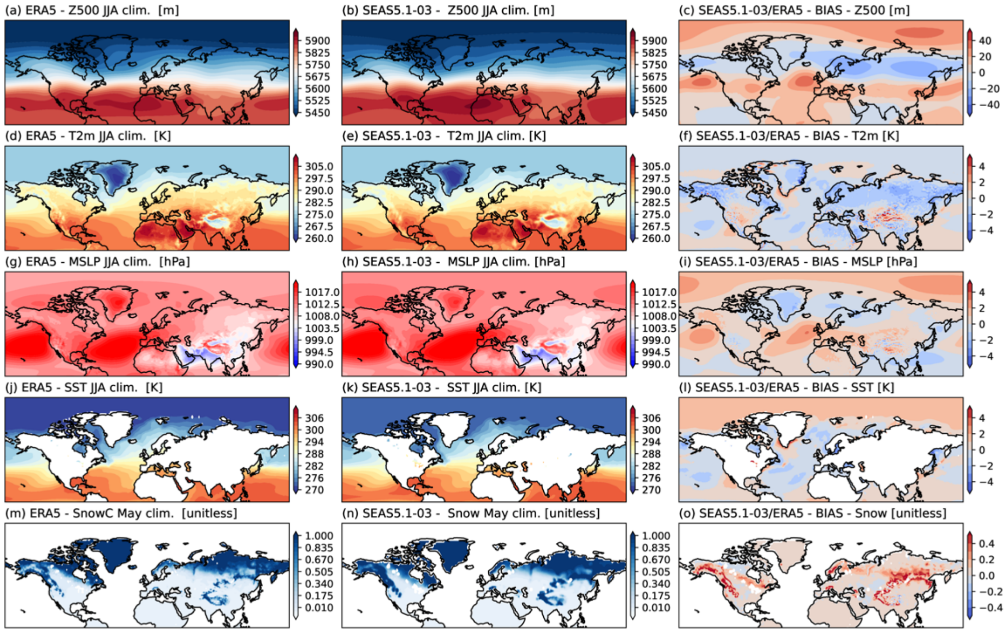

Figure S10. JJA climatology for Z500, T2m, MSLP, SST and snow cover for ERA5 and SEAS5.1-03.

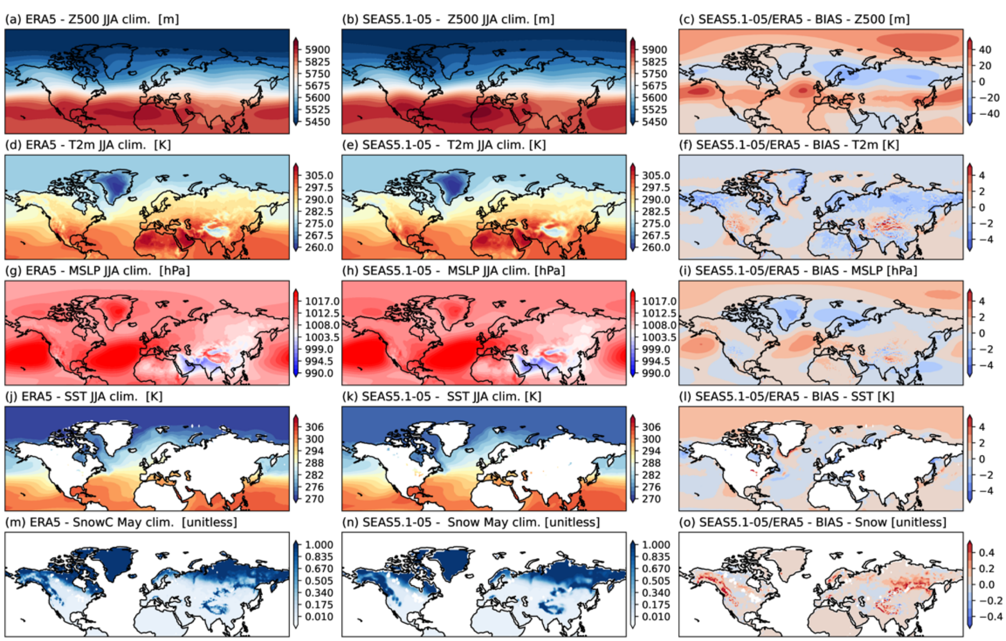

Figure S11. JJA climatology for Z500, T2m, MSLP, SST and snow cover for ERA5 and SEAS5.1-0**5**.