



Sources of Subseasonal Predictability of Extreme Cold in CESM2

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Introduction

- How far in advance can we predict extreme cold and why?
- How much skill does each component of a climate model contribute, specifically for extreme cold?
 - How does this skill change over time?
 - Is the atmosphere most important for weeks 1-2, followed by the ocean beyond 2 weeks?
 - What role does the land model have for cold events?
- Is extreme cold easier to predict in some regions than others?
 - How does each component's contribution vary by region?

Data

- Daily mean 2m-air temperatures from MERRA-2 at every point in the Northern Hemisphere, interpolated onto a 1-degree grid to match CESM2, 1999-2020.
- Richter et al. (2024) ran 11-member ensemble hindcasts of CESM2 out to 45 days.
- Experimental runs with climatological initial conditions for the atmosphere, land, and ocean were run to find forecast skill contributed by each component at each timescale.
- Hindcasts from Richter et al. (2024)
 - climoATM is initialized with climatological atmospheric conditions
 - climoLND is initialized with climatological land conditions
 - climoOCN is initialized with climatological ocean conditions
 - climoALL is initialized with all the above

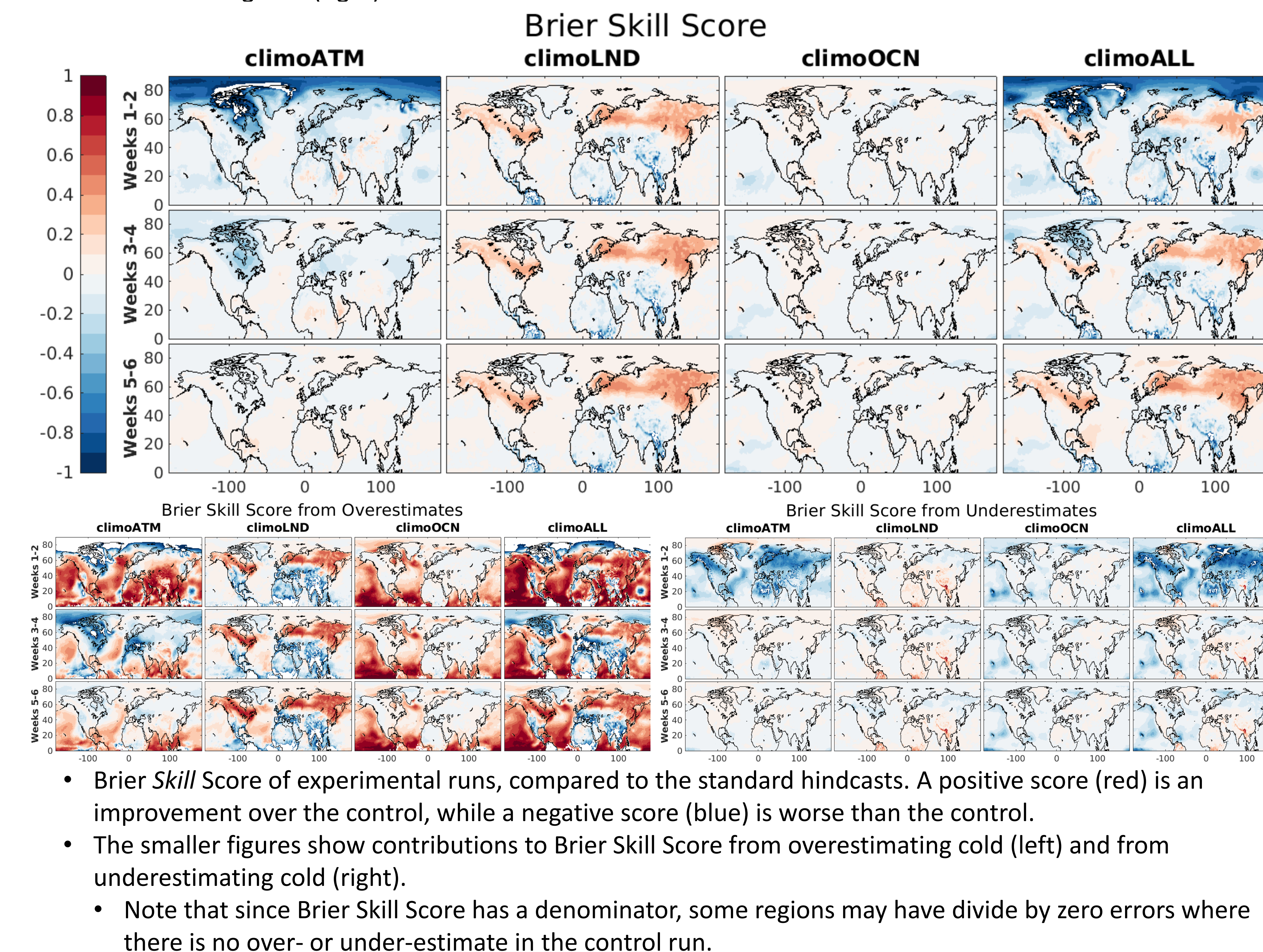
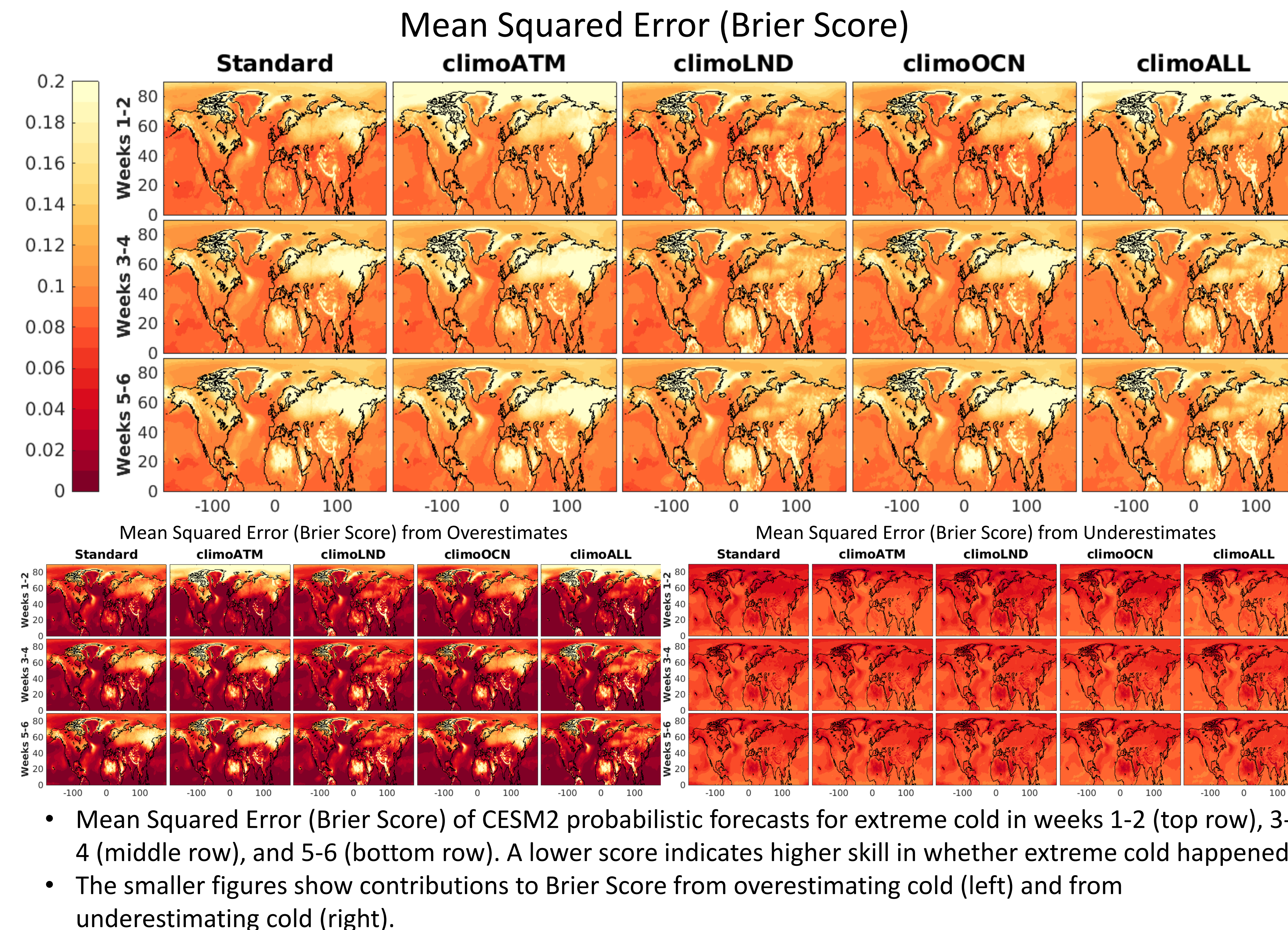
Methods

- Find occurrence of extremely cold days in reanalysis using the coldest 10% of temperatures for each calendar day.
 - For each of 11 ensemble members at every lead time, find how many have temperatures below the 10th percentile from MERRA-2.
 - Divide by 11 to get the forecast probability of extreme cold at that time and grid point.
- Brier Score is the mean squared error of a probabilistic forecast (Brier 1950).

$$BS = \frac{1}{N} \sum_{t=1}^N (f_t - o_t)^2$$

- N is the number of forecasts, 1148 in this case
- f is the forecast outcome, in this case 0/11, 1/11, 2/11, etc.
- o is the actual outcome, a 1 if extreme cold occurred, or a 0 if not.
- We further divide this into the contribution from overestimates of extreme cold (where f > o) and underestimates of extreme cold (where f < o)
- Brier Skill Score measures the improvement in Brier Score from some reference forecast, in this case the standard hindcasts. $BSS = 1 - \frac{BS}{BS_{ref}}$

- As with the regular Brier Score, we also divide this into over- and under-estimates of extreme cold.
- A positive skill score is an improvement, with a maximum possible value of 1. A negative skill score is a worse forecast than the control run.



Discussion

- Predictability of extreme cold decreases with forecast time as expected.
- Most error in the northern midlatitude/Arctic land is from overestimating extreme cold, and this is true at all weeks.
- ClimoATM greatly overestimates extreme cold in the Arctic Ocean in weeks 1-2, with better skill afterwards.
 - ClimoATM also underestimates extreme cold over land, but this difference fades for weeks 3-6.
- ClimoOCN has very little change from standard hindcasts, suggesting that ocean initial conditions play very little role in extreme cold in most regions for most events.
- ClimoLND is better than standard hindcasts over high-latitude land at predicting extreme cold.
 - This suggests that the land model may be problematic in high-latitude coniferous forests.
 - This is true over all weeks checked.
- Since climoATM is worse than standard over the Arctic Ocean but only for weeks 1-2, while climoLND is better in high-latitude land for all weeks, climoALL is on average better than standard for weeks 3-6, mainly due to problems with the land model.
- Results may be sensitive to thresholds from reanalysis differing from climate model output, so next we will repeat this analysis with thresholds from within CESM2 itself.

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