# Drivers and predictability of extreme summer Arctic sea ice conditions with rare event simulation methods

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## Extreme events in summer Arctic sea ice cover 4.0 3.5 20071 3.0 2020 1980 1990 2000 2010

- Due to climate change, summer Arctic sea ice cover is decreasing
- On top of the downward trend, internal climate variability contributes to the year-toyear variations and associated extremes of the annual Arctic sea ice minimum

year
September monthly mean pan-Arctic sea ice area [10<sup>6</sup> km<sup>2</sup>]. Data: OSI SAF 2022.

- Three problems complicate robust statistical and dynamical studies about extreme events in summer Arctic sea ice cover:
  - 1) lack of observational data

sea ice

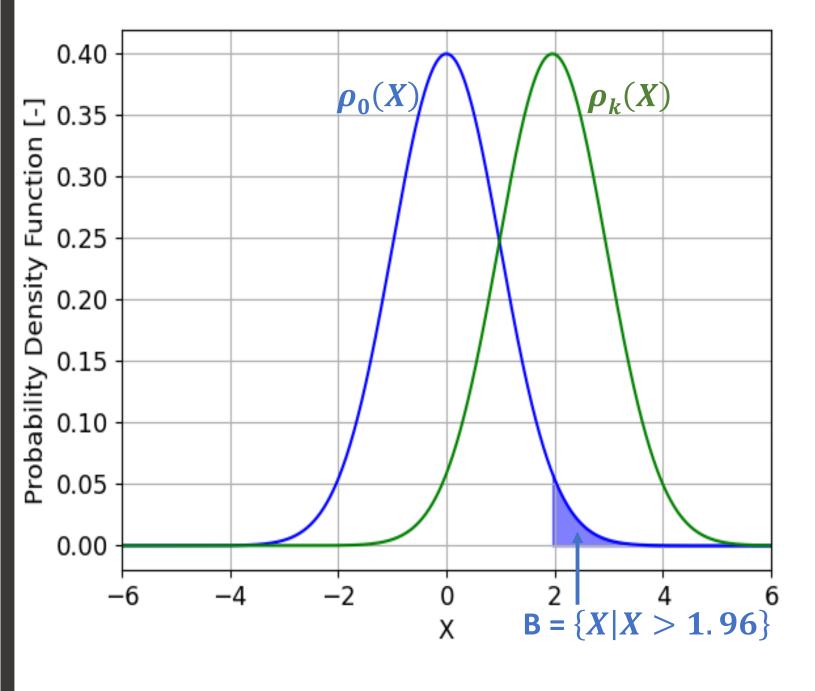
- 2) poor sampling of rare events in computationally expensive climate models
- 3) reliability of climate models
- What is the relative contribution of different atmospheric and oceanic drivers and of natural and forced variability to extremes in summer Arctic sea ice cover?

#### **Project overview** Phase 1: Coupled atmosphere-ocean **Phase 2: EC-Earth with different forcing** configuration of Plasim with stationary scenarios pre-industrial climate Rare event algorithm to oversample rare dynamical trajectories leading to extreme events **Extreme summer Arctic sea ice conditions** Plasim/EC-Earth simulations with initial conditions from **Attribution** arbitrary years analysis Risk of **Precursors** occurrence **Return curve Sensitivity studies** analysis with EC-Earth **Disentangling dynamic** and thermodynamic impact of **climate change EC-Earth** simulations Seasonal with initial conditions predictability from deliberately chosen years Sub-sampling in **Machine learning** climate model models ensemble

### Rare event algorithm

#### Importance sampling

Make rare events more common to reduce the uncertainty of an estimator



• Example: Estimate

$$P(B) = \int \mathbf{1}_B(X) \cdot \boldsymbol{\rho}_0(X) dX$$

by drawing data from  $ho_k$  instead of  $ho_0$ according to

$$P(B) = \int \mathbf{1}_{B}(X) \cdot \frac{\rho_{0}(X)}{\rho_{k}(X)} \rho_{k}(X) dX$$

$$\approx \frac{1}{n} \sum_{k=1}^{n} \mathbf{1}_{B}(X_{k}) \cdot \frac{\rho_{0}(X_{k})}{\rho_{k}(X_{k})}$$

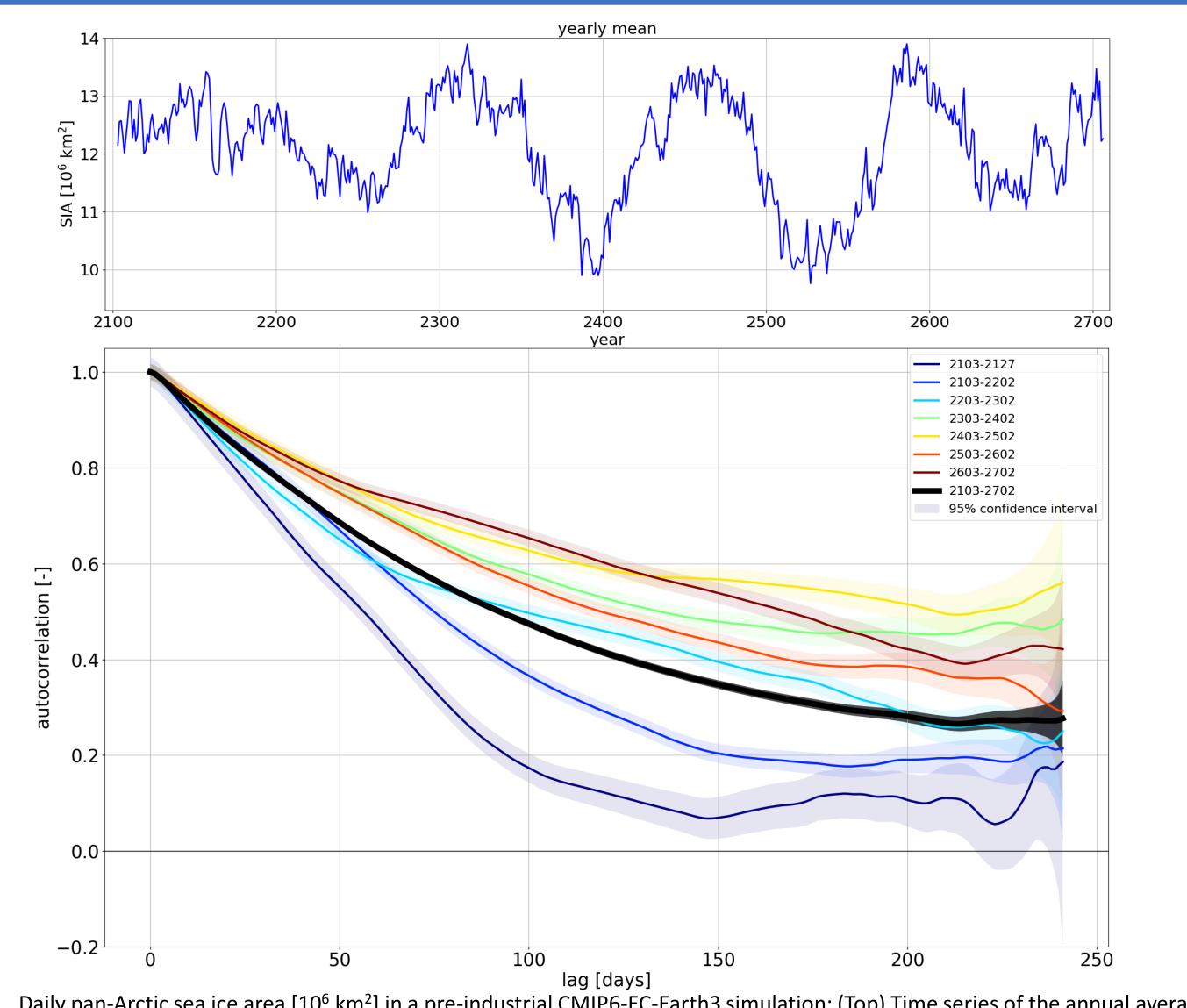
#### Application to climate model ensemble

- Importance sampling at the level of model trajectories  $\{X(t)\}_{0 \le t \le T_a}$  with observable A(X(t))
- The original trajectory distribution  $P_0$  is shifted towards a new distribution  $P_k$  such that extreme events become common

$$P_{k}(\lbrace X(t)_{0 \leq t \leq T_{a}} \rbrace) \underset{N \to \infty}{\sim} \frac{e^{k \int_{0}^{T_{a}} A(X(t))dt}}{E_{0}[e^{k \int_{0}^{T_{a}} A(X(t))dt}]} P_{0}(\lbrace X(t) \rbrace_{0 \leq t \leq T_{a}})$$

Resampling of ensemble trajectories with killing-cloning regular intervals in the order of the integrated autocorrelation time of A(X(t))

## Persistence of pan-Arctic sea ice area anomalies



Daily pan-Arctic sea ice area [106 km2] in a pre-industrial CMIP6-EC-Earth3 simulation: (Top) Time series of the annual averages and (bottom) autocorrelation function applied to the daily data between February and September.

- Autocorrelation function decays with an e-folding time scale of about 140 days
- The inherent persistence of sea ice area anomalies is likely overestimated due to a remaining effect of low-frequency variabiltiy in the data

### References

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