

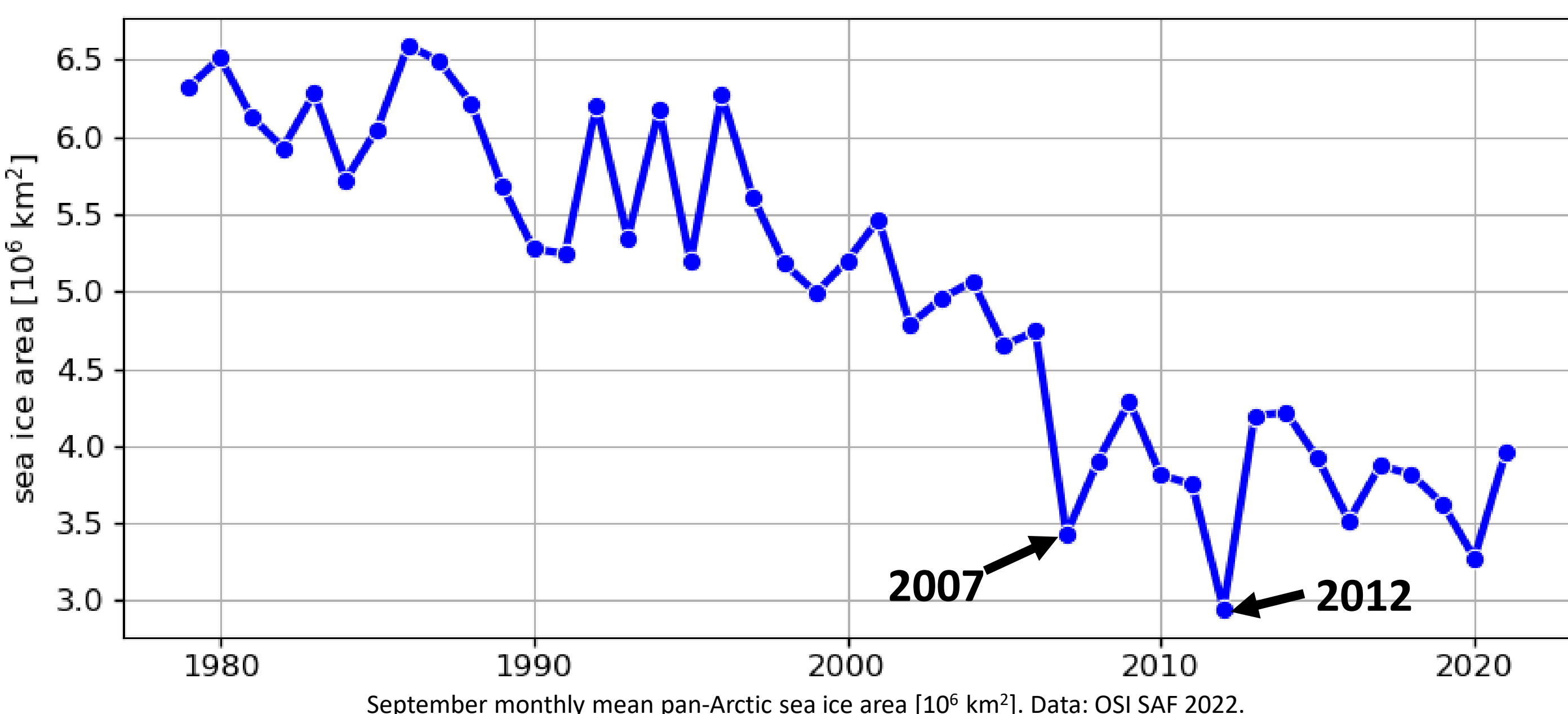
Drivers and predictability of extreme summer Arctic sea ice conditions with rare event simulation methods

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Extreme events in summer Arctic sea ice cover

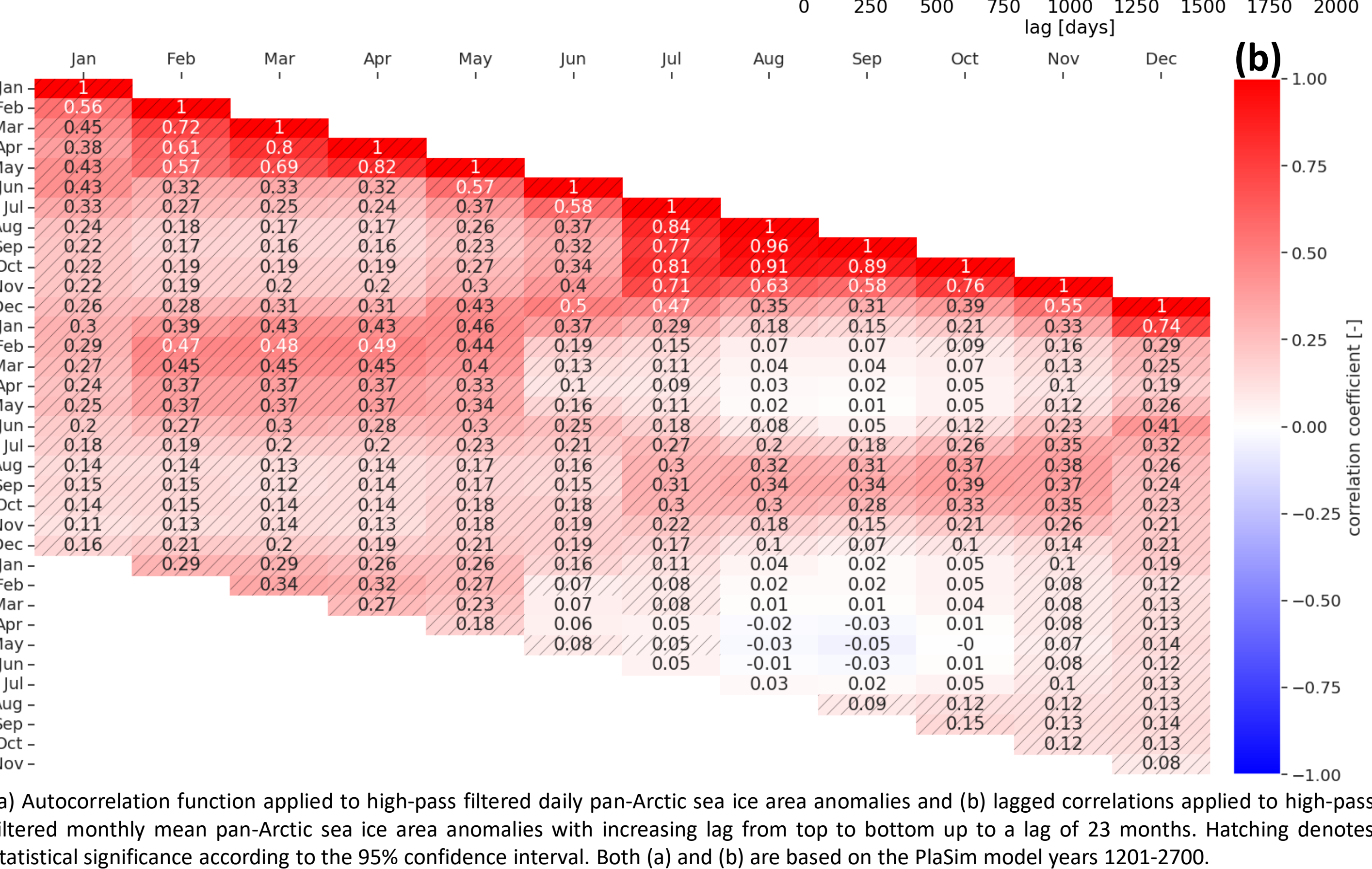
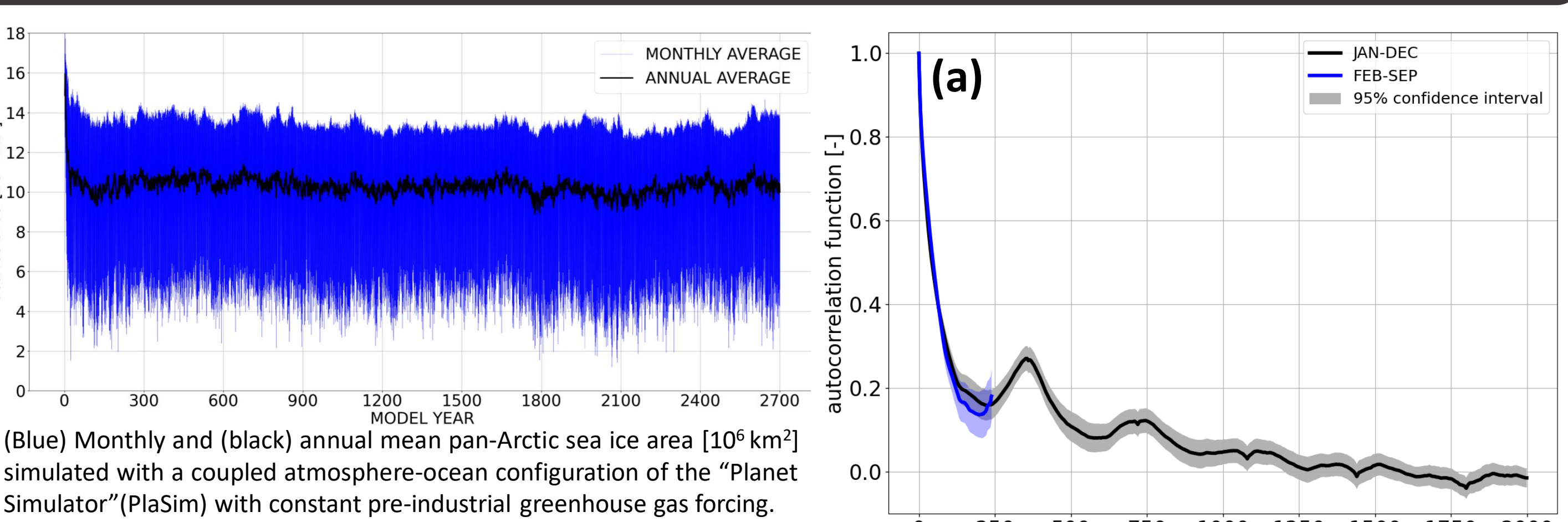


- Due to **climate change**, summer Arctic sea ice cover is decreasing
- On top of the **downward trend**, **internal climate variability** contributes to the **year-to-year variations** and **associated extremes** of the **annual Arctic sea ice minimum**
- Three **problems** complicate **robust statistical** and **dynamical studies** about **extreme events** in summer Arctic sea ice cover:
 - 1) **lack of observational data**
 - 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?

➔ Can we **improve seasonal predictions** of **extreme summer Arctic sea ice cover** by exploiting a **better understanding** of the **physical drivers** of these events?

Persistence of pan-Arctic sea ice area anomalies

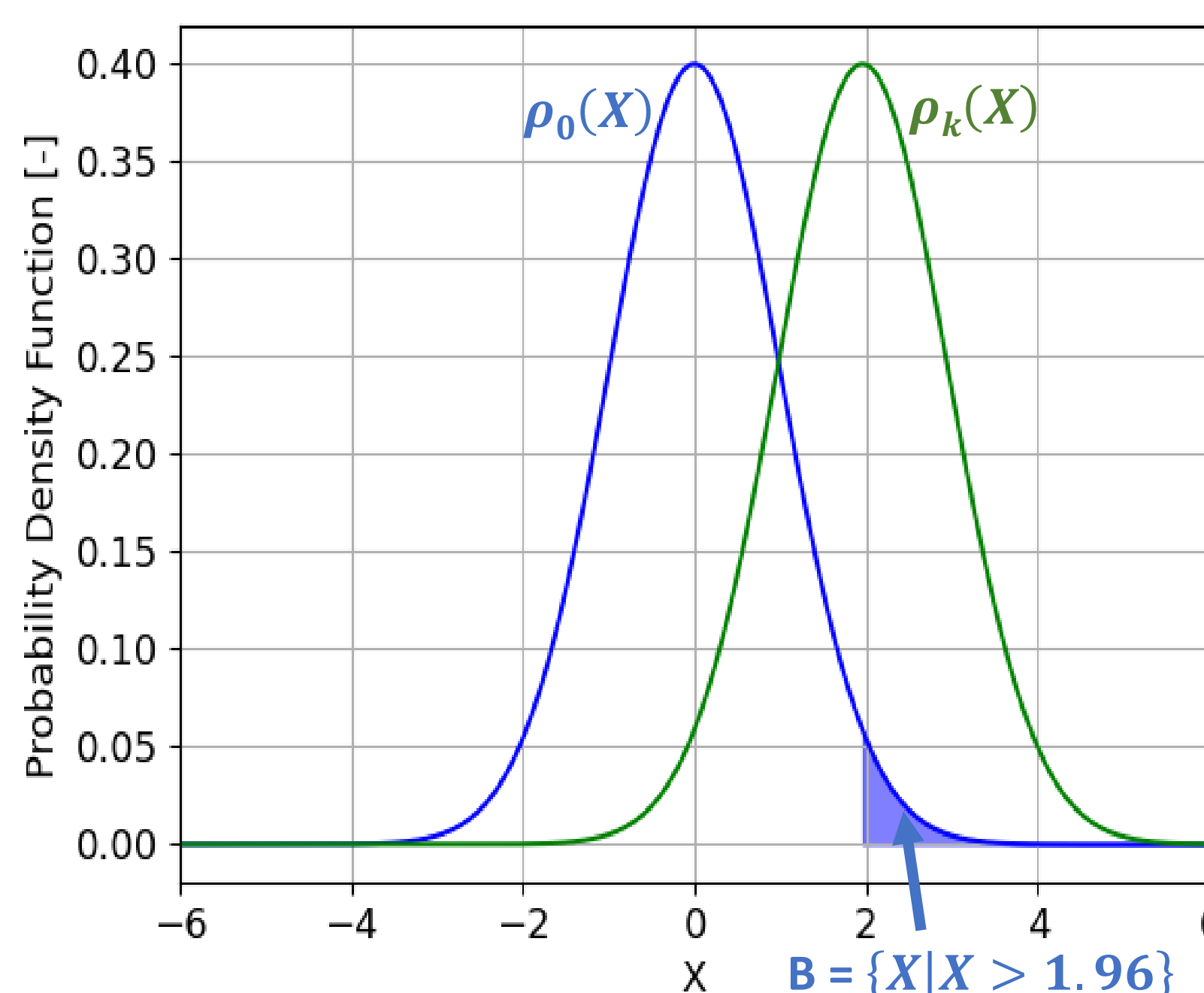


- The **persistence** of the **sea ice area anomalies** is one important criterion for the set-up of the **rare event algorithm experiments**
- Up to a **lag of three months**, the **autocorrelation function** of **pan-Arctic sea ice area anomalies** decays exponentially with an **e-folding time scale** of about **70 days**
- The **memory** of **sea ice area anomalies** has a strong **seasonality**, shows **melt-to-growth** and **growth-to-melt** season reemergence and **vanishes completely** after **3 to 5 years**

Coupling climate model ensembles to a rare event algorithm

Importance sampling

Goal: Make **rare events** more common to reduce the **statistical uncertainty** of an estimator



- Synthetic example:** Estimate

$$P(B) = \int \mathbf{1}_B(X) \cdot \rho_0(X) dX$$

by drawing data from ρ_k instead of ρ_0 with

$$P(B) = \int \mathbf{1}_B(X) \cdot \frac{\rho_0(X)}{\rho_k(X)} \rho_k(X) dX \approx \frac{1}{n} \sum_{k=1}^n \mathbf{1}_B(X_k) \cdot \frac{\rho_0(X_k)}{\rho_k(X_k)}$$

Methodology of the rare event algorithm

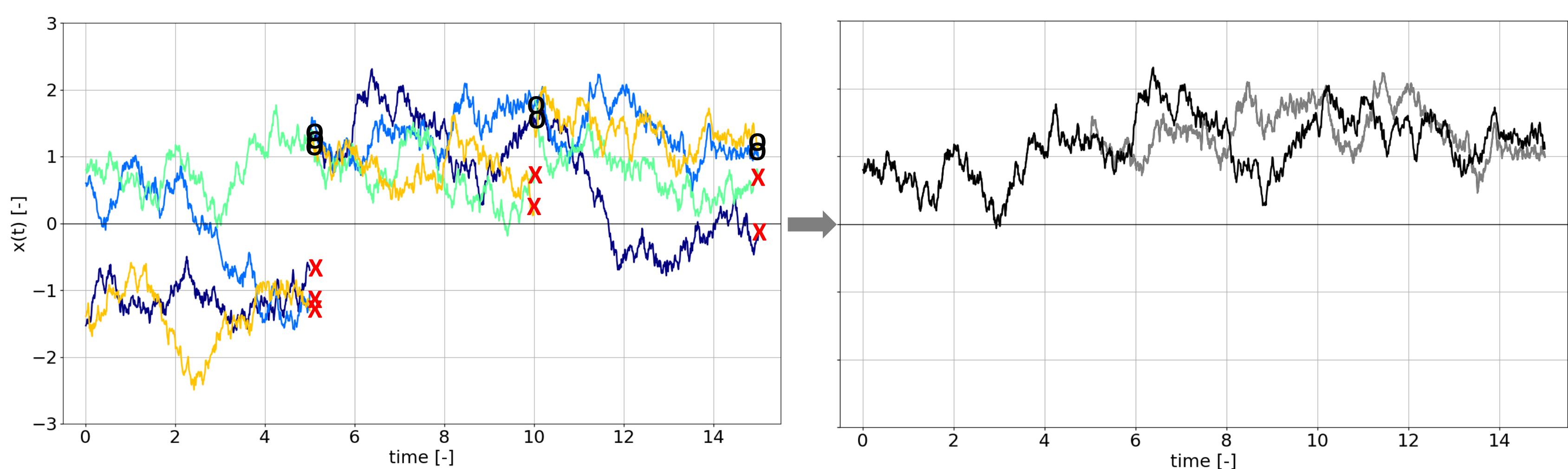
Genealogical rare event algorithm to perform importance sampling at the level of model trajectories

- Run N trajectories $\{X_n(t)\}$ ($n = 1, 2, \dots, N$) for **total simulation time** T_a and define **observable** $A(\{X_n(t)\})$
- At **resampling times** $t_i = i\tau$ ($i = 1, \dots, \frac{T_a}{\tau}$), the **trajectories** generate a **number of copies** of itself given by the **weights**

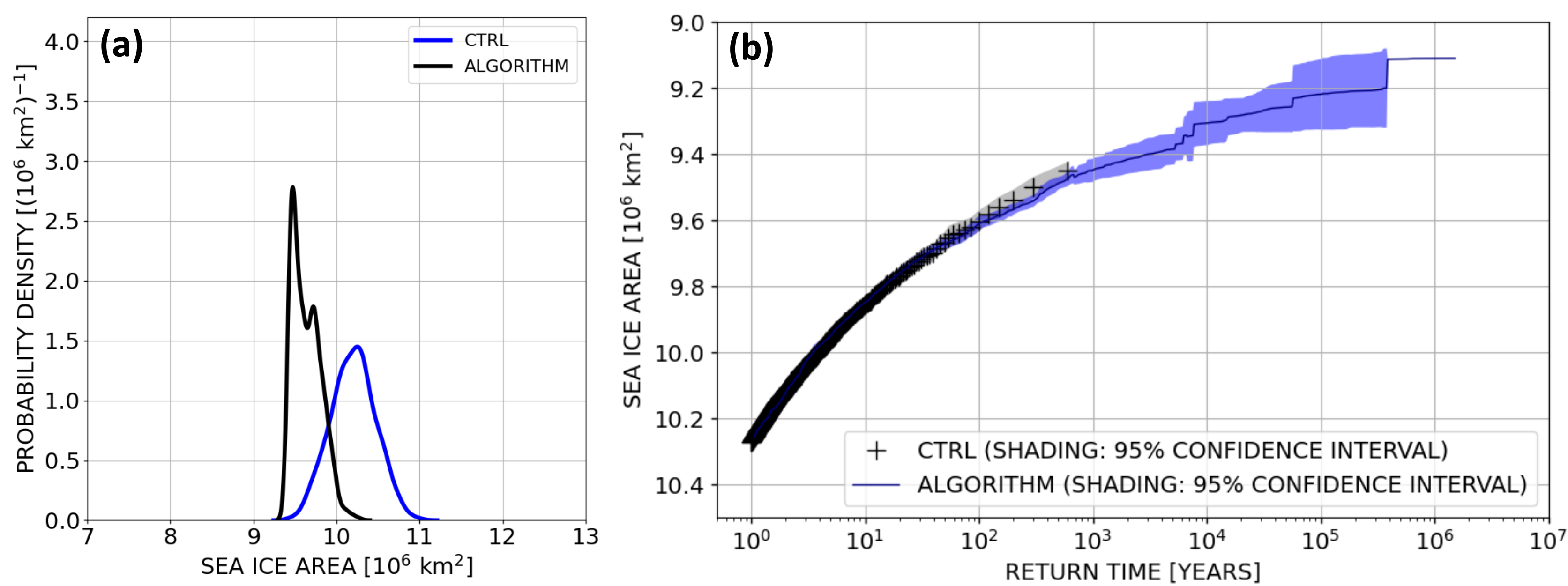
$$w_{n,i} = \frac{e^{k \int_{t_{i-1}}^{t_i} A(\{X_n(t)\}) dt}}{R_i}, \quad R_i = \frac{1}{N} \sum_{n=1}^N e^{k \int_{t_{i-1}}^{t_i} A(\{X_n(t)\}) dt}, \text{ with } k \text{ parameter of the algorithm}$$

- The **algorithm** shifts the **original trajectory distribution** P_0 towards a **new distribution** P_k such that **trajectories with large values** of the **time-averaged observable** become **common**:

$$P_k(\{X(t)\}_{0 \leq t \leq T_a}) = \frac{e^{k \int_0^{T_a} A(\{X(t)\}) dt}}{R} P_0(\{X(t)\}_{0 \leq t \leq T_a})$$



Results from the experiments with the rare event algorithm



Probability distributions (a) and return curves (b) of pan-Arctic February-September averaged sea ice area in PlaSim in the control run and in the algorithm experiment using a resampling time of 30 days. (a) One algorithm experiment with $k = -0.05 \cdot 10^{-6} \text{ km}^2 \text{ day}^{-1}$ and (b) eight algorithm experiments with different k are used.

- The **algorithm** enables to **efficiently sample** rare events with **very low Arctic sea ice area** and to **compute** **return times** up to more than **10⁵ years** from a **total computational cost** of a few **1000 years**

References

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