Northern hemisphere winter forecasts in current climate prediction systems

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The W's of seasonal climate predictions

- **What/Why**: Seasonal climate prediction aims to quantify the change in the likelihood of a specific climatic event happening in the coming months (SPECS definition). Seasonal predictions can be systematically evaluated against reality allowing us to identify and correct model limitations, bias, etc.
- **How**: Using the best knowledge of the current state of climate to initialize climate models in large ensemble simulations spanning a few months. Models have biases, therefore forecasts need to be calibrated. Forecast quality is tested using retrospective forecasts (hindcasts).
- **Who**: if skillful, model output can potentially be translated into important information for the agriculture, insurance, shipping, energy generation, and other economic activities.

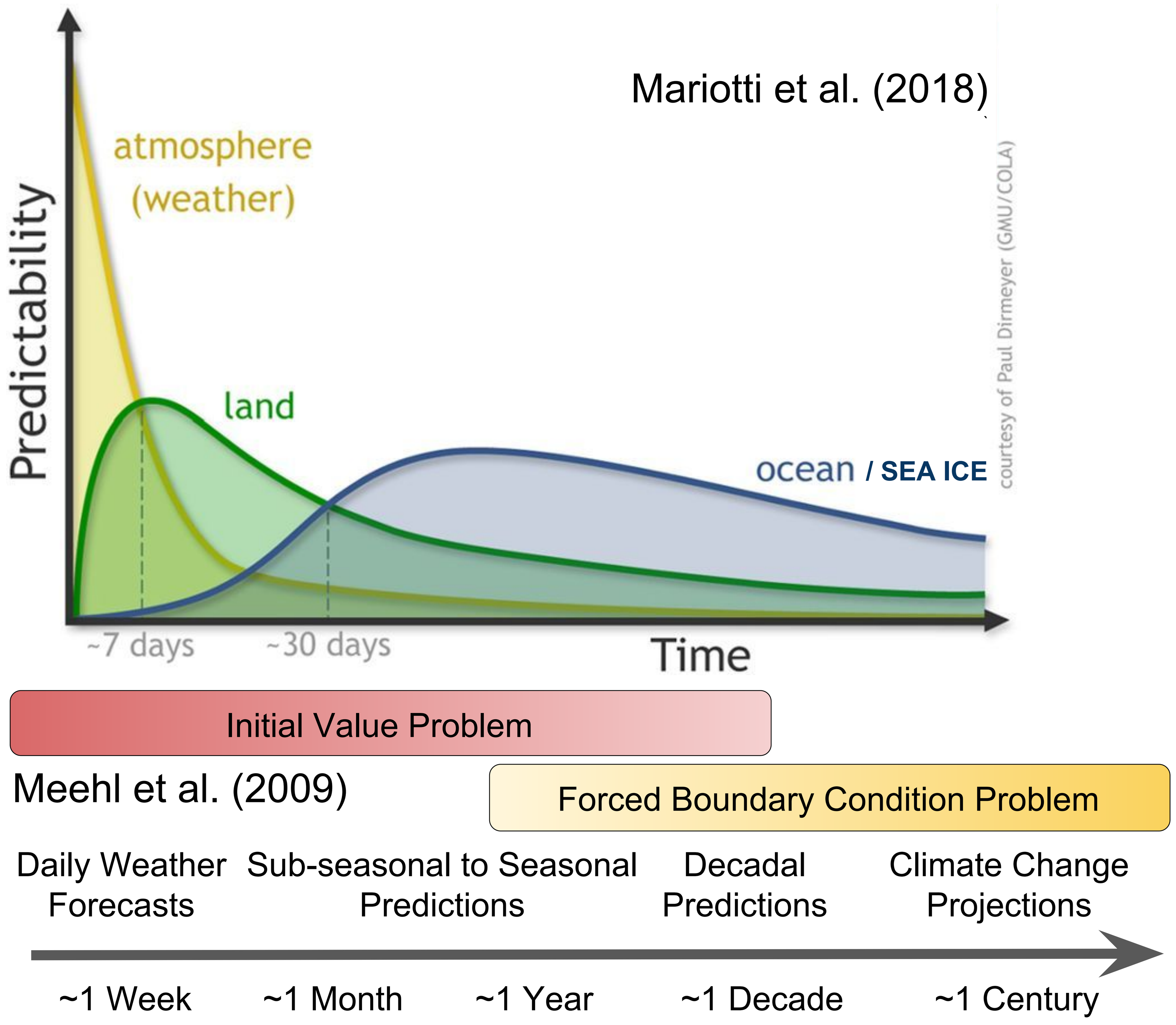

Figure 1: Schematic figure showing the sources of predictability in climate forecast systems (models). From numerical weather prediction to centennial climate projections

Winter (DJF) deterministic skill scores

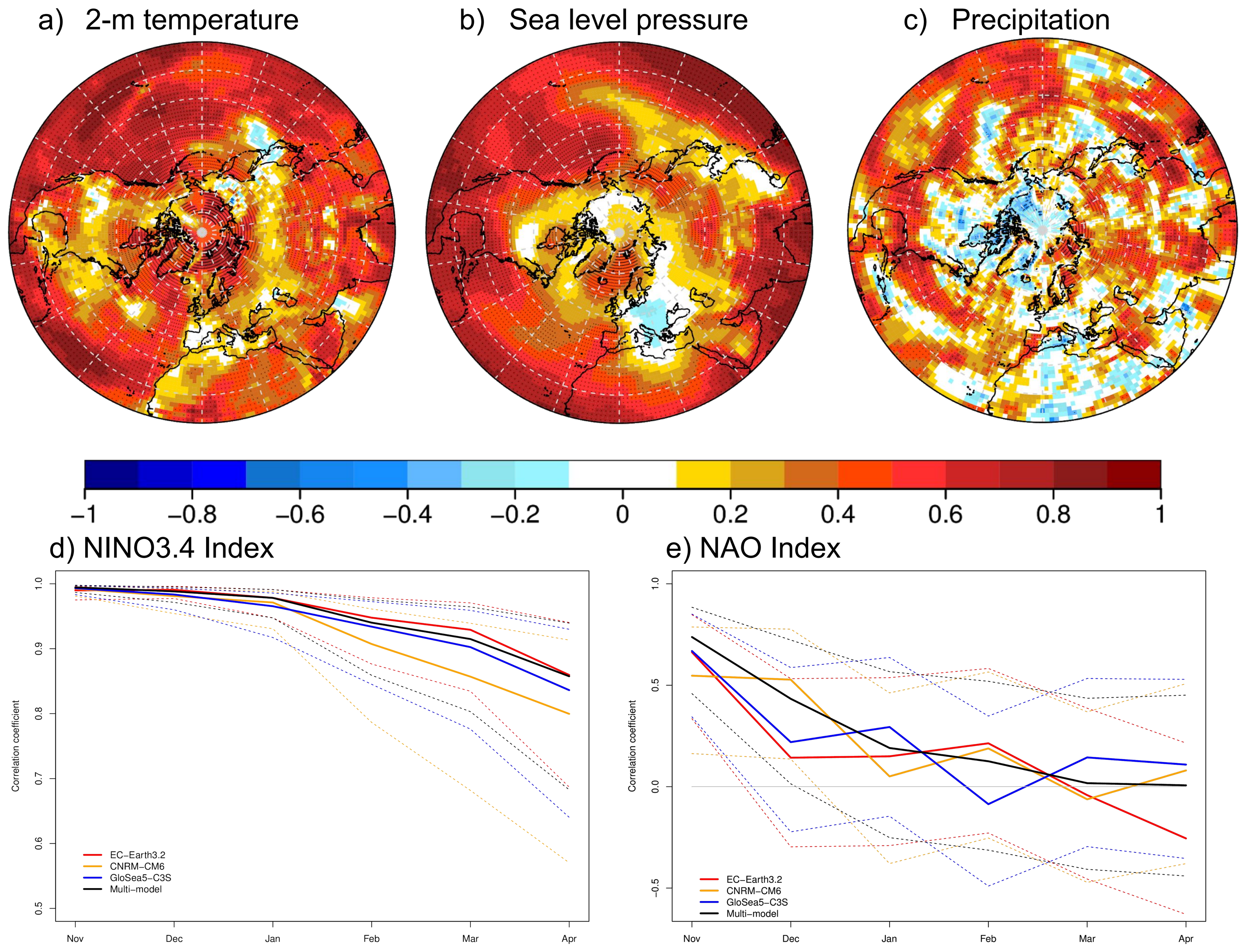

Figure 2: Anomaly correlation coefficients for 1993-2014 a) mean December to February (DJF) multi-model (EC-Earth3.2, CNRM-CM6 and GloSea5, 25 members each) two meter air temperature, b) DJF multi-model sea level pressure, c) DJF multi-model precipitation, d) monthly NINO3.4 index for individual models, and e) monthly NAO (Stephenson et al., 2006, Baker et al., 2018) index for individual models. Dots in a-c) indicate statistically significant results at 95% confidence. Dotted lines in b) and e) indicate 95% confidence intervals. The period of analysis is 1993-2014.

- No or little skill in the North Atlantic Oscillation (NAO) forecast for individual months as opposed to the high ENSO (NINO3.4) skill.
- December-February skill (ACC) for each single model (25 members each): EC-Earth3.2: 0.24, CNRM-CM6: **0.46***, GloSea5: 0.27, Multi-model: **0.38***

Winter (DJF) probabilistic skill scores

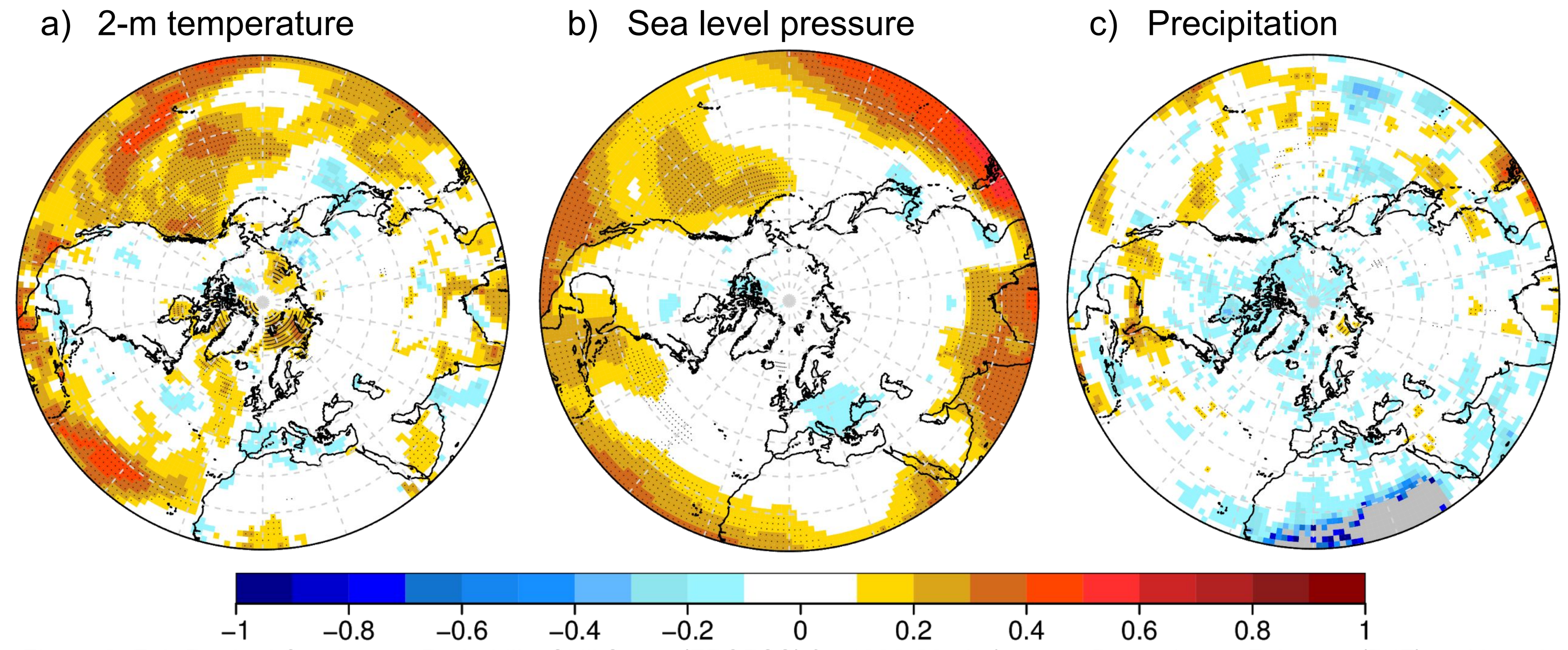

Figure 3: Fair Ranked Continuous Probability Skill Score (FRCPSS) for 1993-2014 a) mean December to February (DJF) multi-model (EC-Earth3.2, CNRM-CM6 and GloSea5) two meter air temperature, b) DJF multi-model sea level pressure and c) DJF multi-model precipitation. Dots in a-c) indicate statistically significant results at 95% confidence level. Dotted lines in b) and e) indicate 95% confidence intervals. The period of analysis is 1993-2014.

- The Fair Ranked Continuous Probability Skill Score (FRCPSS) quantifies the relative improvement of the probability forecast over a reference (climatology) in predicting the observed value.
- Potentially useful forecast metric (among many others) from a user perspective.
- Skillful wintertime predictions of surface temperature in several regions in the Arctic.
- Little skill over continental mid-latitudes for all variables. Calibration method plays small role in this probabilistic forecast metric (Manzanas et al. 2018).

Is a fraction of the NAO predictability coming from ENSO?

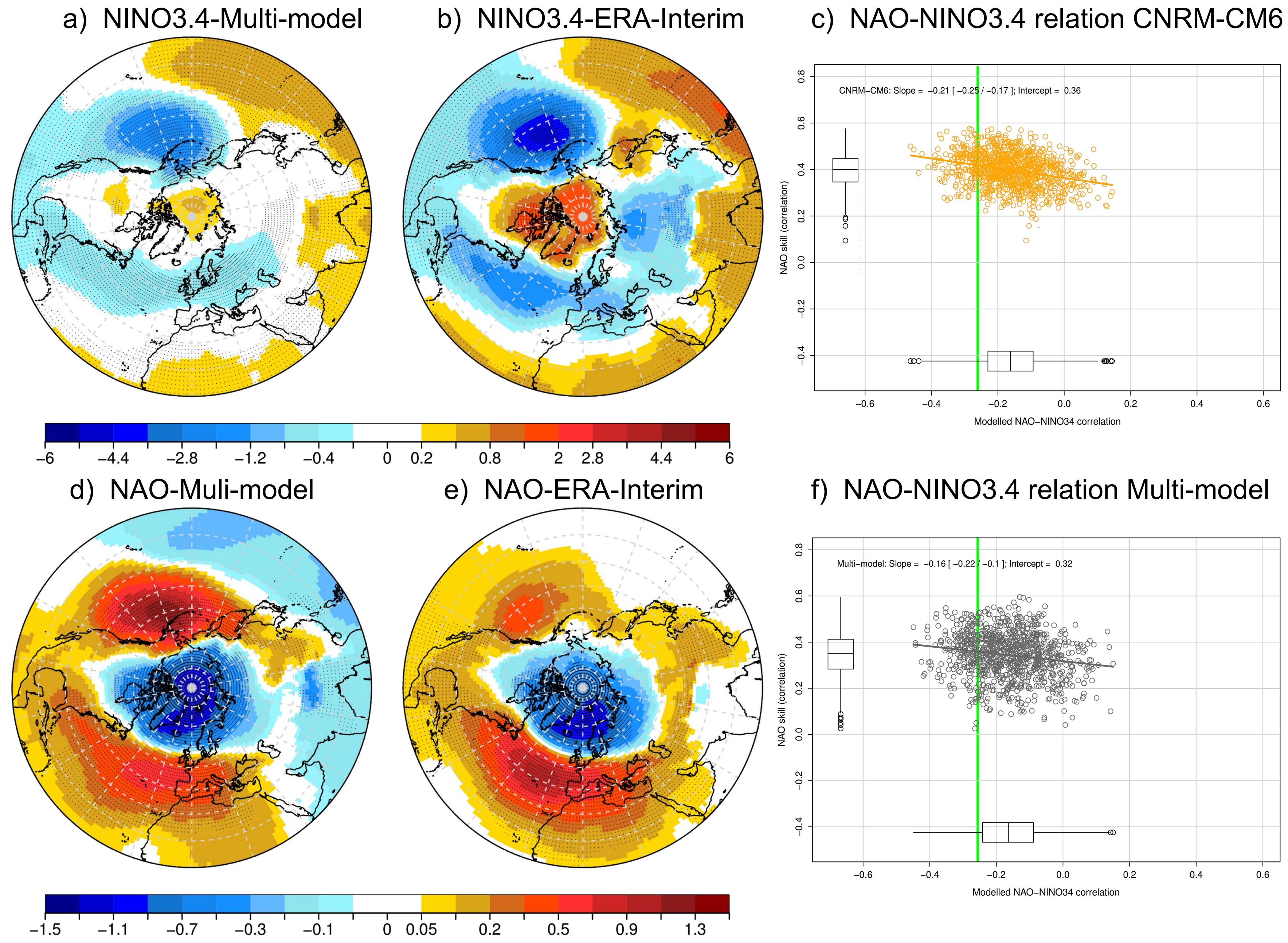

Figure 4: Regression of DJF sea level pressure onto NINO3.4 index for a) multi-model, b) ERA-Interim. Regression of DJF sea level pressure onto NAO index for d) multi-model, and f) ERA-Interim. Dotted areas are statistically significant at 95% confidence. Winter (DJF) NAO forecast skill (y-axis) as a function of DJF NAO and November NINO3.4 index correlation for c) CNRM-CM6 and f) multi-model. Each point (1000 in total) represents a ten-member average (30-member for the multi-model ensemble) of a random subset taken from the full 25 member ensemble from each model (75-member for the multi-model ensemble). The period of analysis is 1993-2014. The units of a) and b) are hPa/K, and of hPa/hPa in d) and e). The green line represents the NAO-NINO3.4 correlation in ERA-Interim for the same period.

- Overall similarity (opposite sign) in regressions of sea level pressure patterns onto NAO and NINO3.4 in the multi-model ensemble and ERA-Interim.
- The one model that predicts the winter NAO with statistical significance, also has a significant NAO-NINO3.4 dependence. I.e. the sets of members with a larger anticorrelation between NINO3.4 (November) and NAO (DJF) tend to have a more skillful NAO. This is similar for the multi-model ensemble and GloSea5.
- In the 1993-2014 period the NINO3.4 (November) and NAO (DJF), the correlation coefficient in ERA-Interim is -0.25. For the period 1880-2015 using HadISST (NINO3.4) and CRU (NAO station based) the correlation coefficient is -0.05.

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