Decadal prediction of sea ice in the Southern Ocean: Testing different initialization methods in an idealized framework

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Background

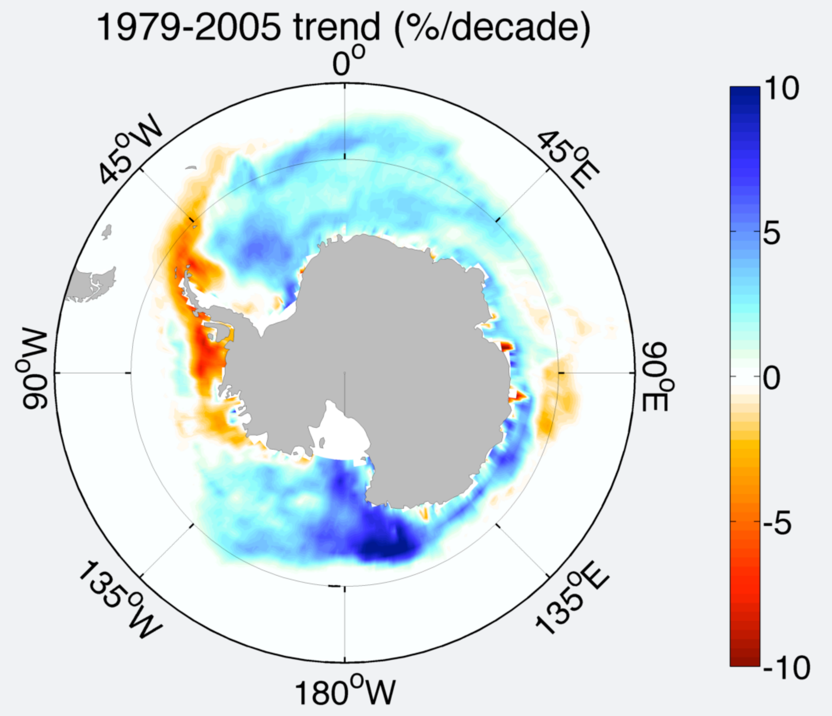

FIG. 1: Trend of observed sea ice concentration from NSIDC (Comiso, 2008)

- The recent expansion of Southern Ocean sea ice is statistically significant.
- It is not known if this expansion stands in the range of natural variability or if it is a response to external forcing.
- Current General Circulation Models overestimate the internal variability, regarding the one of the observations (Zunz et al., 2012) and simulate evolution of sea ice cover in the Southern Ocean that does not fit the observations.

Despite the high internal variability in modeled Southern Ocean sea ice, can an adequate initialization improve the simulated evolution of sea ice in this region?

Take home message

In an idealized framework, i.e. when data from a reference simulation are used as observations, we have shown that:

- initialization through a data assimilation of sea surface temperature improves the simulated evolution of Southern Ocean sea ice extent;
- initialization with incomplete dataset nearly divides by 2 the predictive skill of the model in the Southern Ocean;

Results from idealized simulations are encouraging but the initialization method could be improved by the assimilation of 3D ocean data and by an optimal perturbation of the initial state. Furthermore, the impact of different initialization strategies in real conditions needs to be assessed.

1. Strategy

LOVECLIM (Goosse et al., 2010)
- Earth-system Model of Intermediate Complexity.
- Low computational cost that allows us to perform many simulations.

Idealized framework
- Dataset from a reference simulation to which noise has been added is used as if it was observations, herein after referred to as pseudo-observations.

5 series of hindcasts
- Hindcast: «forecast» simulation spanning a past period.
- Each series is initialized through a different initialization method (see section 2.).
- Ensemble simulations belonging to the same series are initialized following the same initialization method.
- Within a series of hindcasts, an ensemble of 96 members starts every 5 years between 1900 and 1990

2. Initialization method

Initial conditions extracted from different simulations with data assimilation.

- Data assimilation: method that uses informations from the pseudo observations dataset to constrain the solutions of the model to get closer to the latter.
- Data are assimilated over the Southern Ocean.
- 2 different pseudo-observations dataset are used: a complete one (data available everywhere at any time step) and one whose some data have been removed.

3 data assimilation methods

Nudging	Particle filter (PF)	Efficient particle filter (EPF)
Adding a term in the model equations to pull the solution towards the pseudo-observations.	Launching an ensemble of simulations and select the ones that are closer to the pseudo-observations (Dubinkina et al., 2011).	Combination of a particle filter and the nudging (van Leeuwen, 2010).

3. Hindcasts series

Sea ice extent in the Southern Ocean

Initialized without pseudo-observations

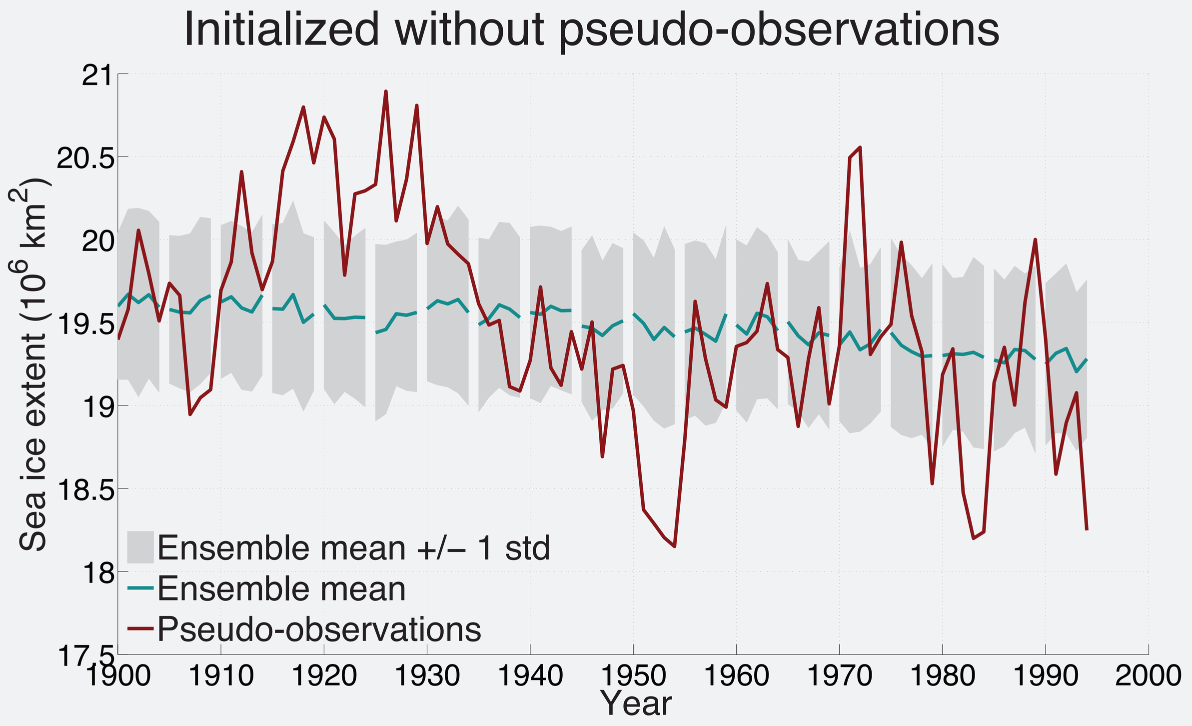

FIG. 2: 96 members hindcast simulations, initialized every 5 years without pseudo-observations constraints.

Initialized with pseudo-observations through EPF

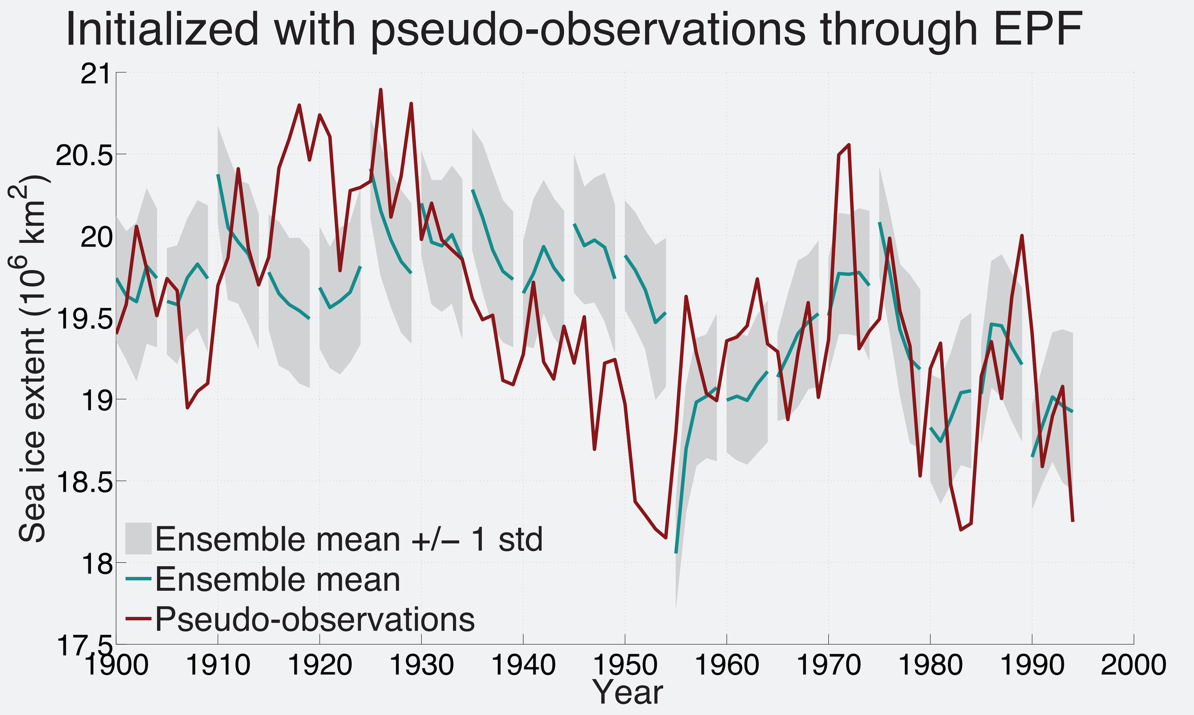

FIG. 3: 96 members hindcast simulations, initialized every 5 years from a simulation assimilating pseudo-observations on every grid point from 30°S with an efficient particle filter.

- Hindcasts initialized through a data assimilation procedure seem to agree better with pseudo-observations.
- The impact of different initialization methods needs to be quantified (see section 4. and 5.).

4. Quantifying the accuracy

Anomaly correlation coefficient (Pohlmann et al., 2009)

hindcast (member j of ensemble i)
pseudo-observations
lead time

$$\mathrm{COR}(t) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M}[x_{ij}(t)-\bar{x}]\,[o_i(t)-\bar{o}]}{\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M}[x_{ij}(t)-\bar{x}]^2\,\sum_{i=1}^{N} M\,[o_i(t)-\bar{o}]^2}}$$

ensemble index
member index
climatological means

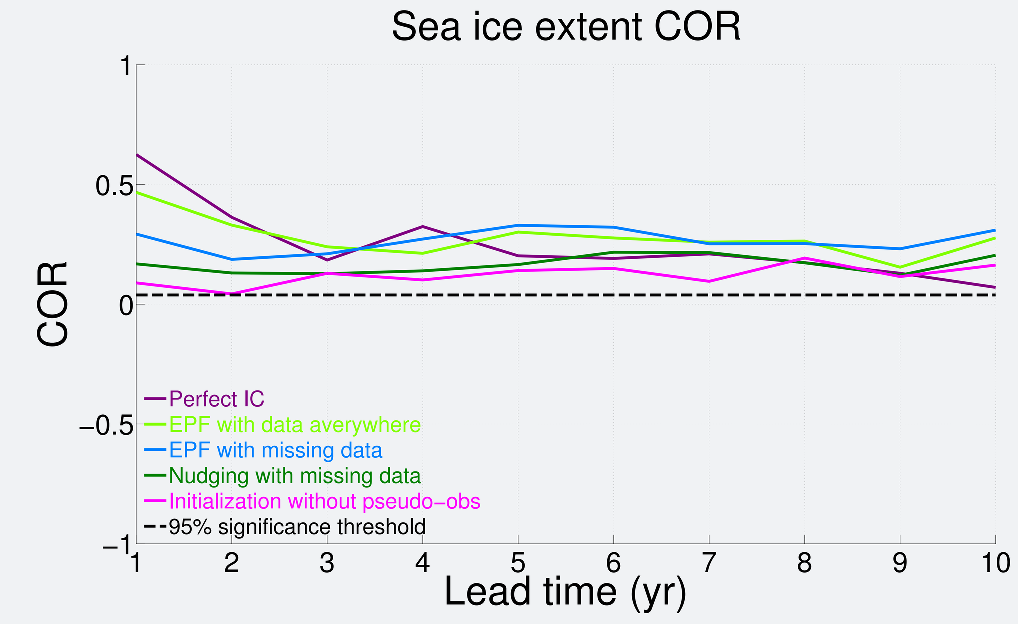

FIG. 3: Anomaly correlation coefficient computed for 5 series of hindcasts, shown with different colors.

5. Quantifying the uncertainty

Prognostic potential predictability, PPP (Pohlmann et al., 2004)

PPP is the ratio between the ensemble spread and the variance of a control simulation.

member index
hindcast (member j of ensemble i)
lead time

$$\mathrm{PPP}(t) = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{M-1}\sum_{j=1}^{M}[x_{ij}(t)-\bar{x}_i(t)]^2}{\sigma^2_{\mathrm{clim}}(t)}$$

ensemble index
variance of a control simulation
ensemble mean of ensemble i

PPP=1 ➡ the ensemble spread is small compared to the reference variance, high potential predictability.
PPP=0 ➡ the ensemble spread is large compared to the reference variance, low potential predictability.

/!\ This potential predictability must be interpreted cautiously because a small ensemble spread may be not representative of the range of solutions provided by the model.

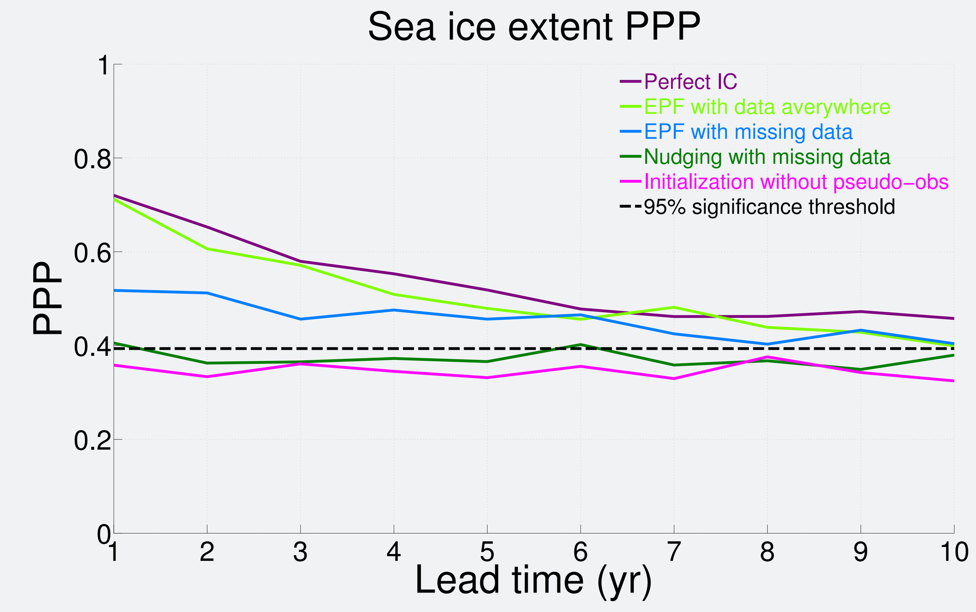

FIG. 4: Prognostic potential predictability computed for 5 series of hindcasts, shown with different colors.

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