Impact of the initialisation on the predictability of the Southern Ocean sea ice at interannual to multi-decadal timescales

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Objectives

- Measuring the **predictive skill** of a climate model for the sea ice in the Southern Ocean, at **interannual** to **multi-decadal** timescales, in a **perfect model framework**.
- Assessing the **impact of different initialisation strategies** on the predictive skill of the model.

Take home message

Predictability of the Southern Ocean sea ice at interannual timescale

- Limited to 3 years ahead.
- Reemergence of the predictability during winter months, likely thanks to heat anomalies stored in the ocean.

Predictability of the Southern Ocean sea ice at multi-decadal timescale

- Correlation between the multi-decadal trend in sea ice extent from hindcast and from observations statistically significant, ~ 0.5.
- Trend in ice edge location or in sea ice extent is better simulated if the ocean below the sea ice is well initialised.

This study, carried out in a perfect model framework, suggests potential skill to perform predictions of the sea ice in the Southern Ocean at multi-decadal timescale.

See also poster B810, Today in Session NP5.2, *How does a freshwater flux impact the forecast skill of the simulated sea ice in the Southern Ocean?*

References

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1. Experimental setup

LOVECLIM model (Goosse et al., 2010)

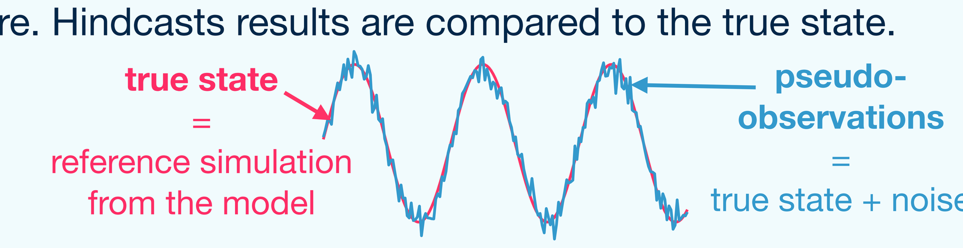
- Earth-system Model of Intermediate Complexity.
- Low computational cost → many simulations.

Hindcasts

- «Forecast» simulations spanning past periods.
- 30-yr ensemble simulations, made up of 96 members.
- One ensemble launched every 5 years between 1900 and 1995.

Perfect model framework

- Hindcasts are initialised with **pseudo-observations** of the surface air temperature. Hindcasts results are compared to the true state.



2. Initialisation of the hindcasts

No initialisation

No pseudo-observation taken into account to initialise the hindcast.

Perfect initialisation

Initial state is directly extracted from the pseudo-observations and a small perturbation is added to generate an ensemble

Initialisation through data assimilation of surface air temperature

- **Nudging**

  Adding a term to the heat flux between the atmosphere and the ocean to pull the surface air temperature towards the pseudo-observations.

- **Particle filter with sequential resampling (PF)**

  Launching an ensemble of simulations and selecting the ones whose surface air temperature is closer to the pseudo-observations (Dubinkina et al., 2011).

- **Nudging proposal particle filter (NPPF)**

  Combination of a particle filter and the nudging (Dubinkina et al., 2013).

- **2 pseudo-observations datasets**

  - data available everywhere (dense pseudo-observations).
  - data partially missing (sparse peudo-observations), as in the actual observation dataset HadCRUT3.

3. Predictive skill measurement

Prognostic potential predictability (Pohlmann et al., 2004)

Ratio between the ensemble standard deviation and the climatological one,

$PPP(t)=1-\frac{\sigma^2_{ens}}{\sigma^2_{clim}}$

Forecast quality (Pohlmann et al., 2009)

Anomaly correlation coeffictient (ACC) or classical correlation between the ensemble mean of the simulation and the pseudo-observations.

4. Interannual timescales

4.1. Ice edge location

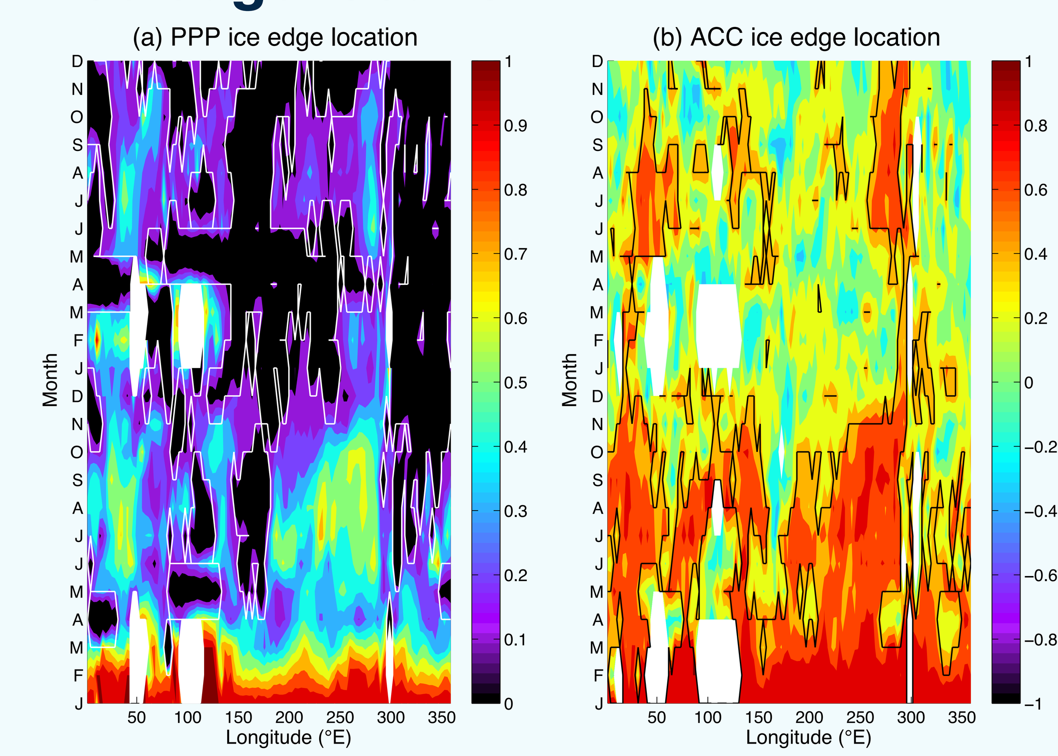


Fig. 1: (a) Prognostic potential predictability and (b) anomaly correlation coefficient of the ice edge location. The hindcasts are initialised with perfect initial conditions. The white (a) or black contour (b) highlights the values that are significant at the 95% level. The white areas correspond to undefined values.

➡**Significant PPP (Fig. 1a) and ACC (Fig. 1b) of the ice edge location up to a few years ahead.**

➡**Reemergence of the predictability during winter, likely thanks to heat anomalies stored in the interior ocean and entrained towards the surface during winter (not shown, see Zunz et al., 2013).**

4.2. Sea ice extent

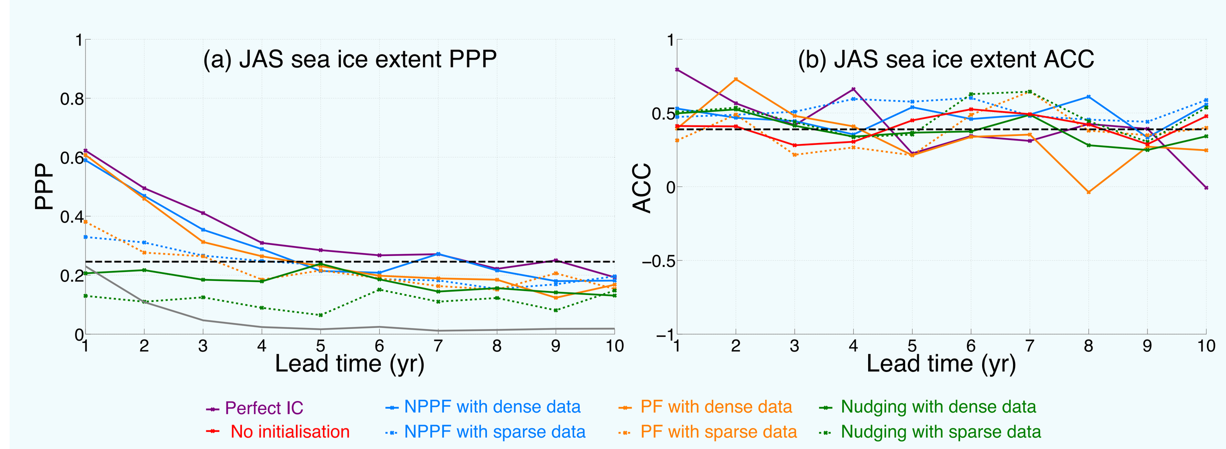


Fig. 2: (a) Prognostic potential predictability and (b) anomaly correlation coefficient for winter (JAS) sea ice extent. The different colors correspond to different initialisation methods. Colored solid lines correspond to an initialisation with dense data while colored dashed lines correspond to an initialisation with sparse data. The dashed black line shows the 95% significant level. The grey line in (a) corresponds to the square of the autocorrelation that indicates the predictability arising from the persistence.

➡**Hindcast ensemble is better constrained when initialised from the assimilation of dense data with the PF or the NPPF (Fig. 2a).**

➡**Significant ACC limited to 4 years ahead (Fig. 2b), likely due to the quickly varying atmosphere that overwhelms the low frequency signal provided by the ocean.**

5. Multi-decadal timescales

5.1. Trend in ice edge location

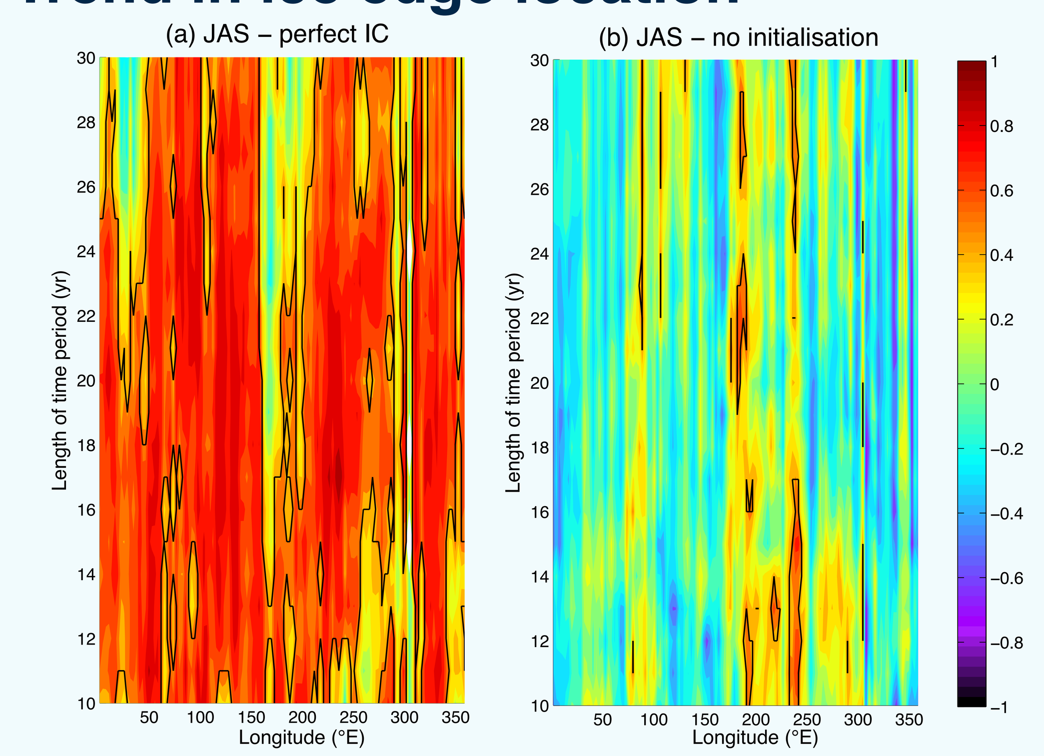


Fig. 3: Correlation between the trend of the hindcasts ensemble mean and the trend of the pseudo-observations of the ice edge location in winter, (a) for perfectly initialised hindcasts and (b) for hindcasts initialised without taking into account the pseudo-observations. The vertical axis refers to increasing length of the time period over which the trends are computed. The black contour highlights the values that are significant at the 95% level. The white areas correspond to undefined values.

➡**Clear improvement of the correlation of the trend in ice edge location in perfectly initialised hindcasts (Fig. 3a), compared to the non-initialised ones (Fig. 3b), indicating a gain of predictability at multi-decadal timescales provided by the initialisation with pseudo-observations.**

5.2. Trend in sea ice extent

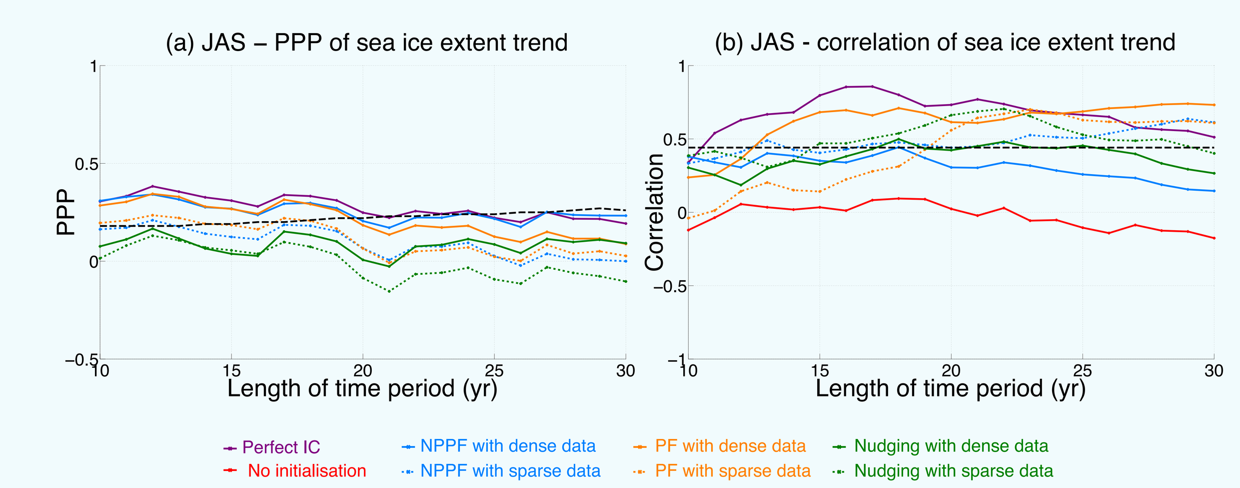


Fig. 4: (a) Prognostic potential predictability and (b) correlation with the pseudo-observations of the trends in winter sea ice extent, for increasing length of the time period over which the trends are computed. The different colors correspond to different initialisation methods. Colored solid lines correspond to an initialisation with dense data while colored dashed lines correspond to an initialisation with sparse data. The dashed black line shows the 95% significance level.

➡**Low values for the PPP indicate a relatively large spread of the ensemble.**

➡**Correlation ~ 0.5 for the trend in sea ice extent (Fig. 4b), depending on the initialisation method and on the length of the time period.**

➡**Correlation for the trend in sea ice extent is systematically higher in hindcast initialised with pseudo-observations (Fig. 4b).**

➡**There exists a link between the quality of the simulated trend in sea ice extent and the initialisation of the ocean below it (see details in Zunz et al., 2013).**