Extreme Arctic sea ice lows investigated with a rare event algorithm

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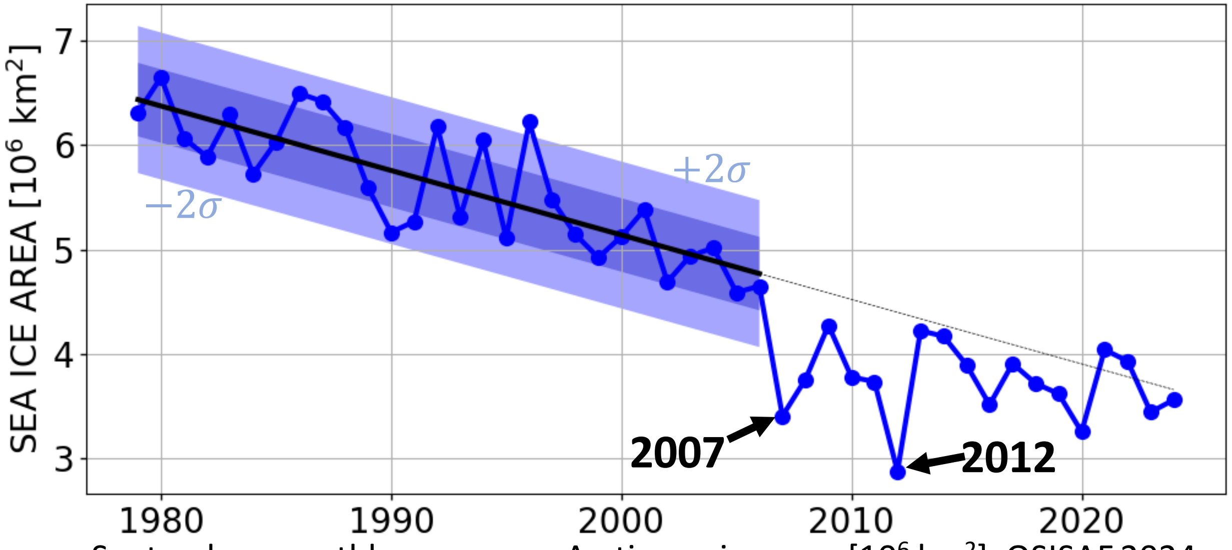
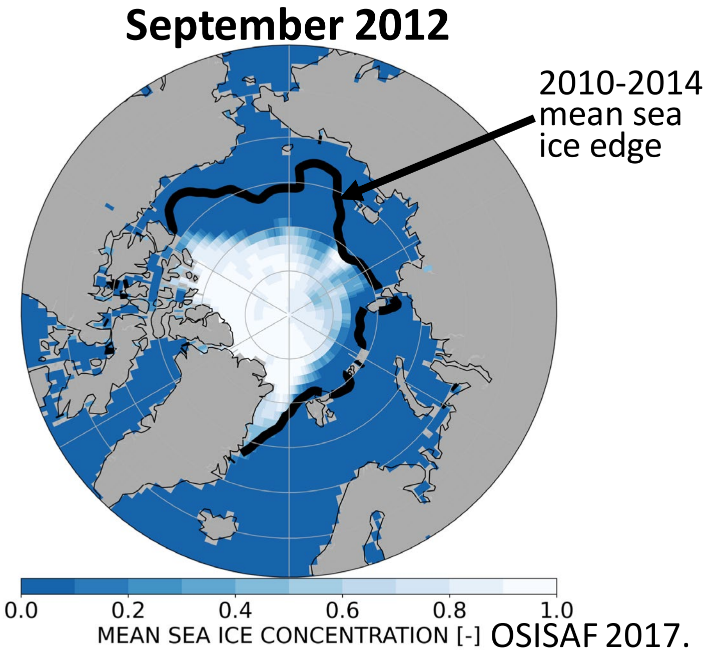
Extreme reductions of the summer pan-Arctic sea ice area



September monthly mean pan-Arctic sea ice area [10^6 km^2]. OSISAF 2024.



OSISAF 2017.

- What are the typical drivers of extreme sea ice lows considering a large amount of extreme events?
- What is the probability of a 2012-like event for a given initial/climate state? -> extreme event attribution

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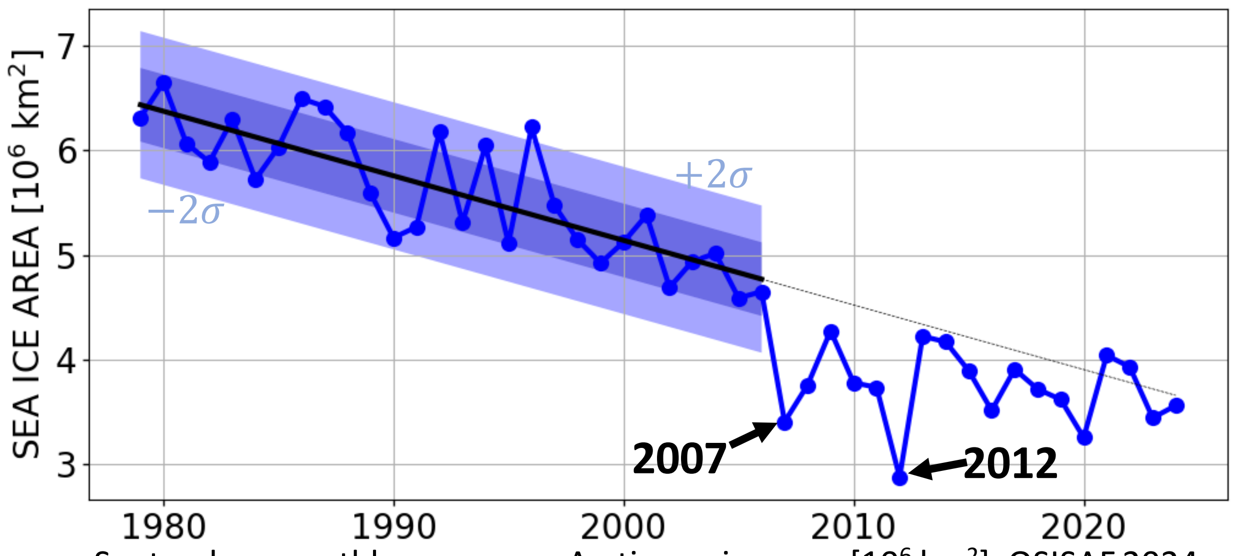

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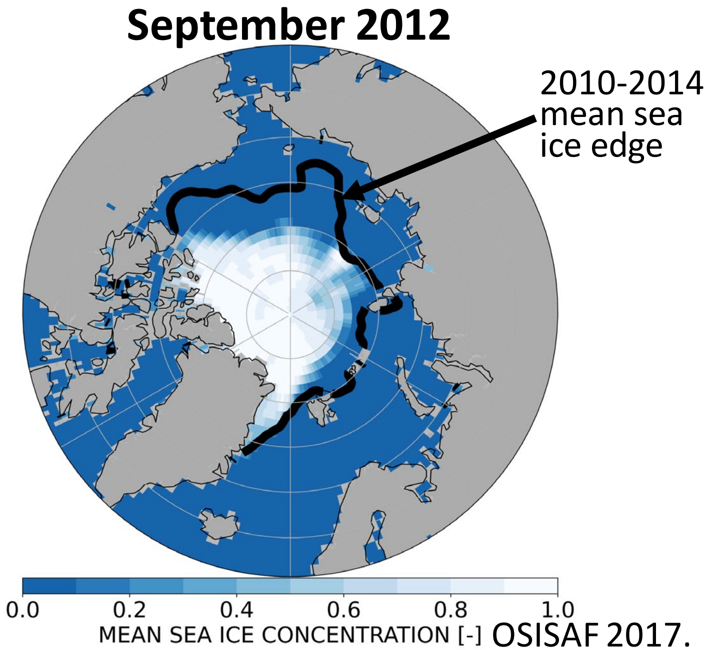

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- What are the typical drivers of extreme sea ice lows considering a large amount of extreme events?

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- Problem: quantitative statistical and dynamical studies of climate extremes hindered by lack of data
  -> lack of observations, poor sampling with numerical models due to large computational cost

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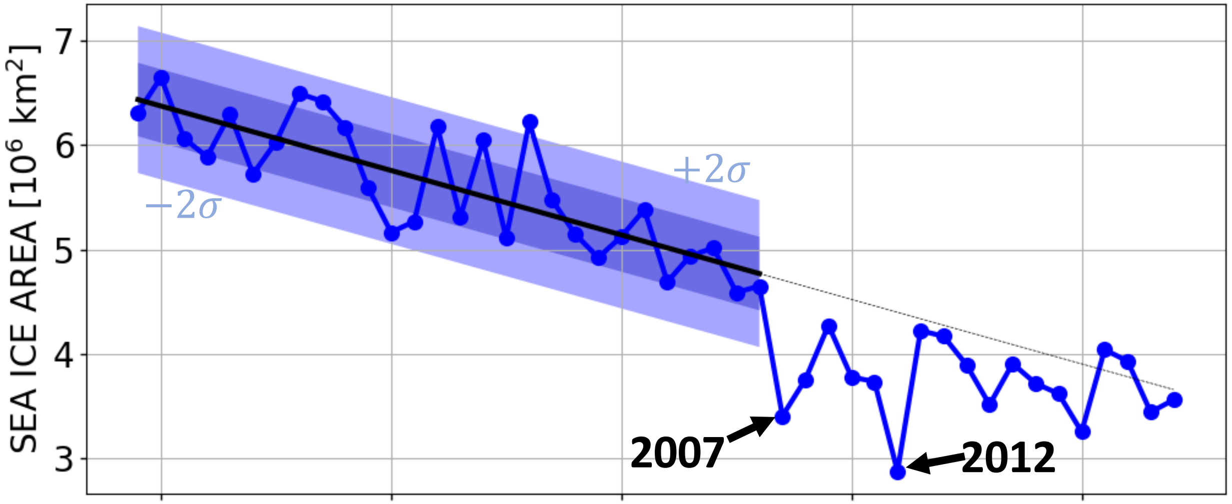

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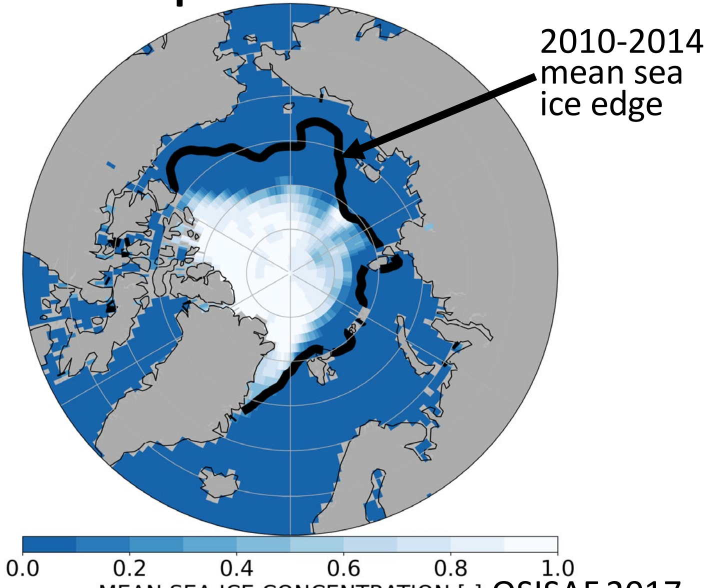


OSISAF 2017.

- Problem: quantitative statistical and dynamical studies of climate extremes hindered by lack of data

-> From statistical physics: improve the sampling efficiency of extreme events with rare event algorithms

-> Genealogical selection algorithm adapted from Del Moral and Garnier (2005); Giardina et al. (2011) (Ragone et al. 2018; Ragone and Bouchet 2019; 2021): Efficient to study time-persistent extremes

Importance sampling and rare event algorithm

- Importance sampling of trajectories in ensemble simulation with numerical model
  -> make trajectories leading to large anomalies of an observable common

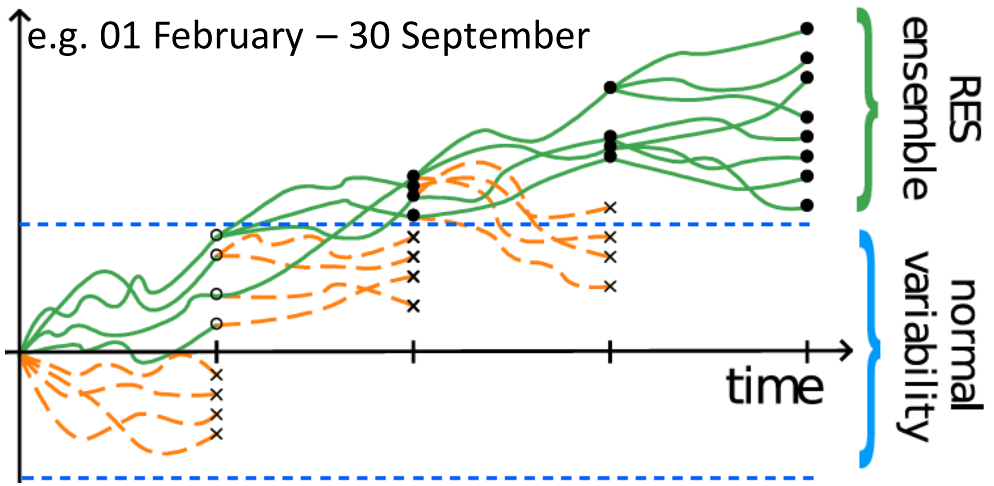
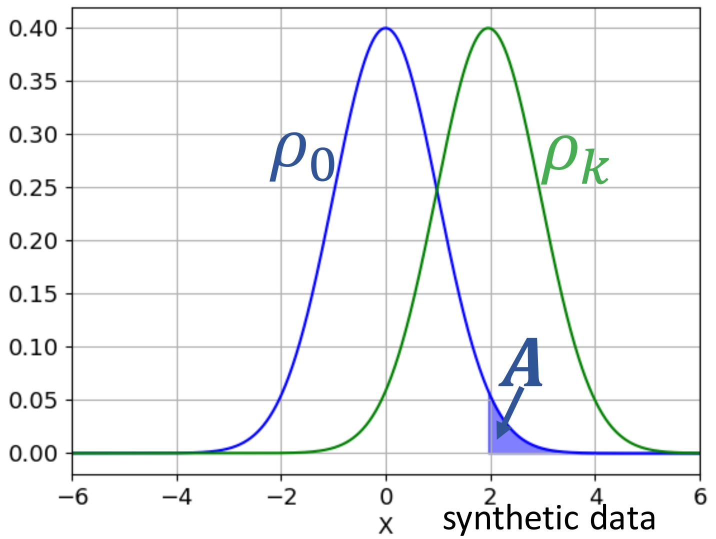


Figure from Wouters et al 2023



Importance sampling and rare event algorithm

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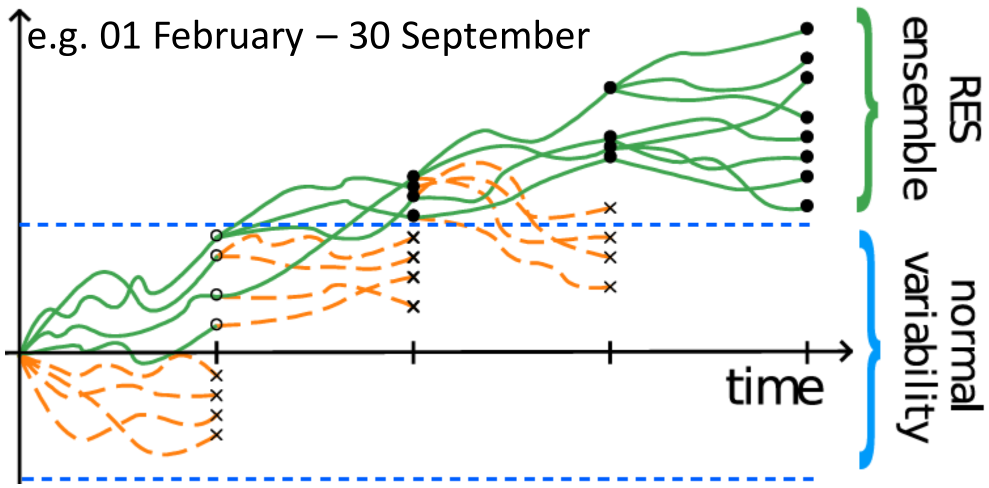
  -> make trajectories leading to large anomalies of an observable common
  -> better statistics on extremes (e.g. composites, probabilities, return times) + generation of ultra-rare events



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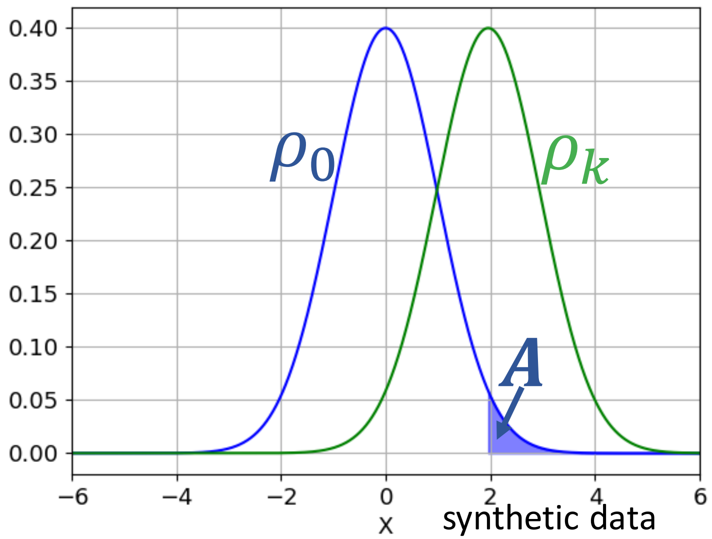

Importance sampling and rare event algorithm

- Importance sampling of trajectories in ensemble simulation with numerical model
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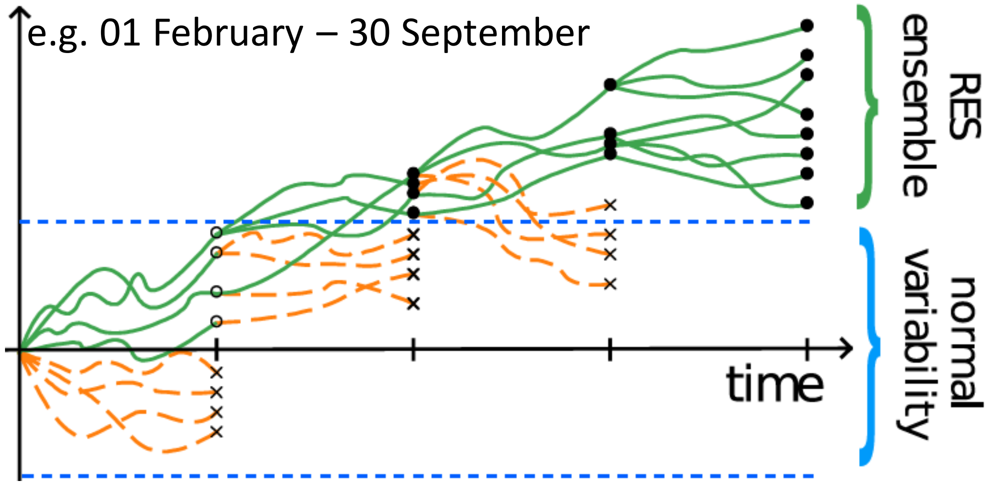
- Resampling at constant time intervals: trajectories are killed or cloned depending on weights measuring the likelihood to develop an extreme for the target observable



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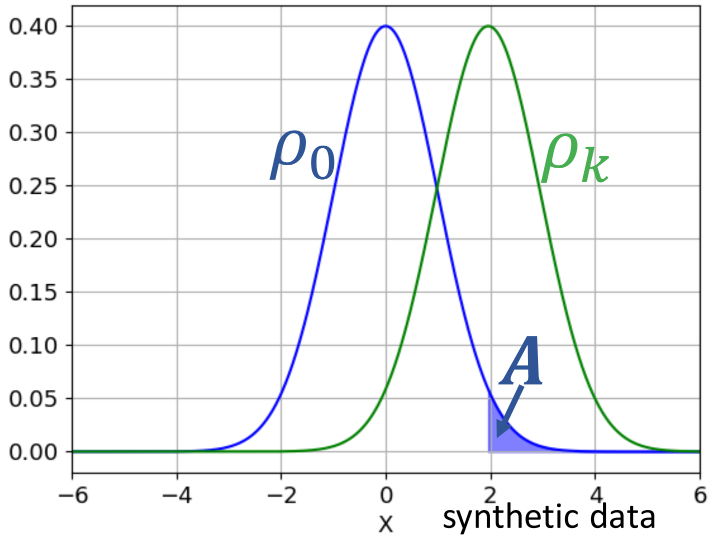

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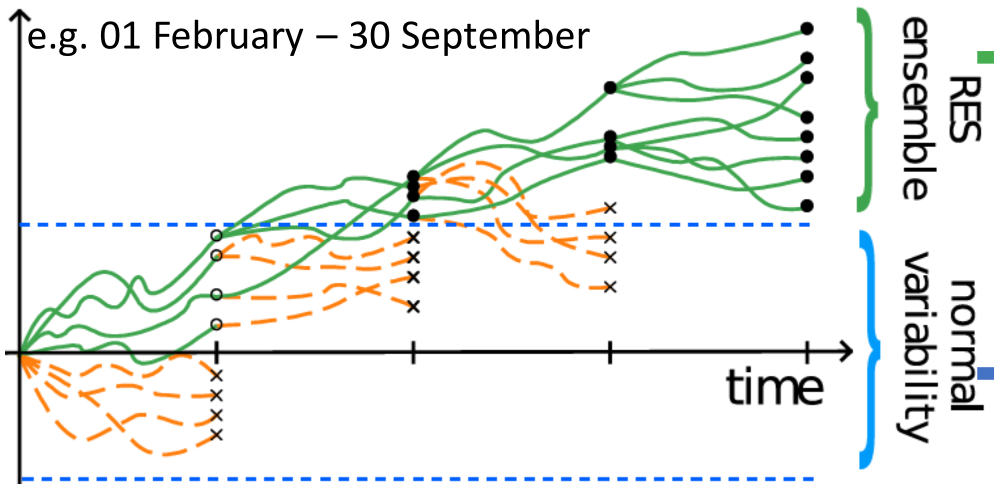

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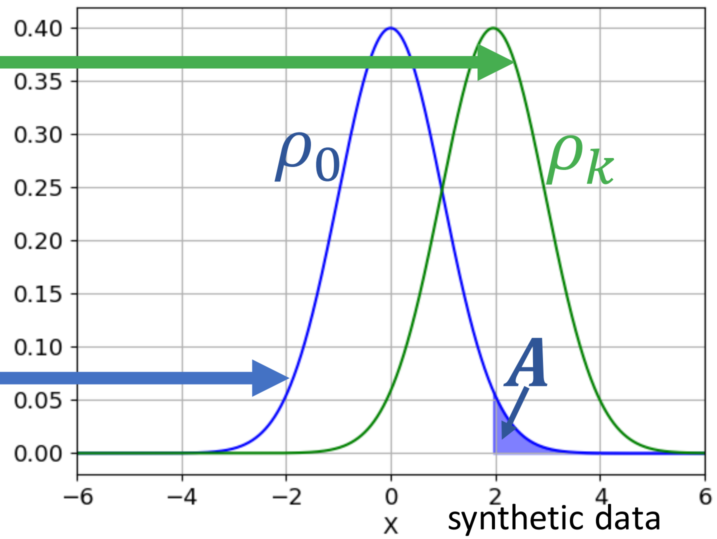

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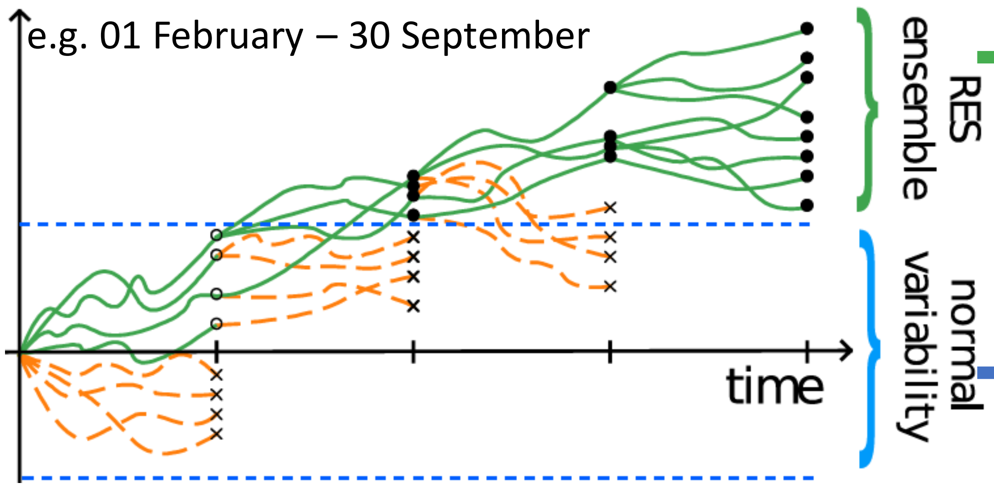
- Importance sampling formula: relates probabilities of trajectories between biased and unbiased statistics

$$\boldsymbol{P_k(\{X_n(t)\}_{0\le t\le T_a}) = \frac{e^{k\int_0^{T_a} A\,(\{X_n(t)\})\,dt}}{R} P_0(\{X_n(t)\}_{0\le t\le T_a})}$$

P_k, P_0: Probability density in biased and unbiased statistics
k, R: Controling parameter and normalization term
t, T_a: Time and simulation length
$A, \{X_n(t)\}$: Observable and model trajectories



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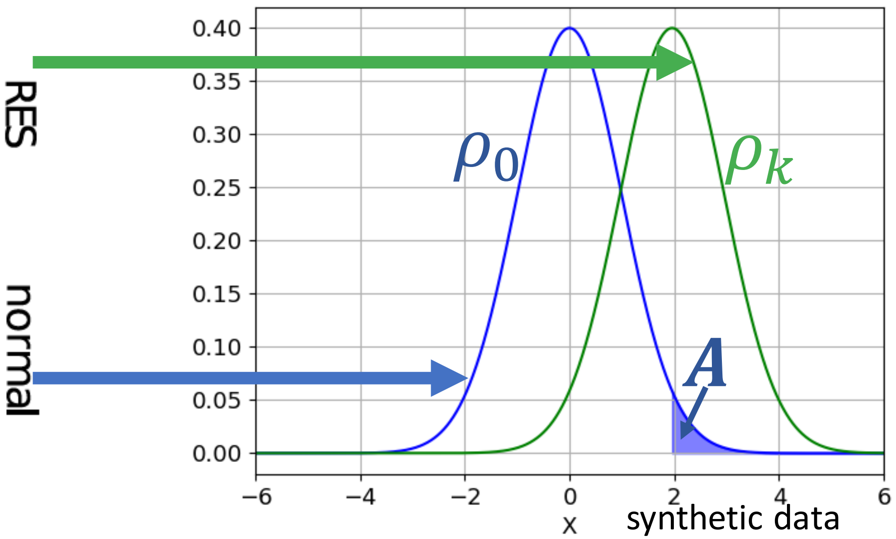
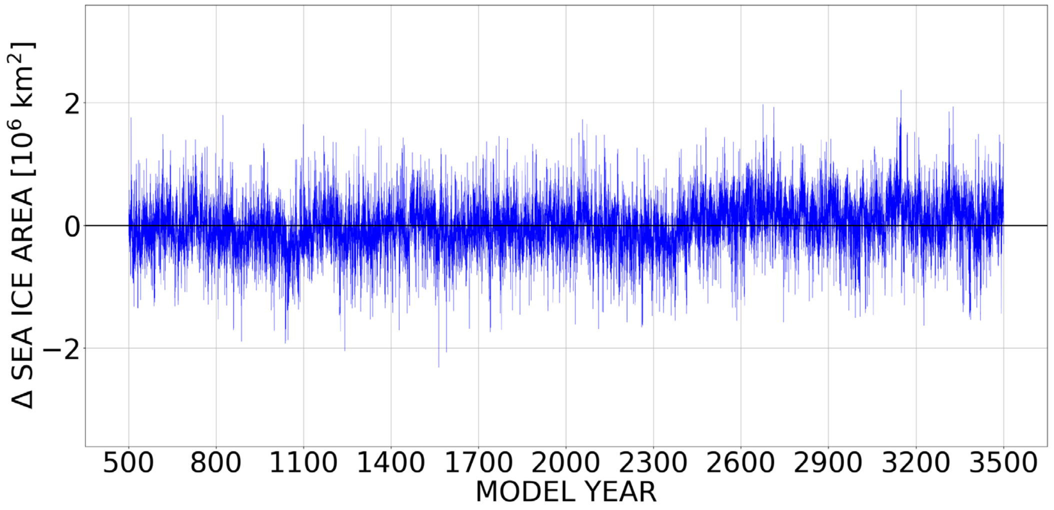
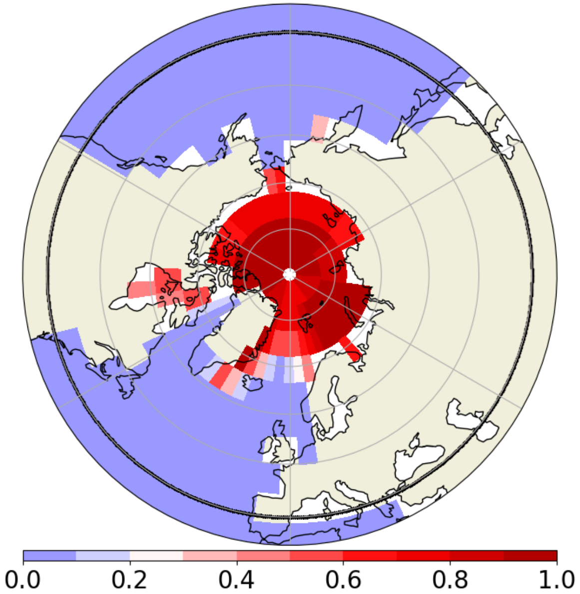


Experiments with coupled climate model PlaSim

3000-year control run: independent initial conditions for five 600-member ensemble simulations with the algorithm



Control run: anomalies of monthly mean pan-Arctic sea ice area [10^6 km^2]



Control run: climatological mean sea ice concentration [-]

Experiments with coupled climate model PlaSim

PlaSim: Intermediate complexity general circulation model

Coupled version: Large-Scale Geostrophic ocean and a zero-layer thermodynamic sea ice model

Resolution: T21 horizontal (32x64), 10 vertical layers

Forcing: constant pre-industrial greenhouse gas conditions

Observable: pan-Arctic sea ice area

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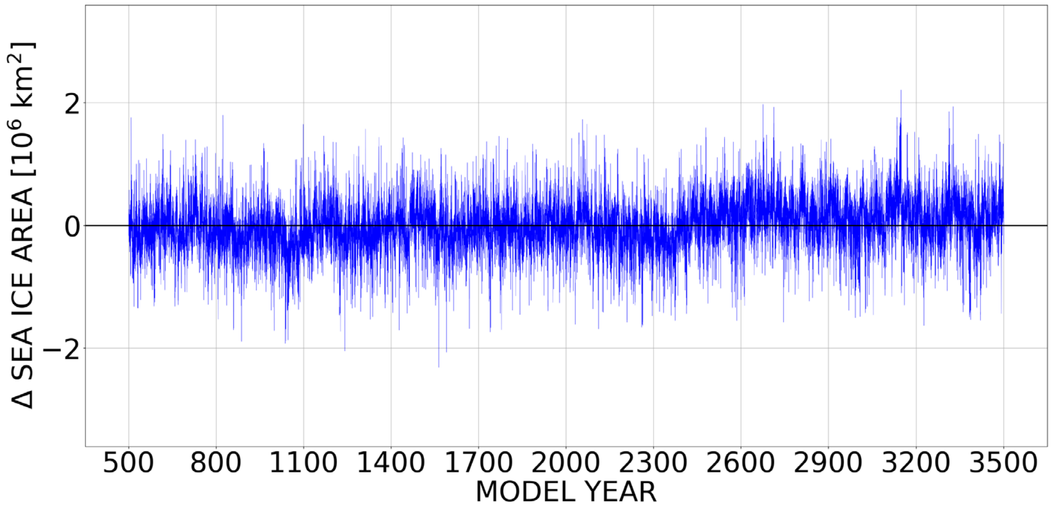

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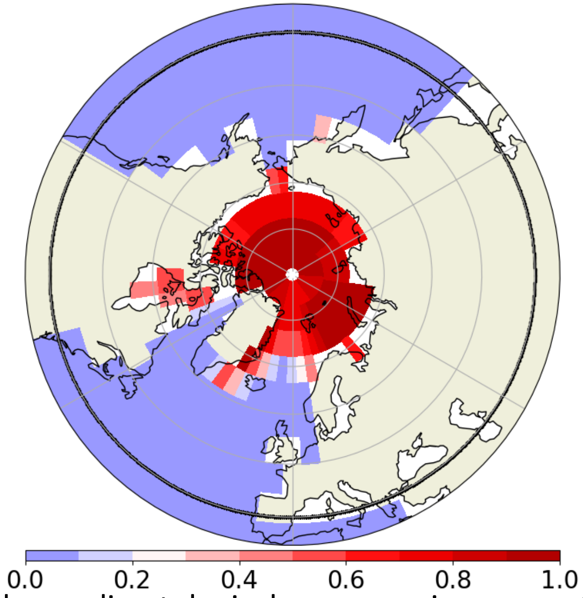
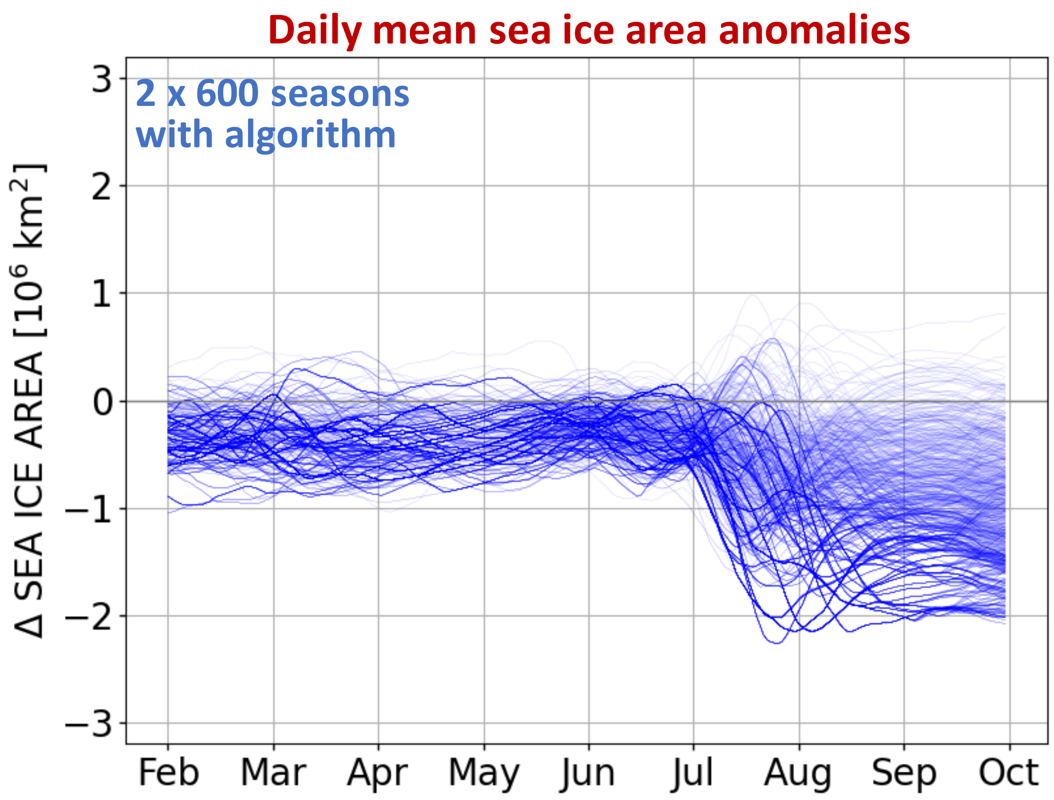


Control run: climatological mean sea ice concentration [-]

Seasons with extremely low pan-Arctic sea ice area in PlaSim



- Independent initial conditions sampled from long control run (stationary pre-industrial climate)

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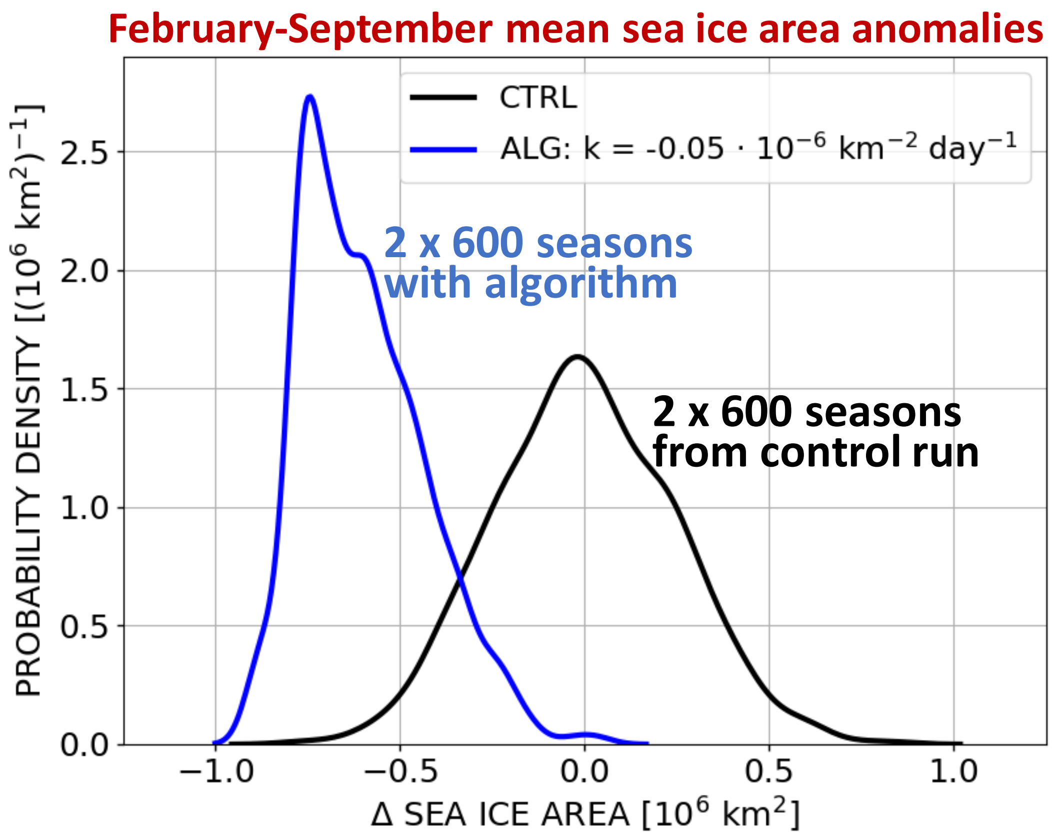

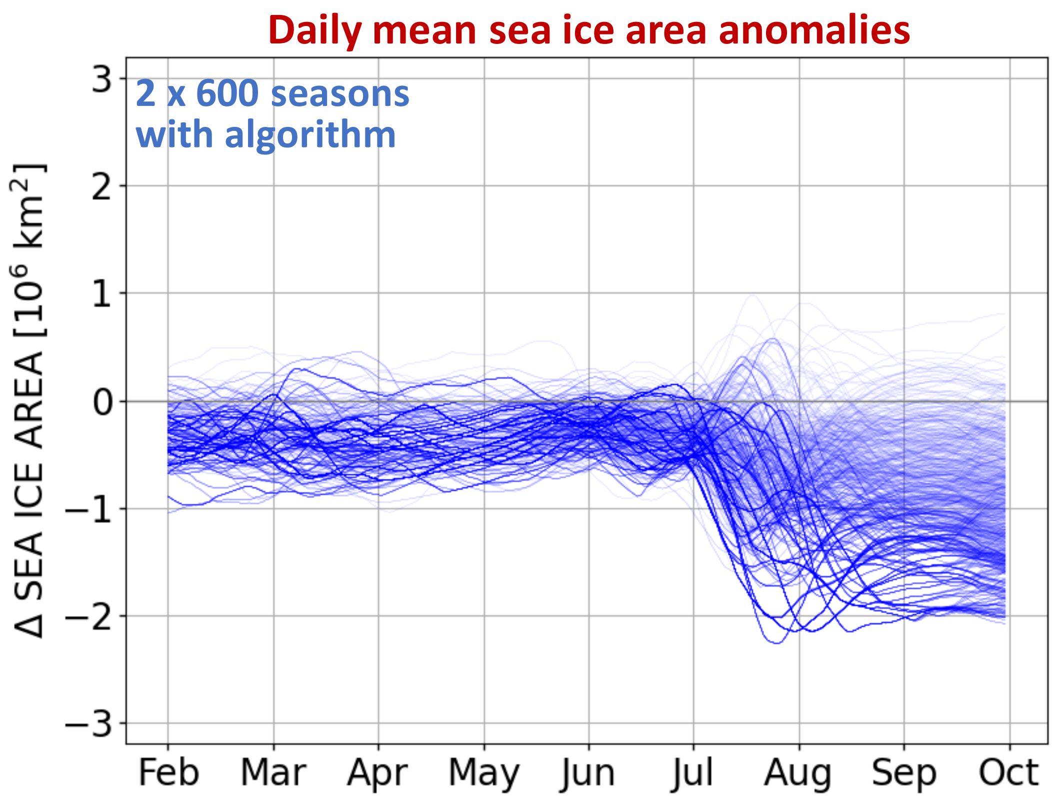

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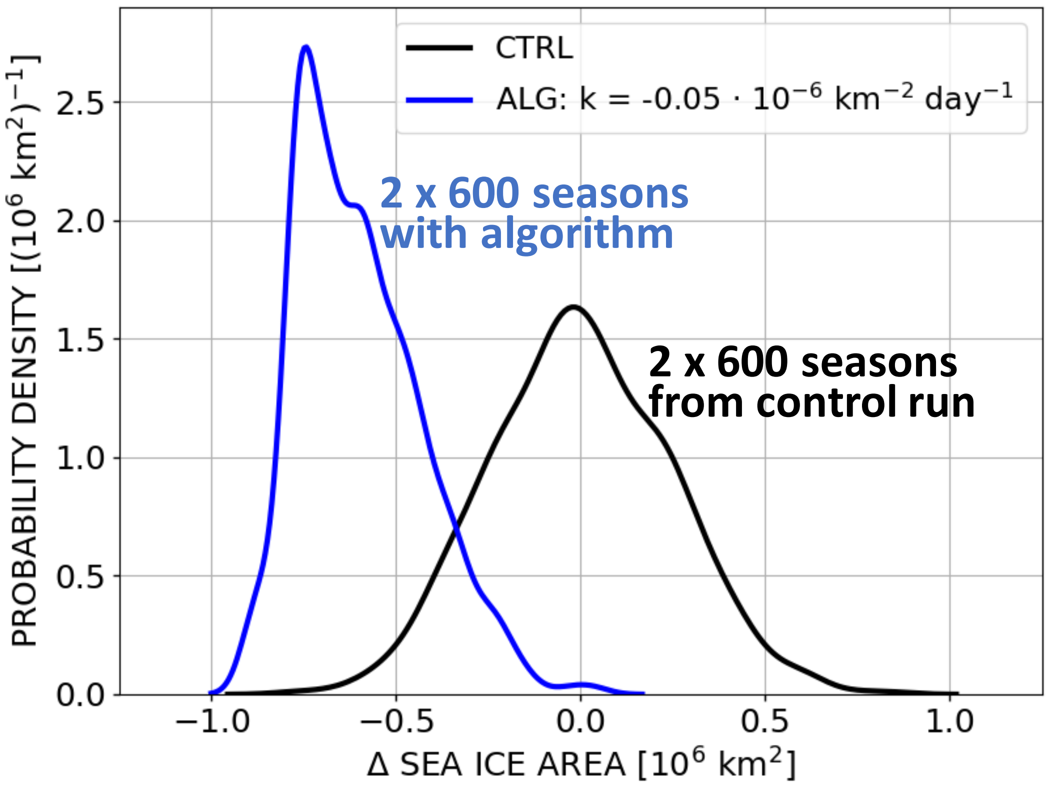
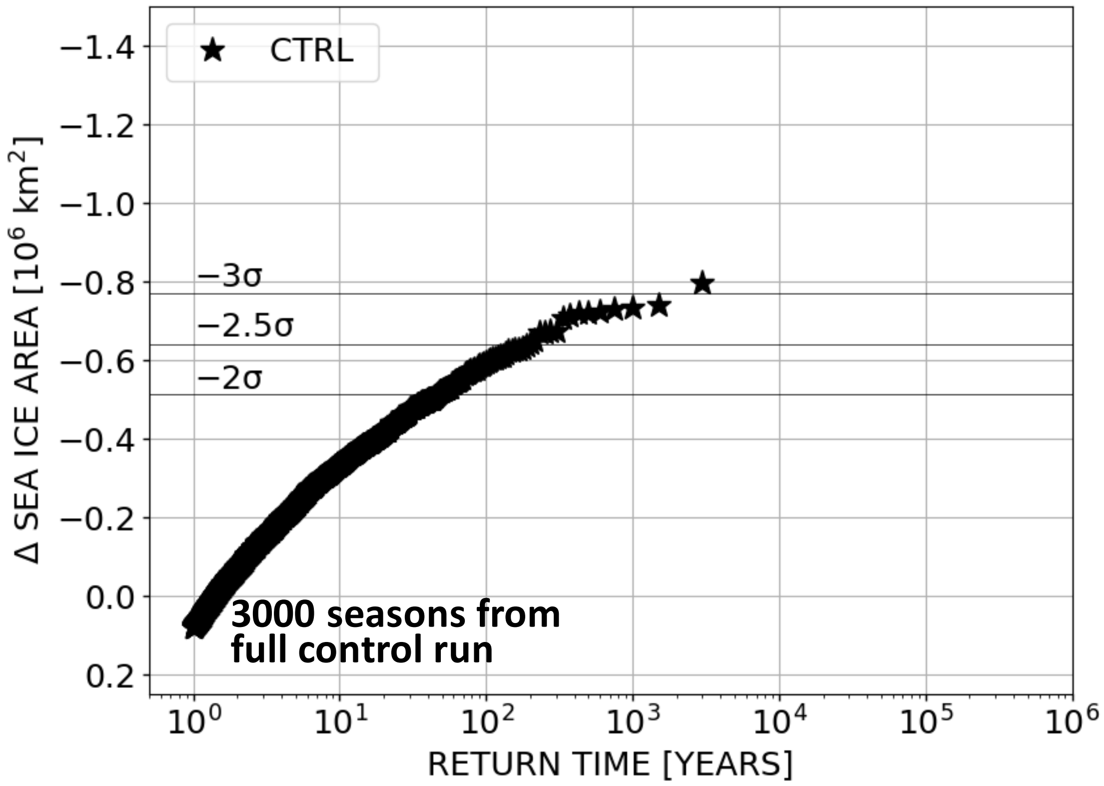
- Importance sampling of extremely negative February-September mean pan-Arctic sea ice area anomalies

Seasons with extremely low pan-Arctic sea ice area in PlaSim

February-September mean sea ice area anomalies





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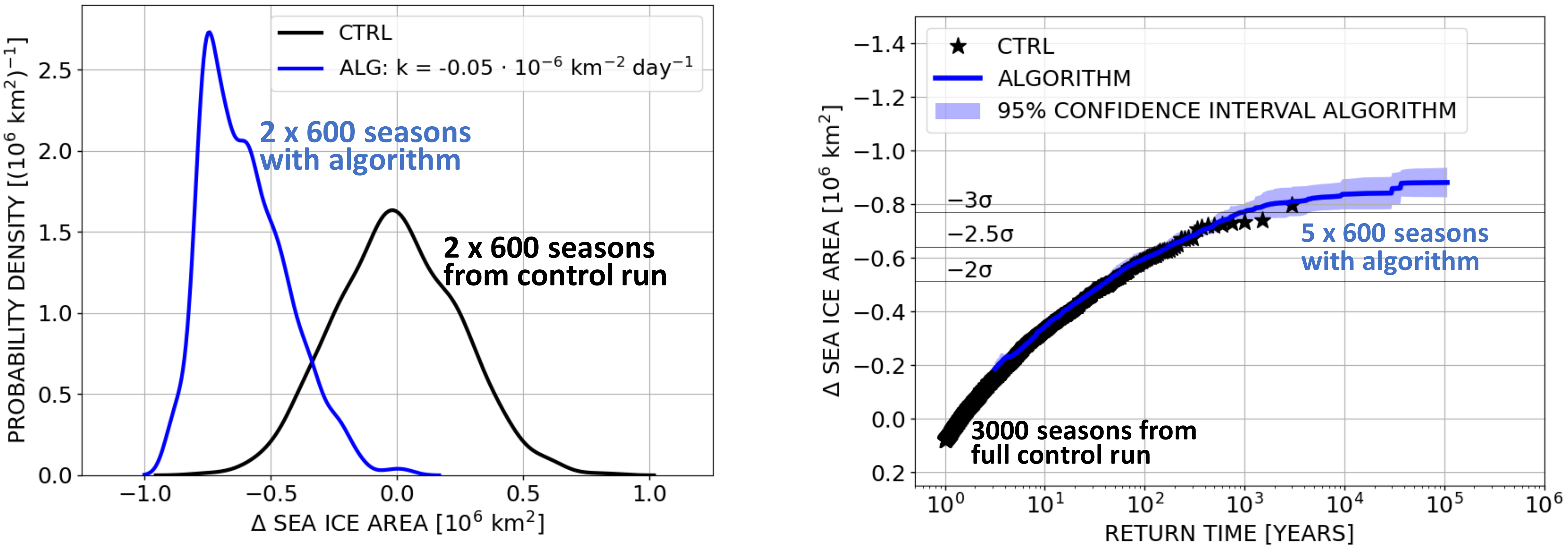
February-September mean sea ice area anomalies

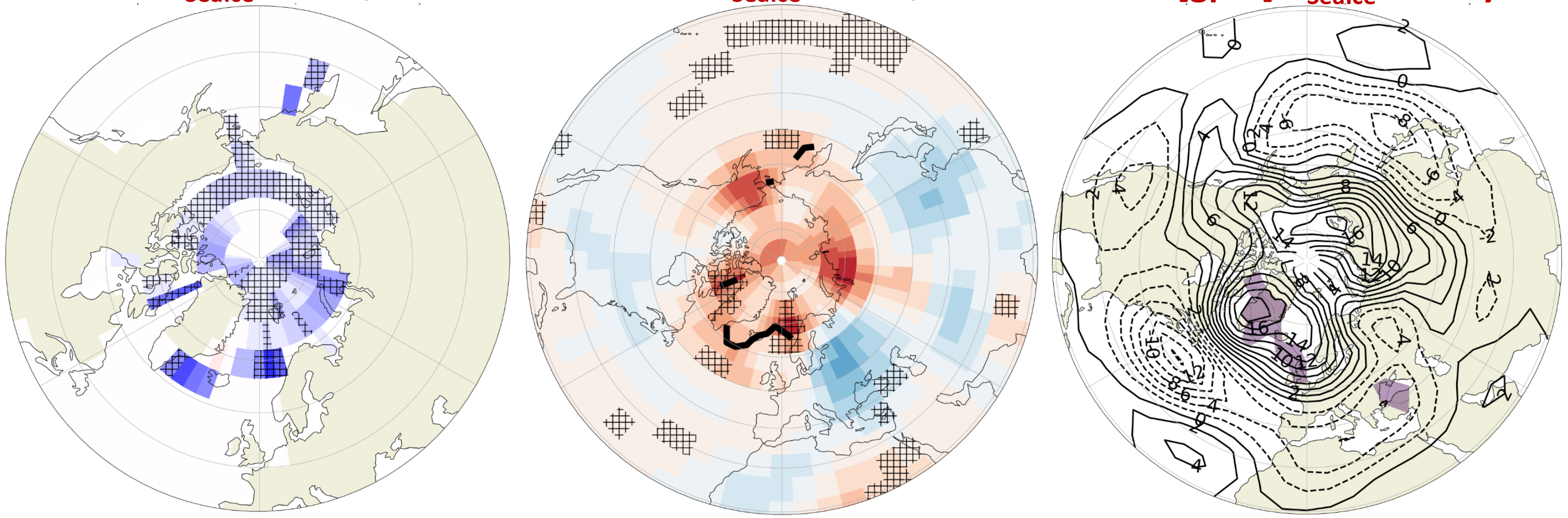


- Independent initial conditions sampled from long control run (stationary pre-industrial climate)
- Importance sampling of extremely negative February-September mean pan-Arctic sea ice area anomalies
- The algorithm allows to compute return times up to 10^5 years with computational cost of order 10^3 years

Seasons with extremely low pan-Arctic sea ice area in PlaSim

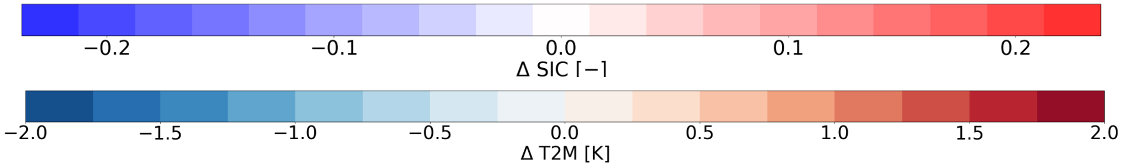
SIC [-]: r_{SeaIce} > 200 years | T2M [K]: r_{SeaIce} > 200 years | Z500 [gpm]: r_{SeaIce} > 200 years

CONTROL

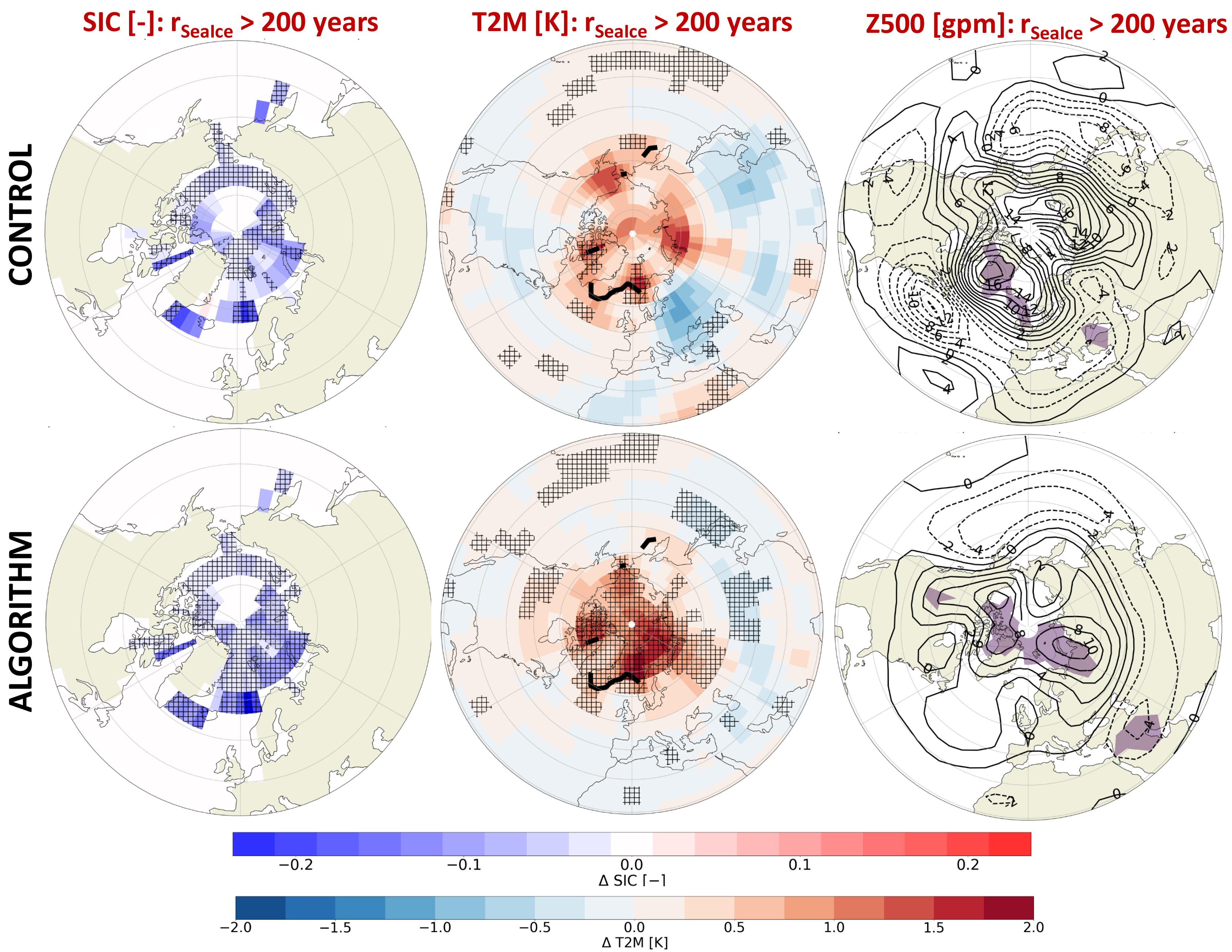


Hatching and shading:
Significance at the 5% level

ALGORITHM



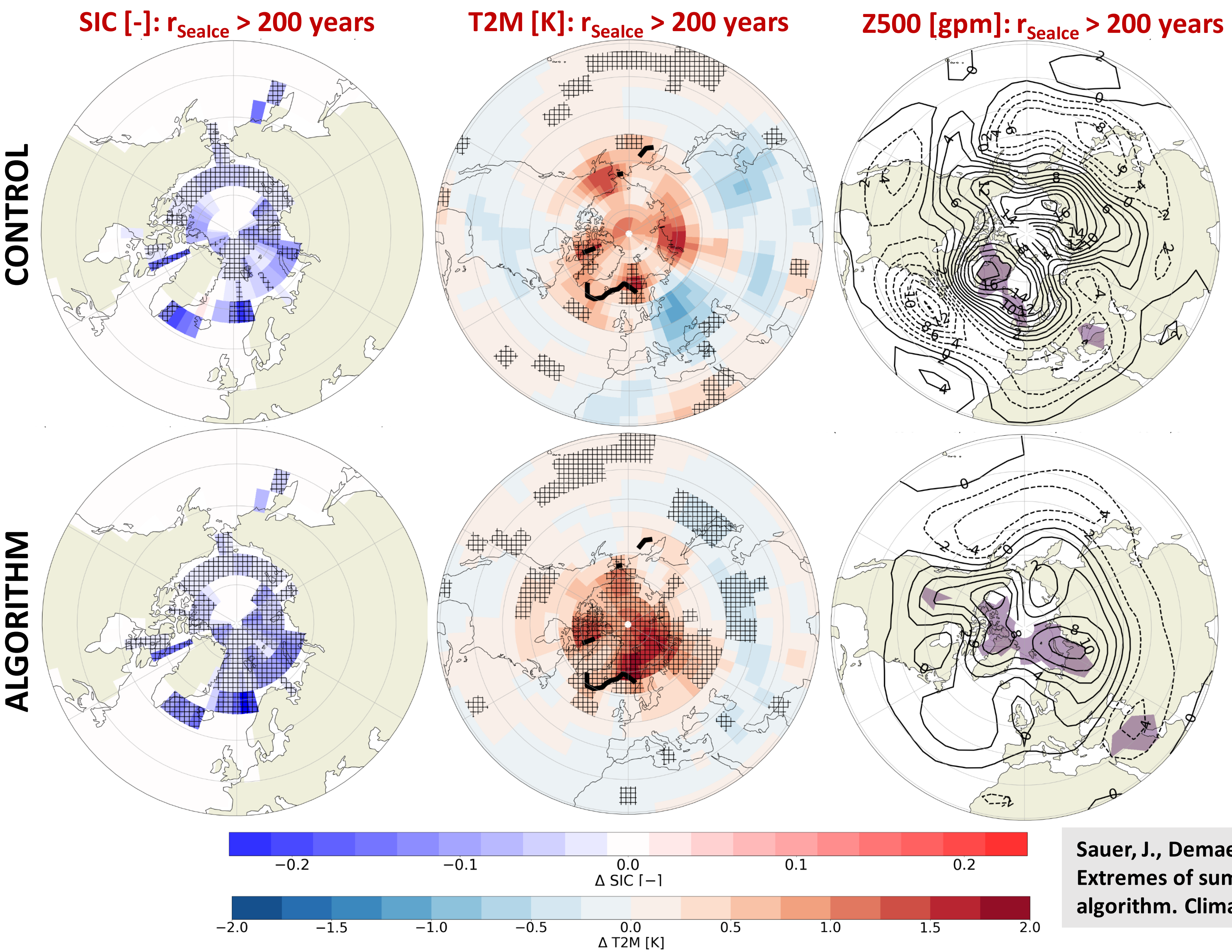
Seasons with extremely low pan-Arctic sea ice area in PlaSim



Hatching and shading: Significance at the 5% level

- Improved composite statistics with the algorithm compared to control run

Seasons with extremely low pan-Arctic sea ice area in PlaSim



Hatching and shading:
Significance at the 5% level

- Improved composite statistics with the algorithm compared to control run

- Drivers of warm Arctic and low sea ice in PlaSim-T21-LSG:
  - sea ice-ocean preconditioning
  - warm and moist/cloudy spring atmosphere
  - early summer "heat wave"

Sauer, J., Demaeyer, J., Zappa, G., Massonnet, F., & Ragone, F. (2024). Extremes of summer Arctic sea ice reduction investigated with a rare event algorithm. Climate Dynamics. https://doi.org/10.1007/s00382-024-07160-y

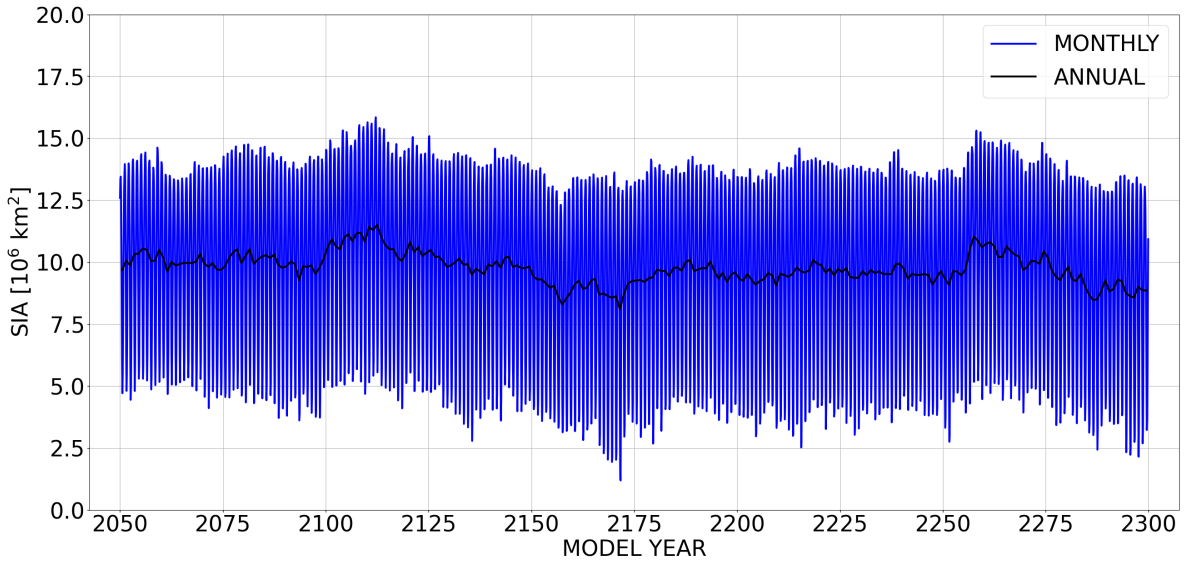
Experiments with the EC-Earth3 climate model

EC-Earth3: European community Earth System Model (Döscher et al. 2022; Coupled Model Intercomparison Project Phase 6)

Components and resolutions: IFS-36r4: T255L91, NEMO3.6-LIM3: ORCA1L75

Compared to PlaSim-T21-LSG: higher resolution, much more complex physics and inclusion of sea ice dynamics

Forcing: year-2000 greenhouse gas conditions and solar forcing



Pan-Arctic sea ice area [10^6 km^2] in the EC-Earth3 control run

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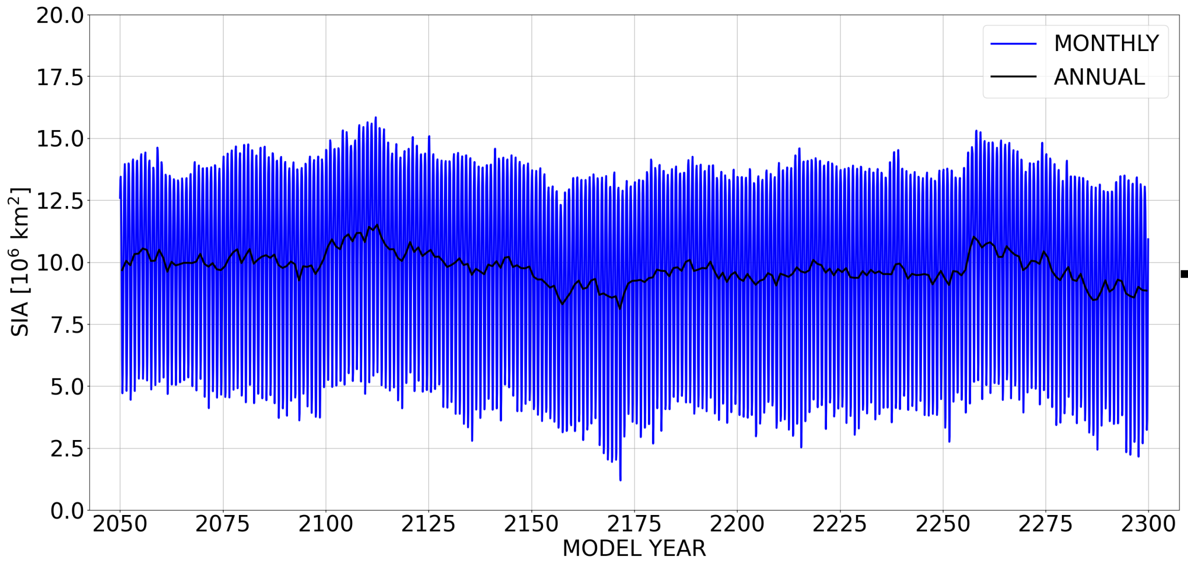
Observables: pan-Arctic sea ice area and pan-Arctic sea ice volume

Seasonal climate prediction set-up: N=300 member ensembles initialized from one single initial condition



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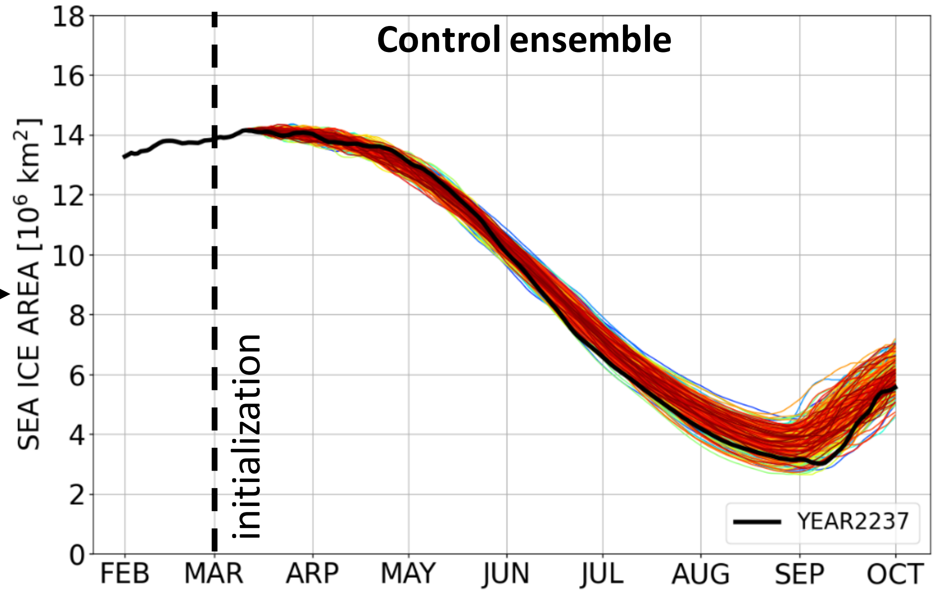
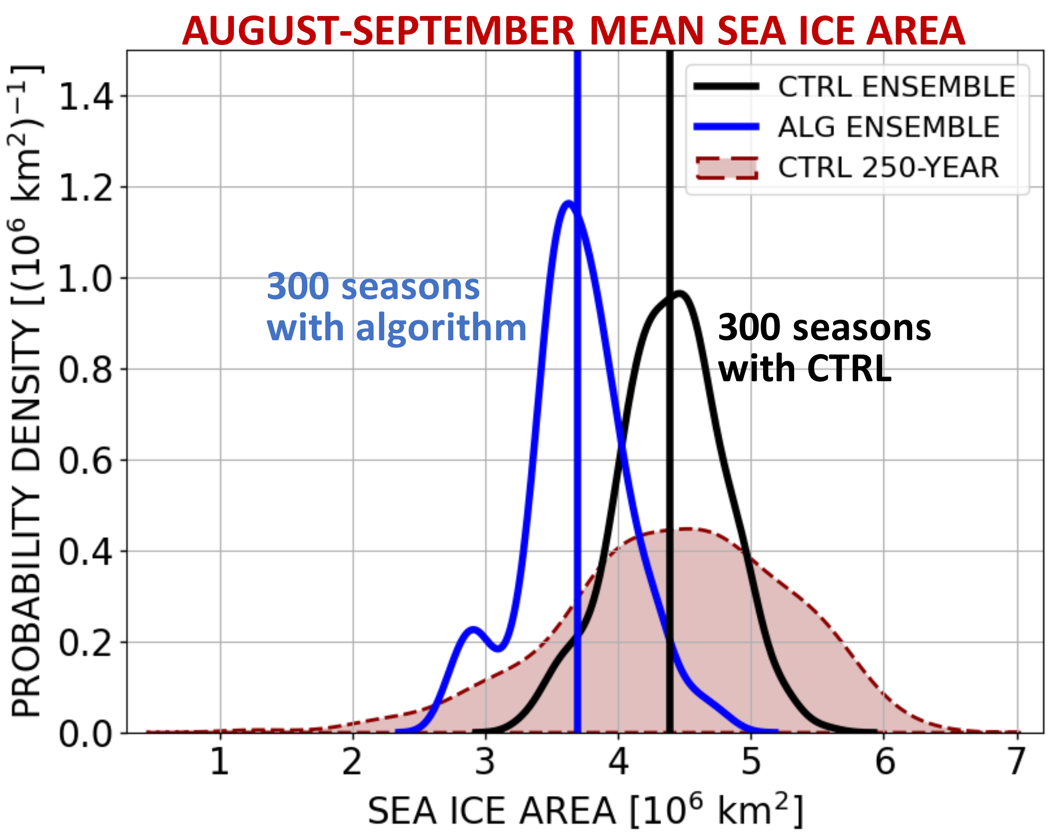
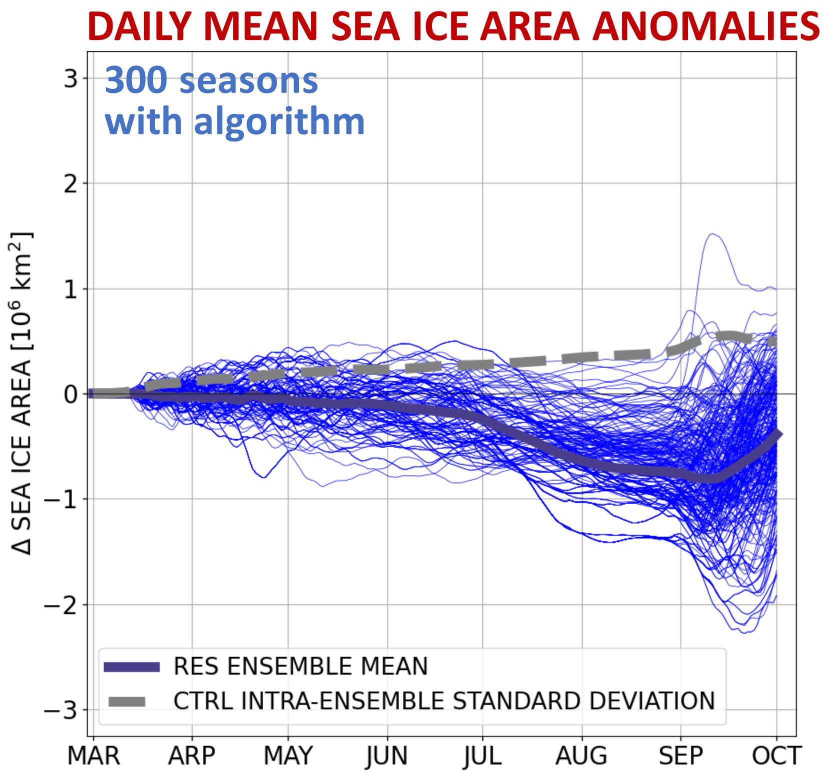


Pan-Arctic sea ice area [10^6 km^2] in the EC-Earth3 control ensemble

Extreme sea ice minima in the EC-Earth3 climate model





- Importance sampling of trajectories leading to low states of late summer sea ice area

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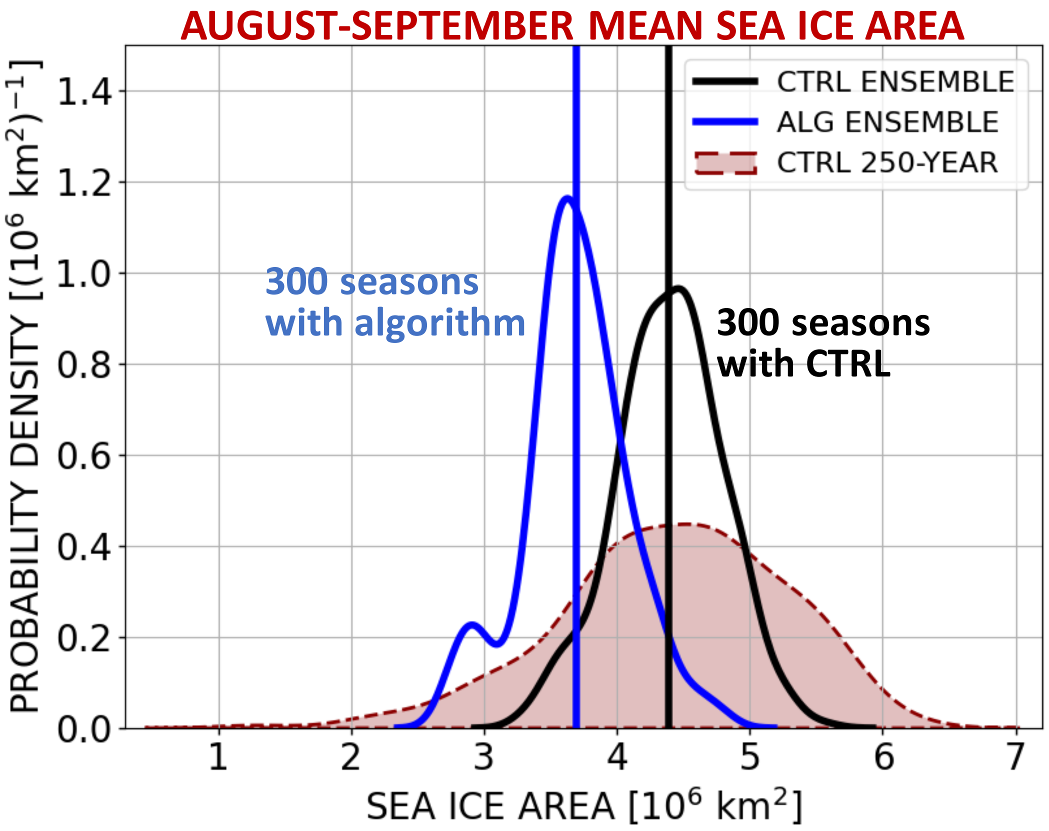
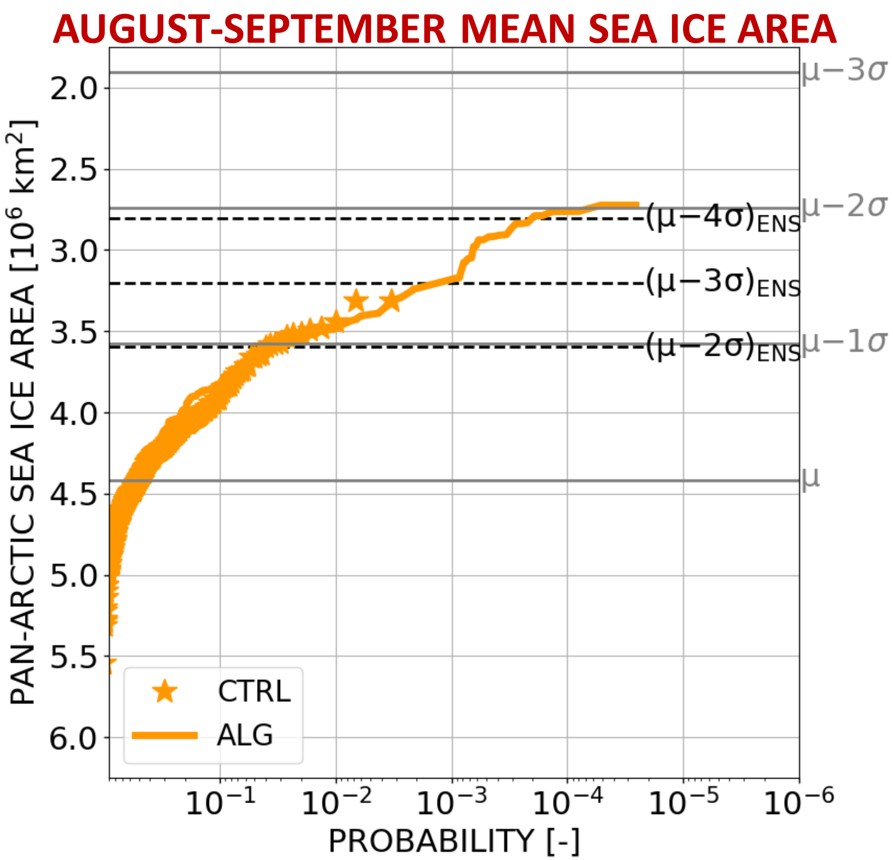
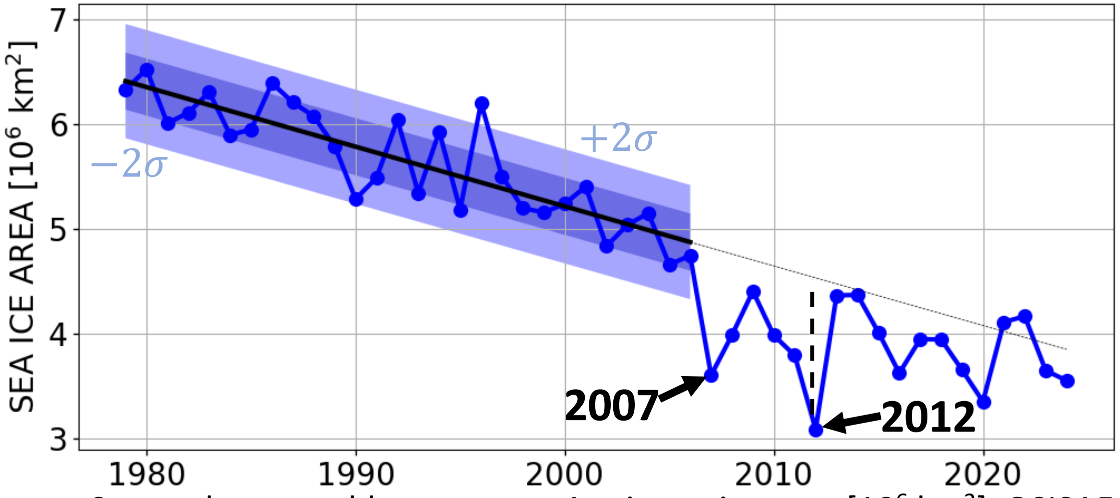


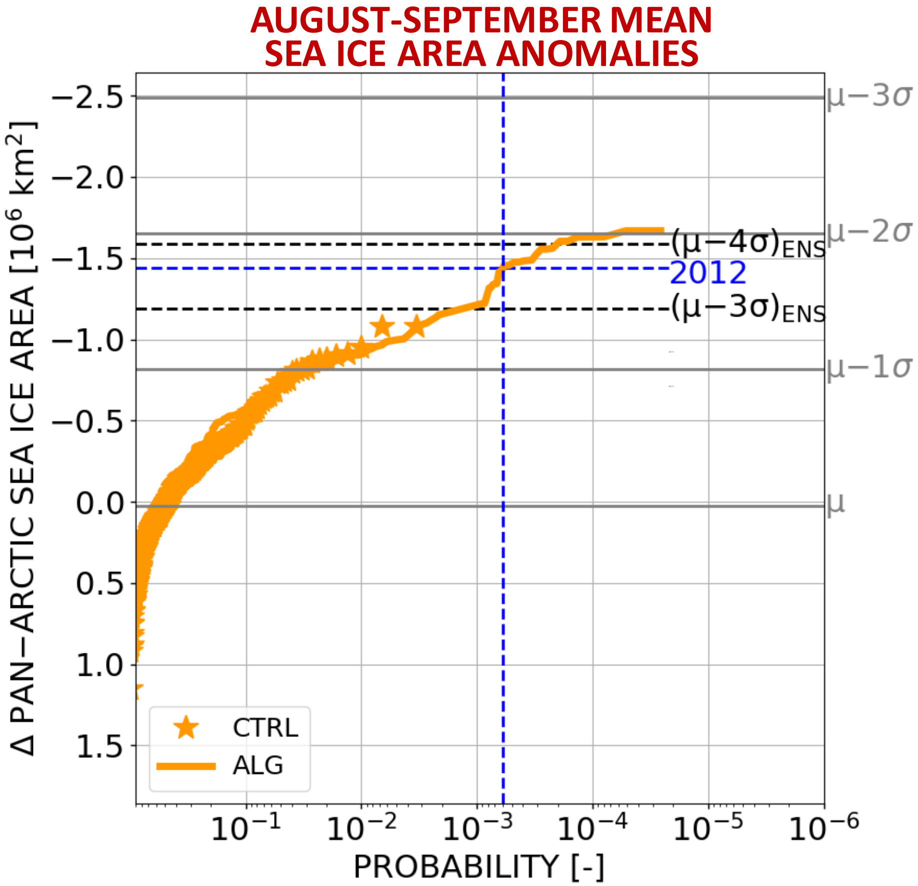


- Importance sampling of trajectories leading to low states of late summer sea ice area
- Simulation of sea ice lows with probabilities of less than 10^{-4} for a computational cost of 10^{2}

Attempt to quantify the probability of a 2012 sea ice low



August-September monthly mean pan-Arctic sea ice area [10^6 km^2]. OSISAF 2024.



- Ensemble contains larger fluctuations than the deviation of the observed 2012 sea ice area from the trend line
- By construction, extremes in the ensemble are purely driven by “fast drivers”, i.e. (sub)seasonal variability

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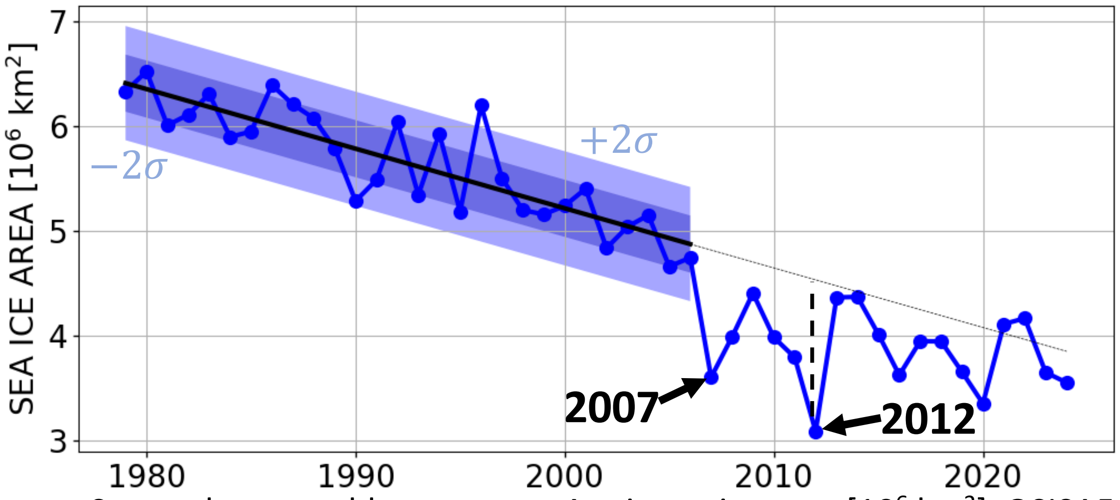

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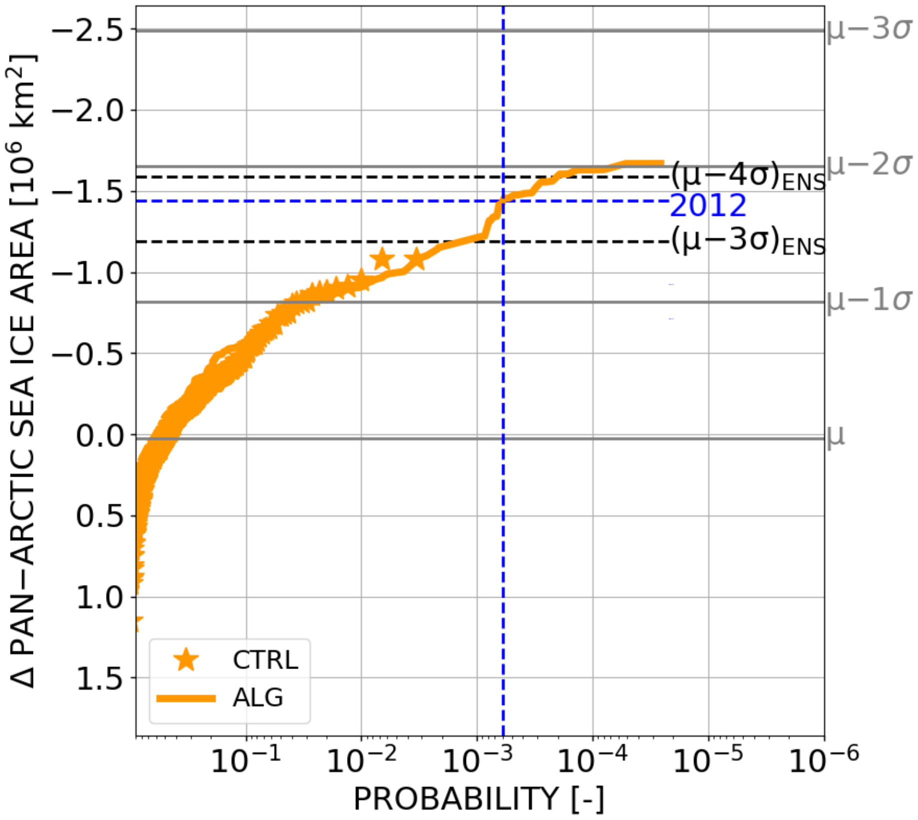

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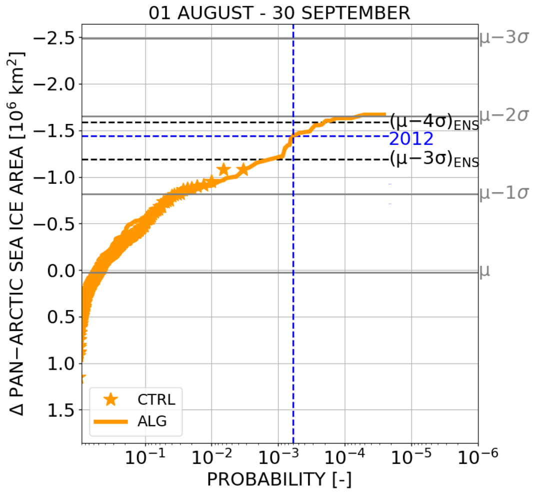
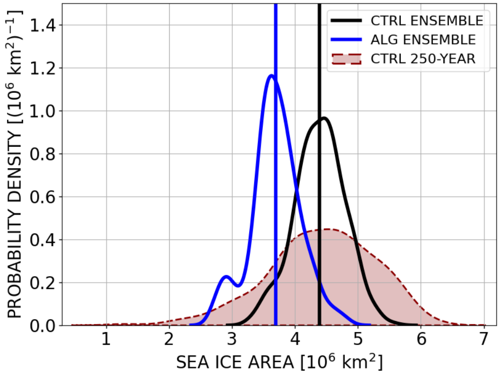
$P(2012)_{EC-Earth3} \approx O(10^{-3} - 10^{-4})$

Summary and ongoing work

- Applications of a rare event algorithm to PlaSim and EC-Earth3: improved sampling efficiency of extremely negative pan-Arctic sea ice area anomalies

- "independent initial condition" *vs.* "seasonal climate prediction" set-up





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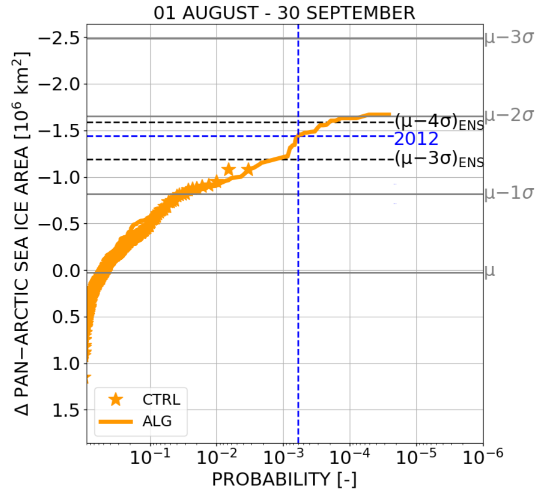

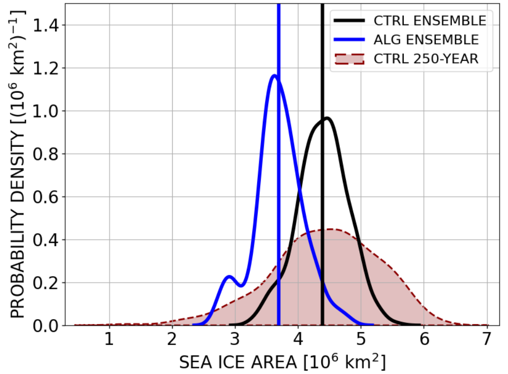

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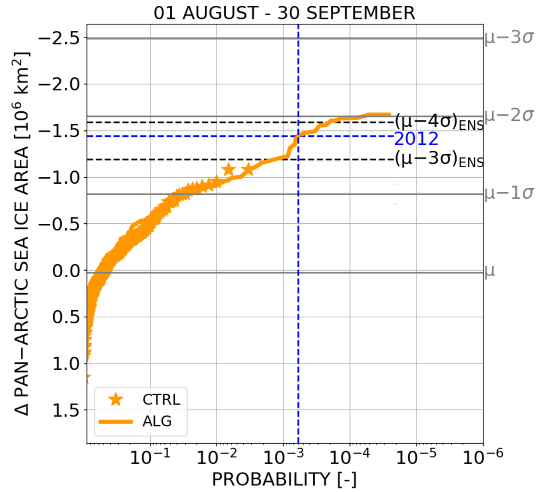
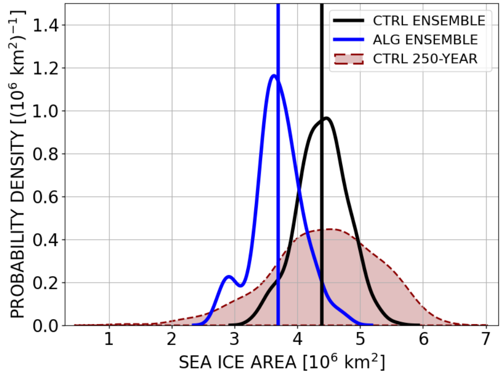
  2) surface energy budget analysis





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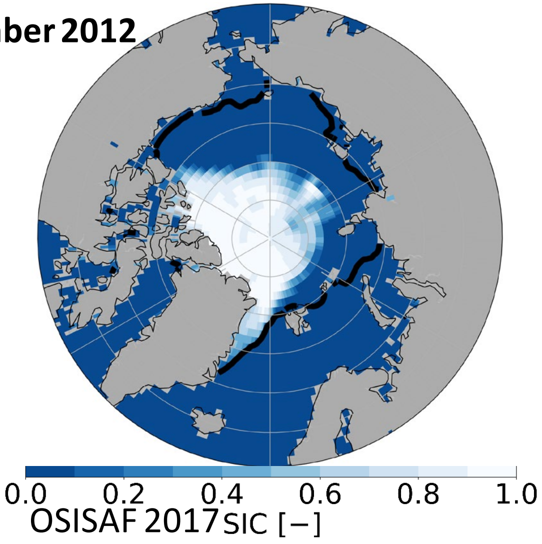
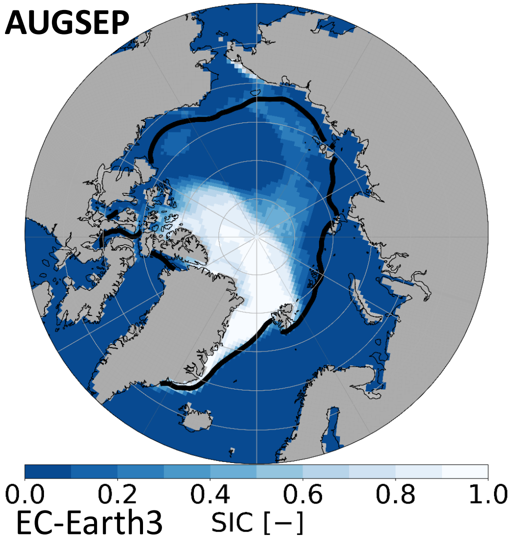


AUGSEP



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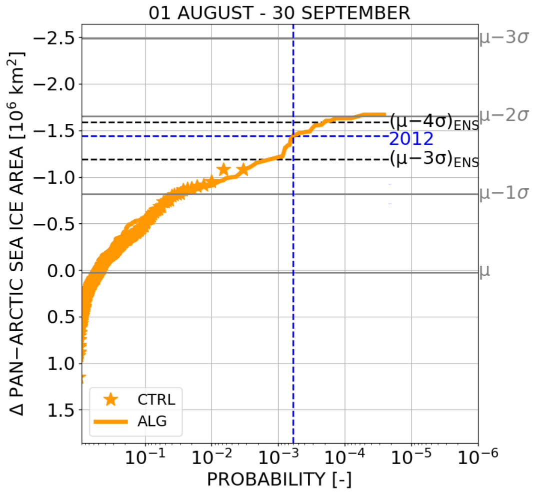
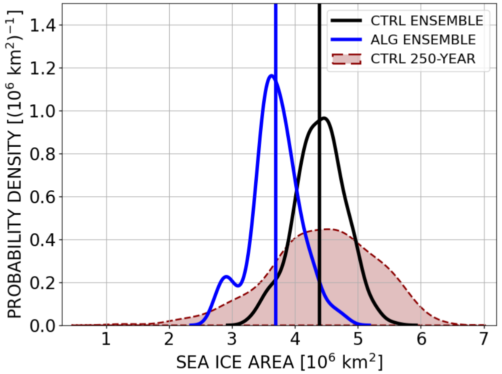
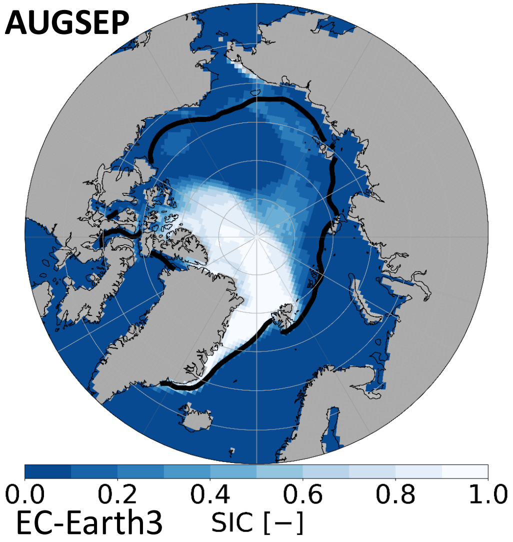
- Sensitivity experiment to quantify the relative contributions of "slow drivers" (sea ice-ocean preconditioning) vs. "fast drivers" (weather/subseasonal variability)
  -> modifiy the initial sea ice state of the first experiment by the difference between 2012 and 1979-2011 ("anomaly initialization"; Tian et al. 2022)







Summary and ongoing work

- Applications of a rare event algorithm to PlaSim and EC-Earth3: improved sampling efficiency of extremely negative pan-Arctic sea ice area anomalies

- “independent initial condition” *vs.* “seasonal climate prediction” set-up

- Allows for a quantititative statistical analysis of extremes of sea ice reduction

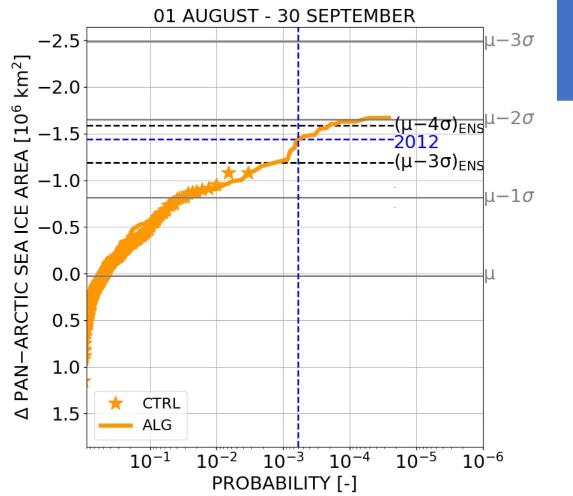
- potential to quantify the probabilities of extreme fluctuations such as in 2012

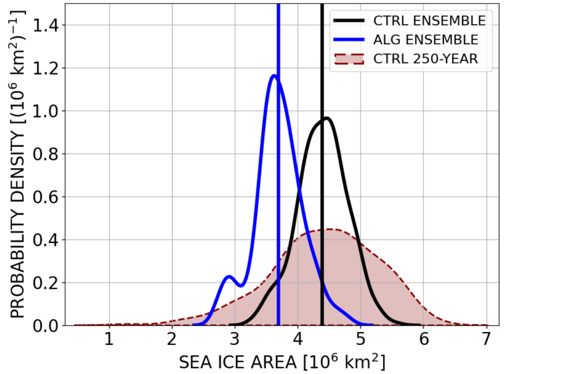
$$P(2012)_{EC-Earth3} \approx O(10^{-3} - 10^{-4})$$

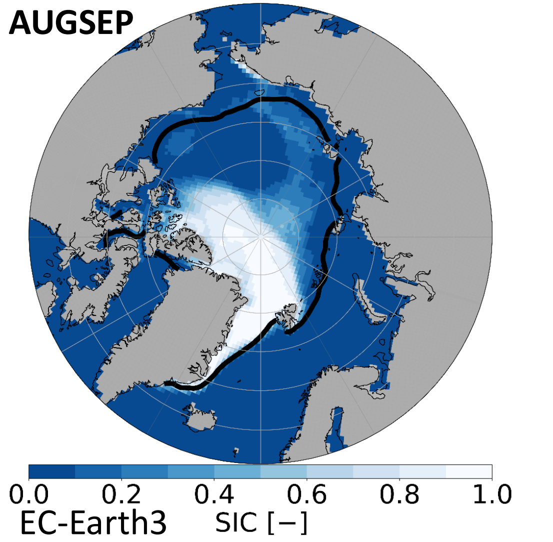
- What is driving extreme sea ice lows in EC-Earth3?:
  1) sea ice area and sea ice volume budget analysis (e.g. Holland and Kwok 2012)
  2) surface energy budget analysis

- Sensitivity experiment to quantify the relative contributions of “slow drivers” (sea ice-ocean preconditioning) vs. “fast drivers” (weather/subseasonal variability)
  -> modifiy the initial sea ice state of the first experiment by the difference between 2012 and 1979-2011 (“anomaly initialization”; Tian et al. 2022)

Thank you for your attention

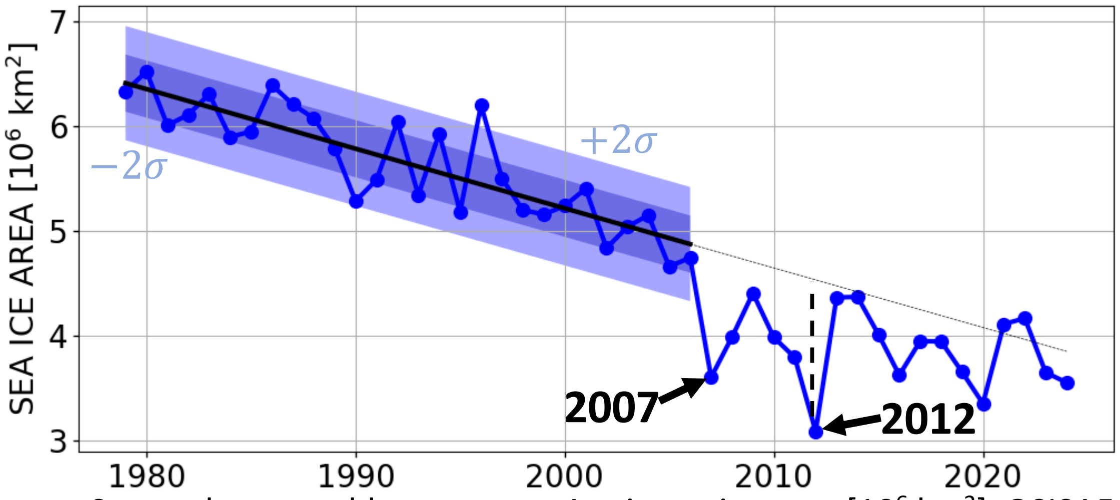




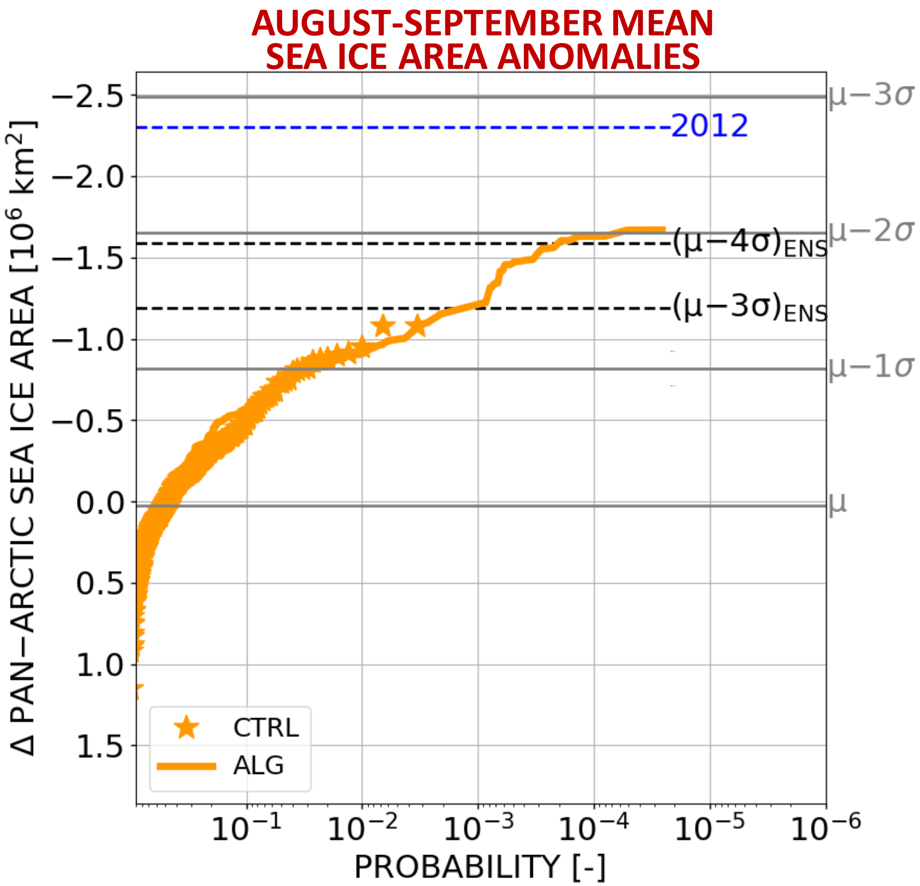


Appendix

Attempt to quantify the probability of a 2012 sea ice low



August-September monthly mean pan-Arctic sea ice area [10^6 km^2]. OSISAF 2024.



- Intra-seasonal dynamics does not produce late summer sea ice area anomalies larger in magnitude than the deviation of the observed 2012 sea ice area from the 1979-2011 average

Validation of the model state

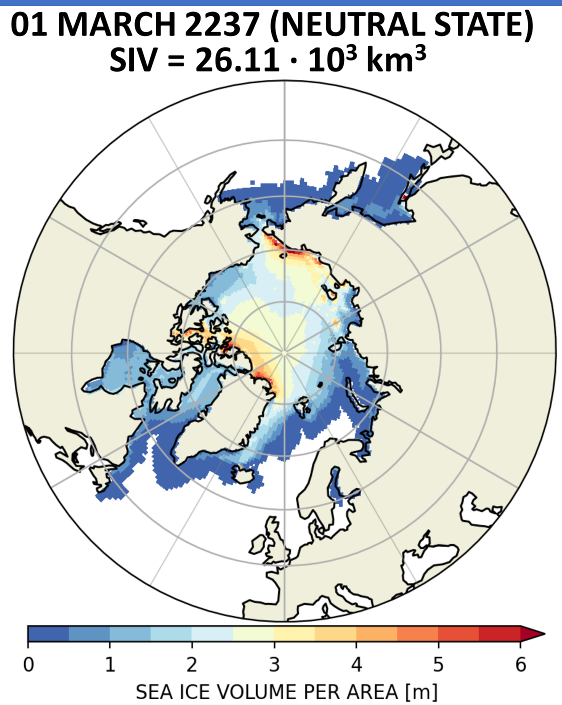
- Standard deviation of August-September mean sea ice area in EC-Earth3 CTRL ENSEMBLE: $0.40 \cdot 10^6$ km^2

- Standard deviation of August-September mean sea ice area of residuals relative to the extrapolated trend line fitted to 1979-2006 in OSISAF: $0.41 \cdot 10^6$ km^2

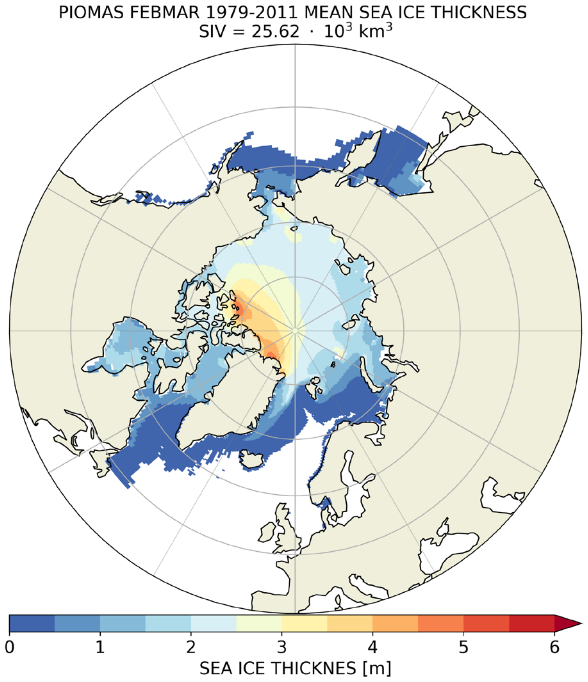
- Standard deviation of August-September mean sea ice area – February-March mean sea ice area of residuals relative to the extrapolated trend line fitted to 1979-2006 in OSISAF: $0.45 \cdot 10^6$ km^2

- Standard deviation of August-September mean sea ice area – March mean sea ice area in EC-Earth3 CTRL ENSEMBLE: $0.40 \cdot 10^6$ km^2

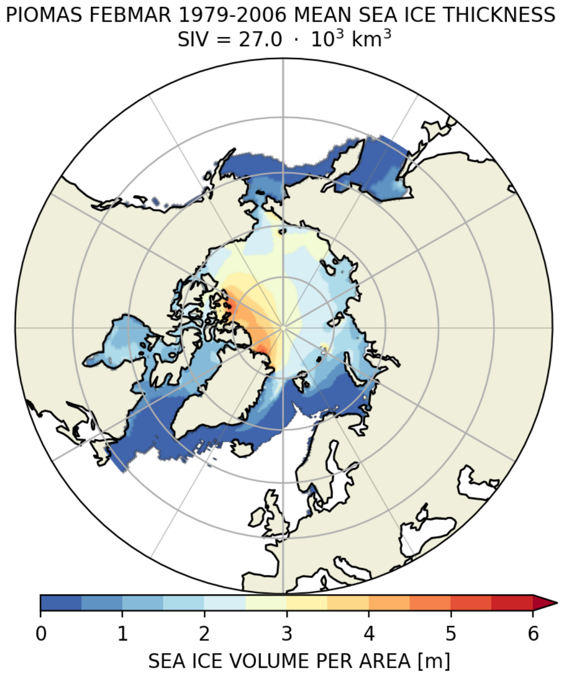
Validation of the model state



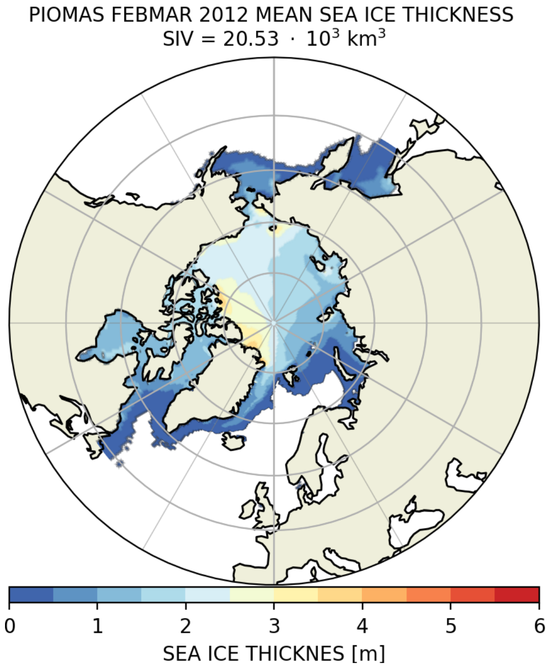
EC-Earth3



PIOMAS 2024

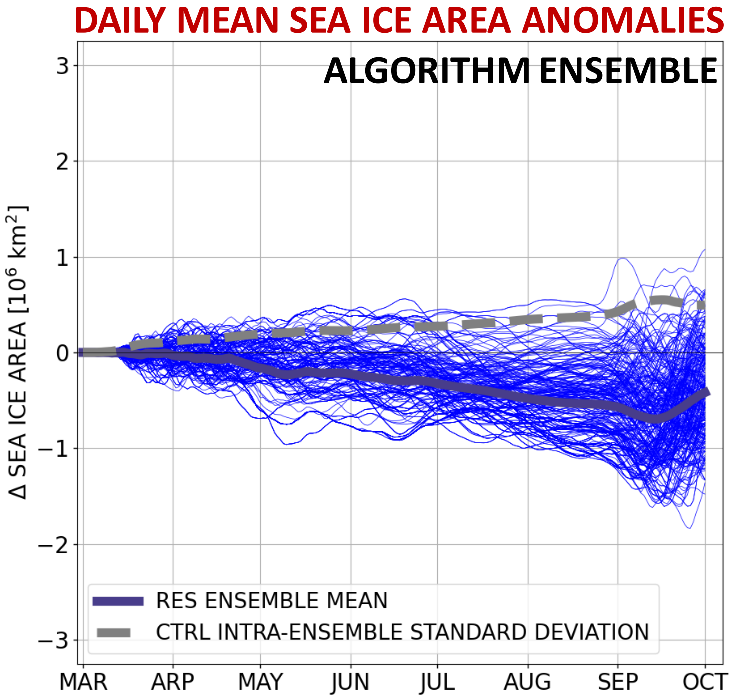


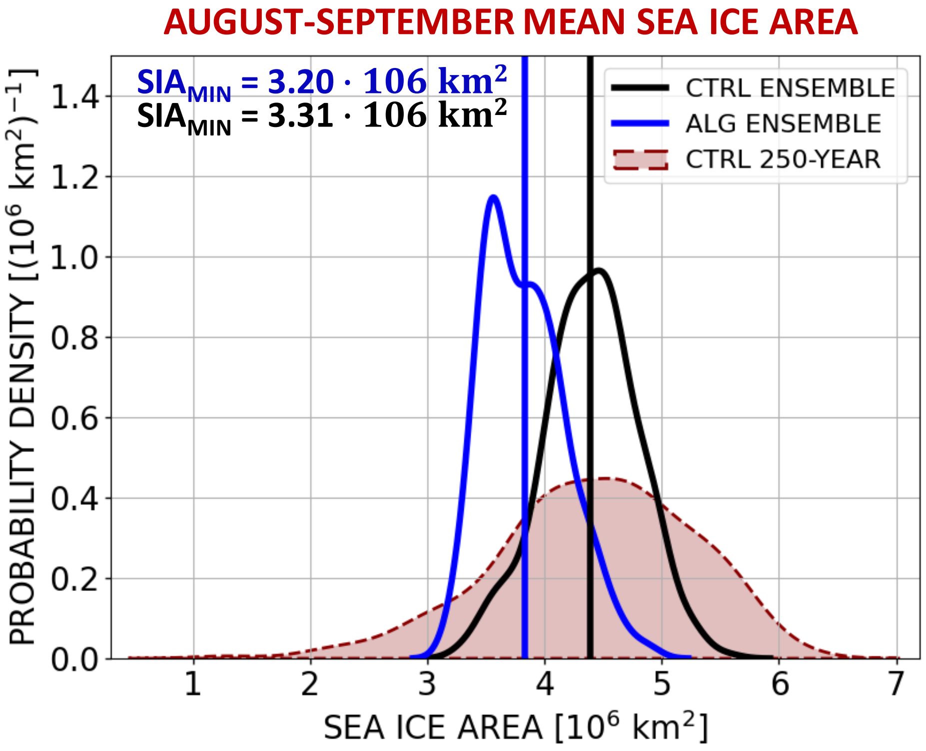
PIOMAS 2024



PIOMAS 2024

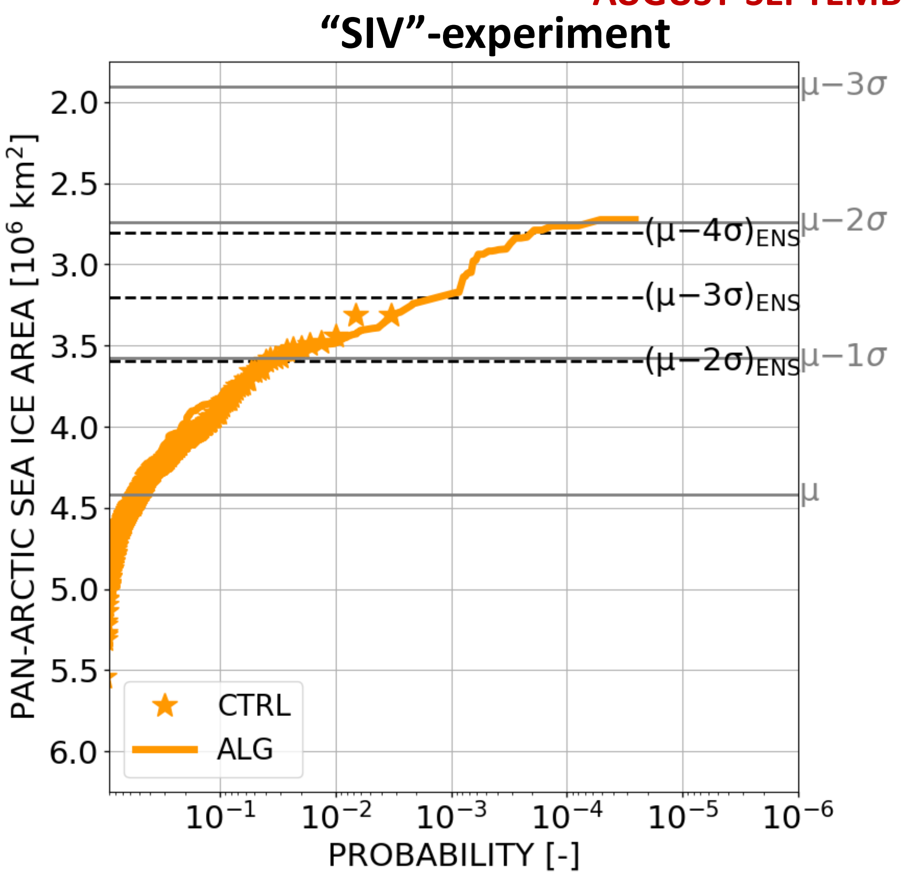
Extreme sea ice minima in the EC-Earth3 climate model

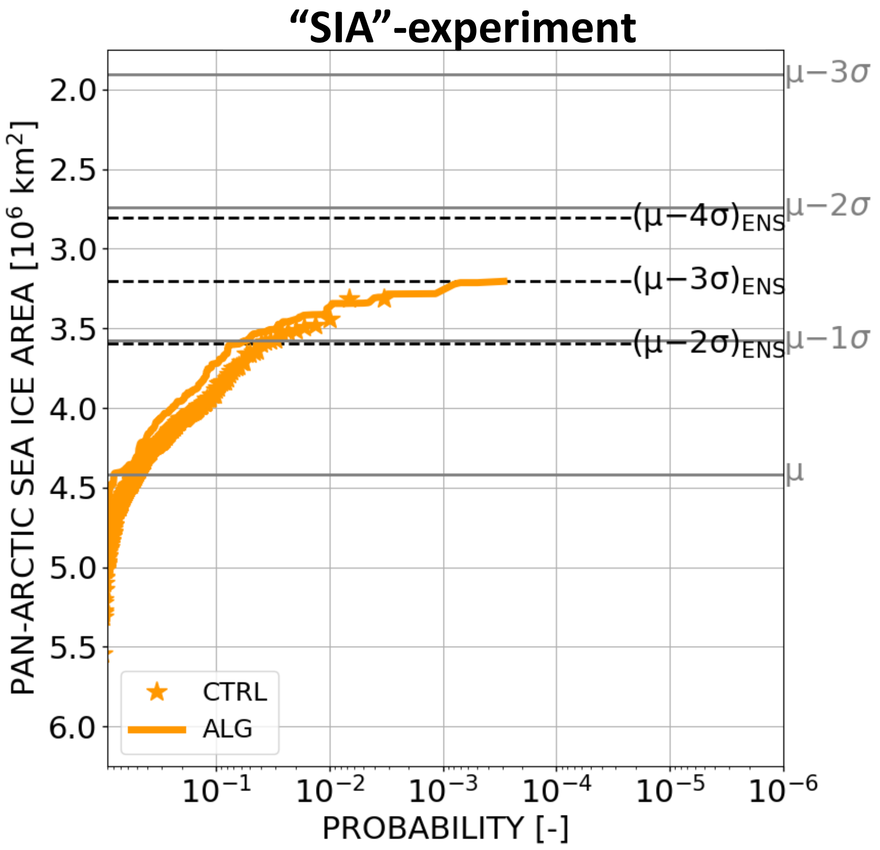




Extreme sea ice minima in the EC-Earth3 climate model

AUGUST-SEPTEMBER MEAN SEA ICE AREA

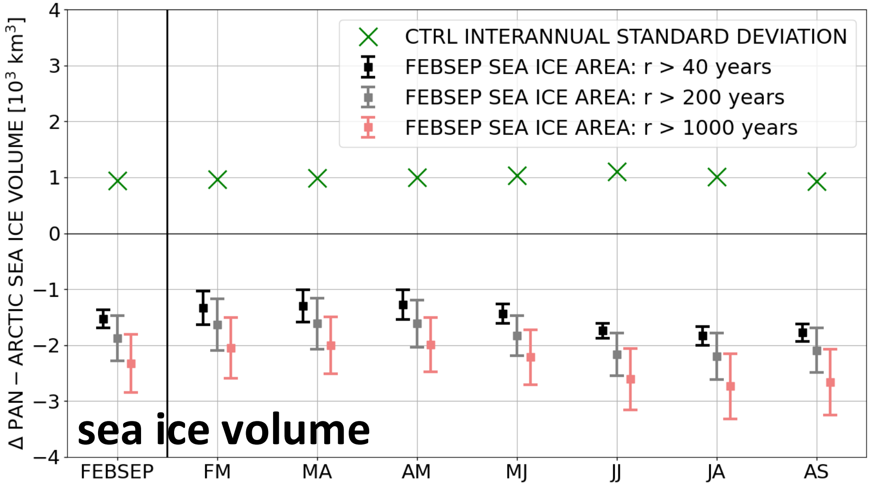




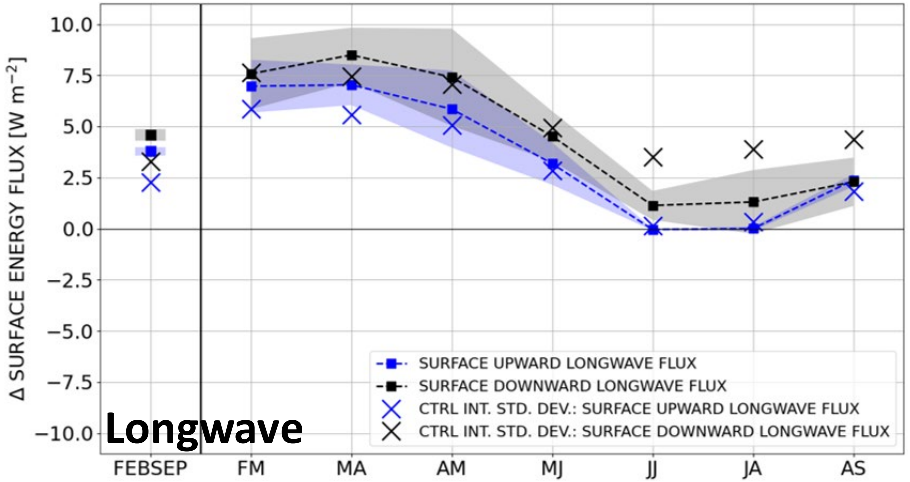
Seasons with extremely low pan-Arctic sea ice area PlaSim-T21-LSG

Drivers of February-September mean pan-Arctic sea ice area anomalies with return times of more than 200 years

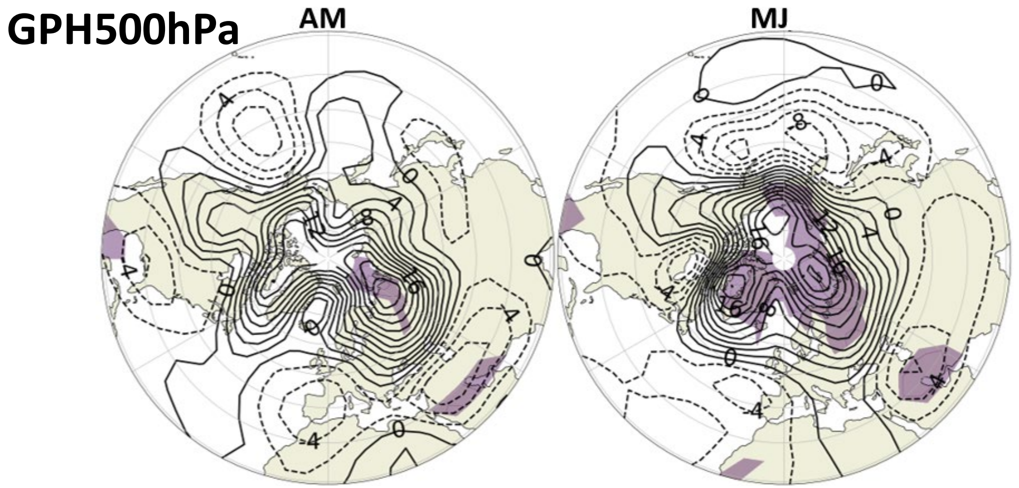
1) Sea ice-ocean preconditioning

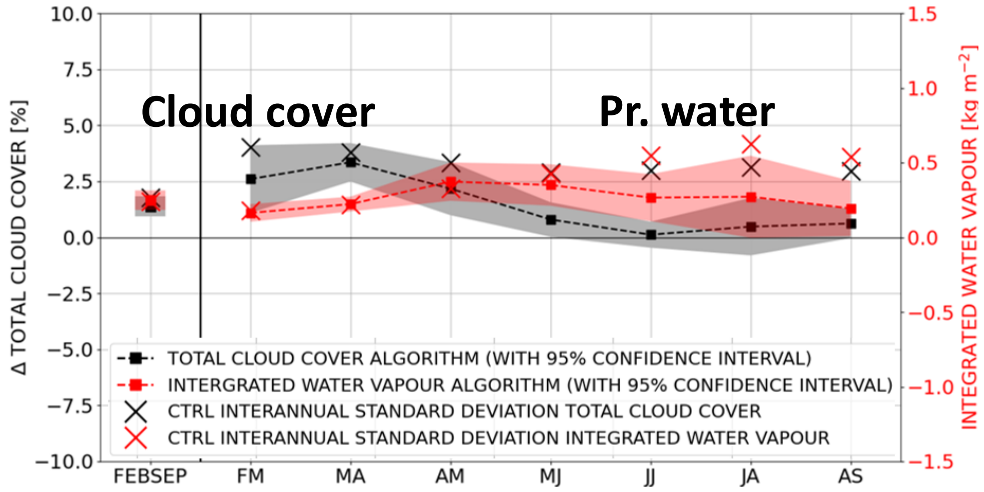


2) Anomalously moist and cloudy spring Arctic atmosphere



3) Late spring "heat wave"





Sauer, J., Demaeyer, J., Zappa, G., Massonnet, F., & Ragone, F. (2024). Extremes of summer Arctic sea ice reduction investigated with a rare event algorithm. Climate Dynamics. https://doi.org/10.1007/s00382-024-07160-y

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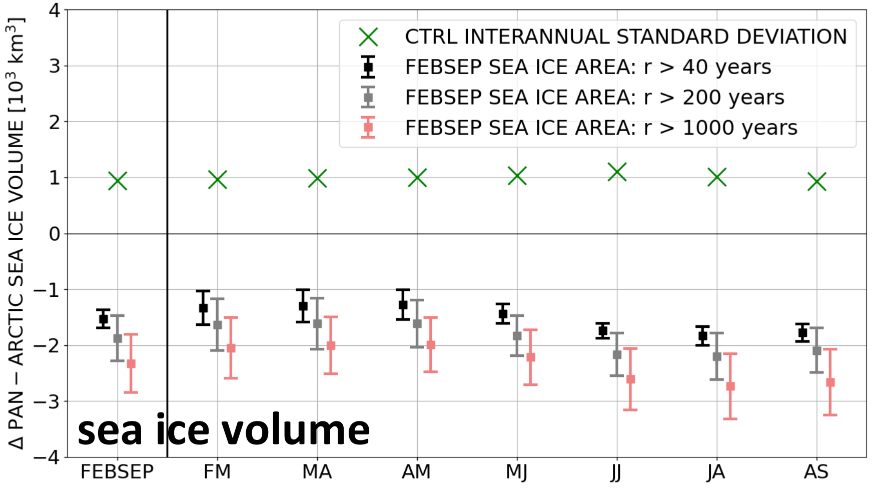

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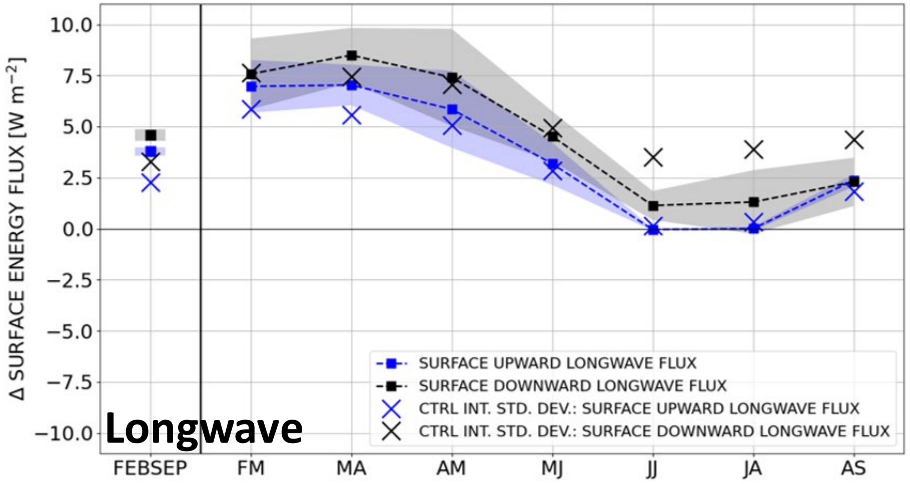
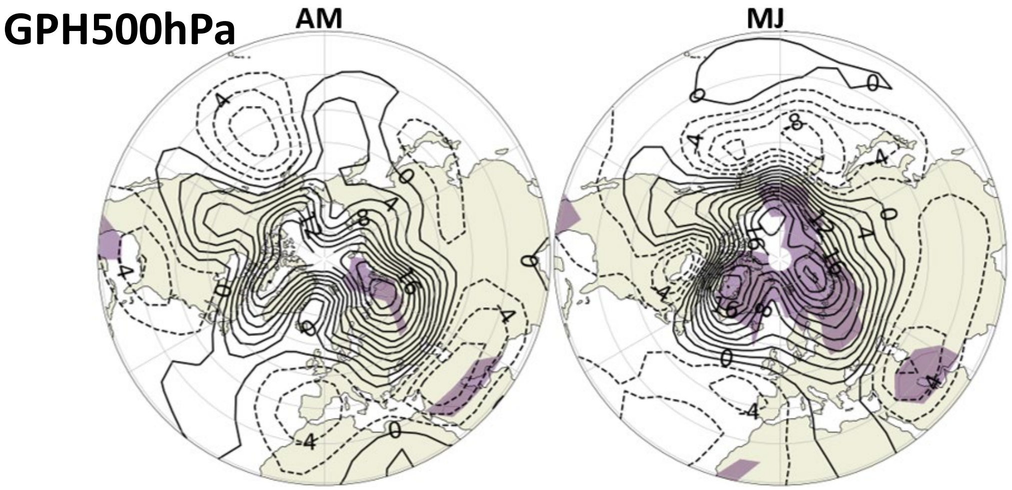
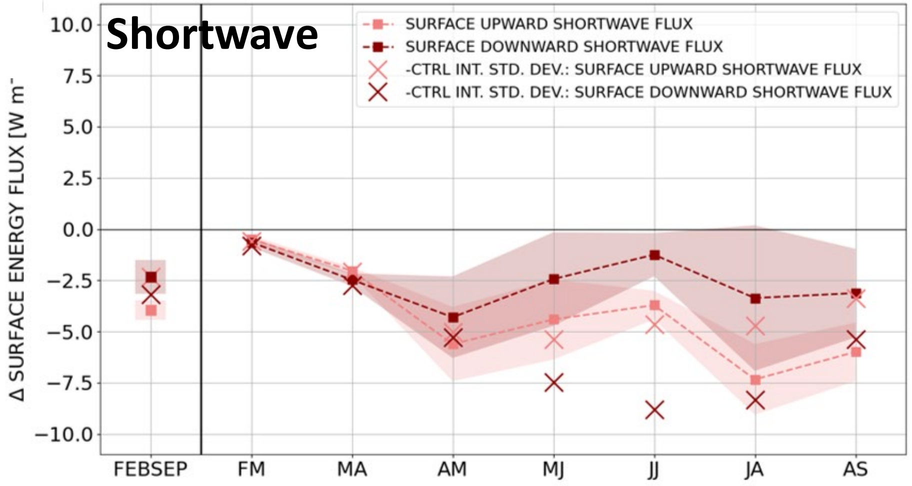


3) Late spring "heat wave"

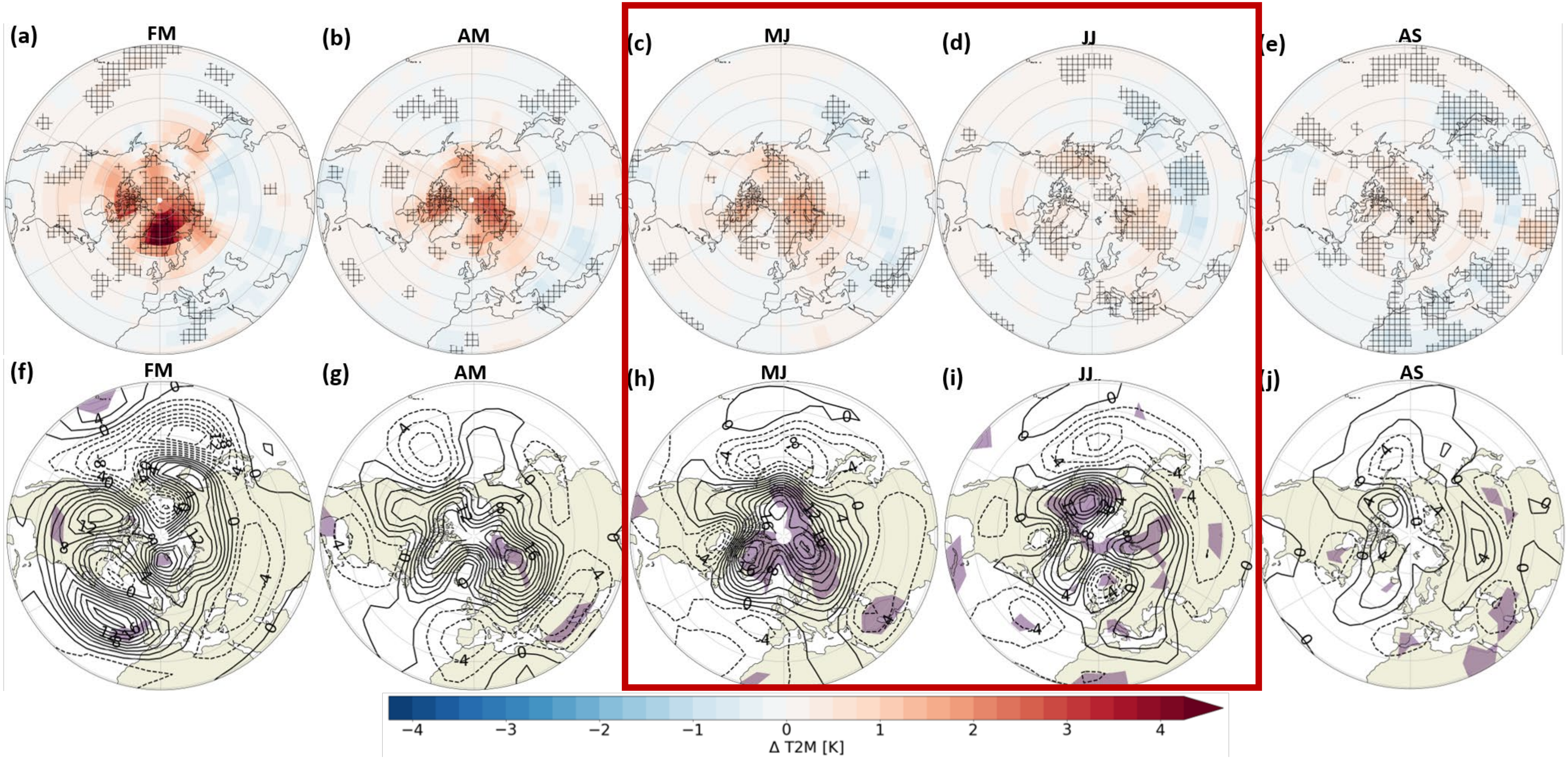


4) Sea ice-albedo feedback



Sauer, J., Demaeyer, J., Zappa, G., Massonnet, F., & Ragone, F. (2024). Extremes of summer Arctic sea ice reduction investigated with a rare event algorithm. Climate Dynamics. https://doi.org/10.1007/s00382-024-07160-y

Seasons with extremely low pan-Arctic sea ice area PlaSim-T21-LSG



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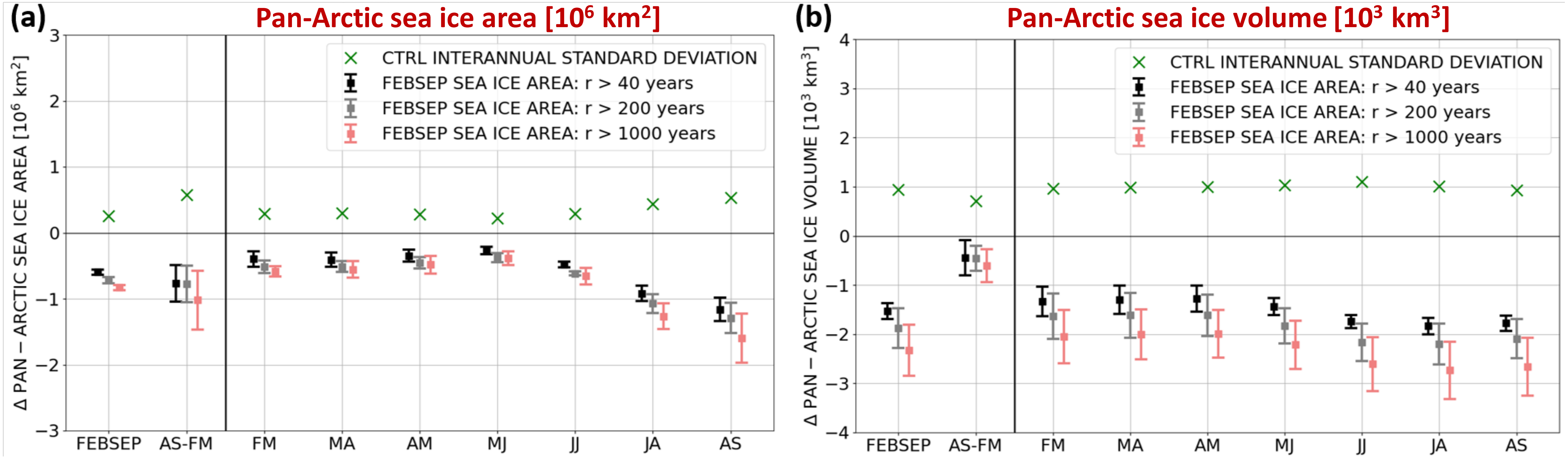
Seasonal: February-September

Hatching and shading: Significance at the 5% level

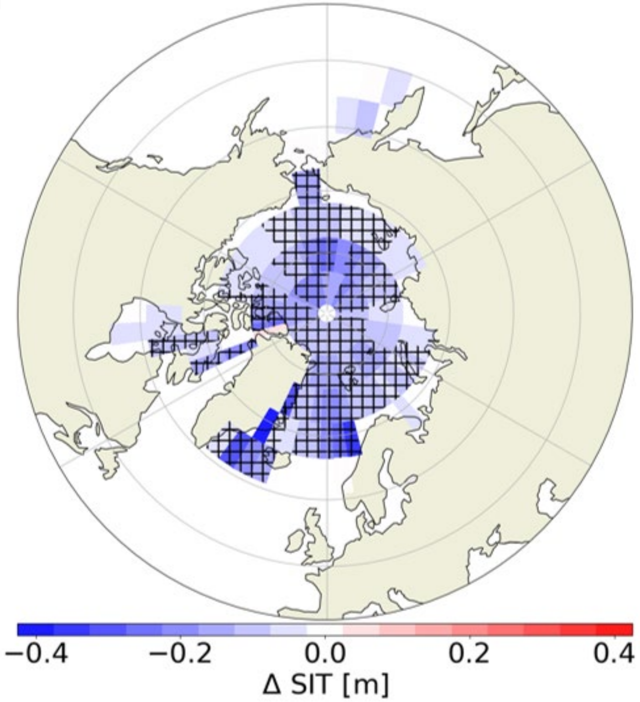
Results: Application of the rare event algorithm to PlaSim-T21-LSG



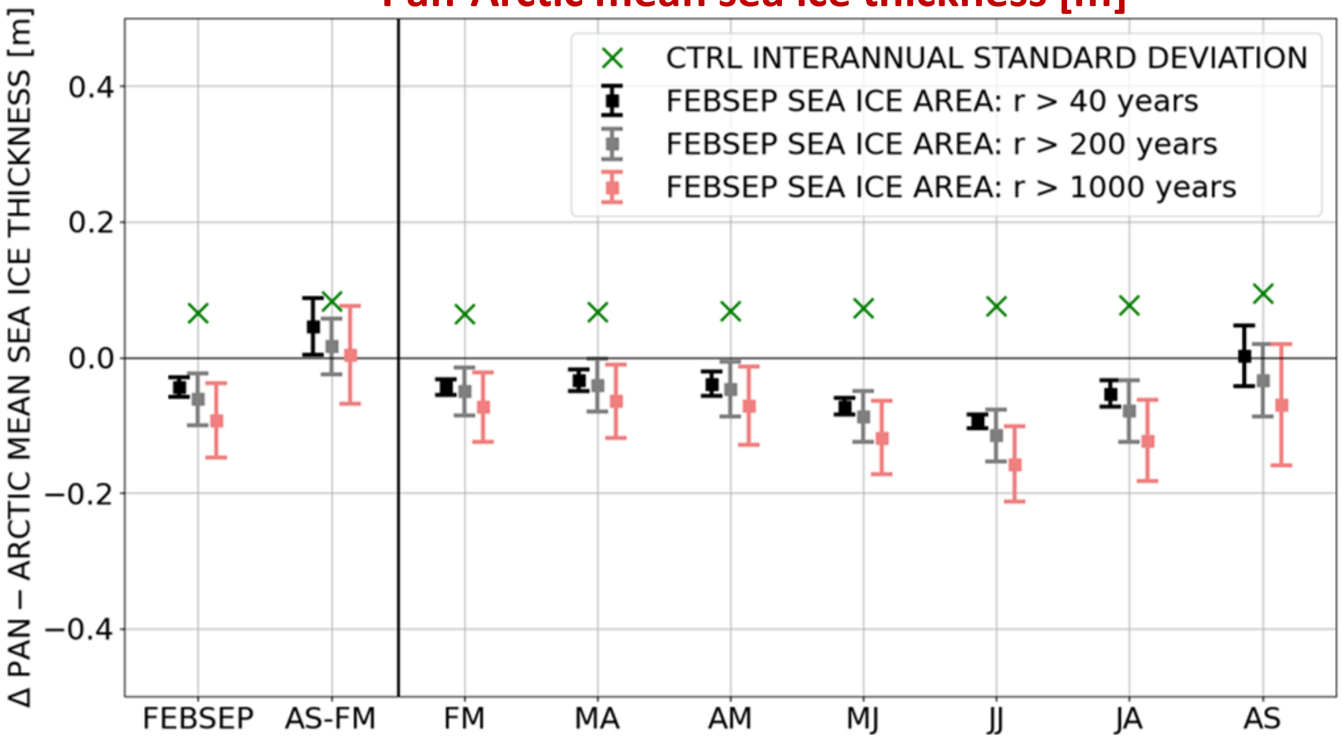
Error bars: 95 % confidence interval

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

(a) FM Sea ice thickness [m]

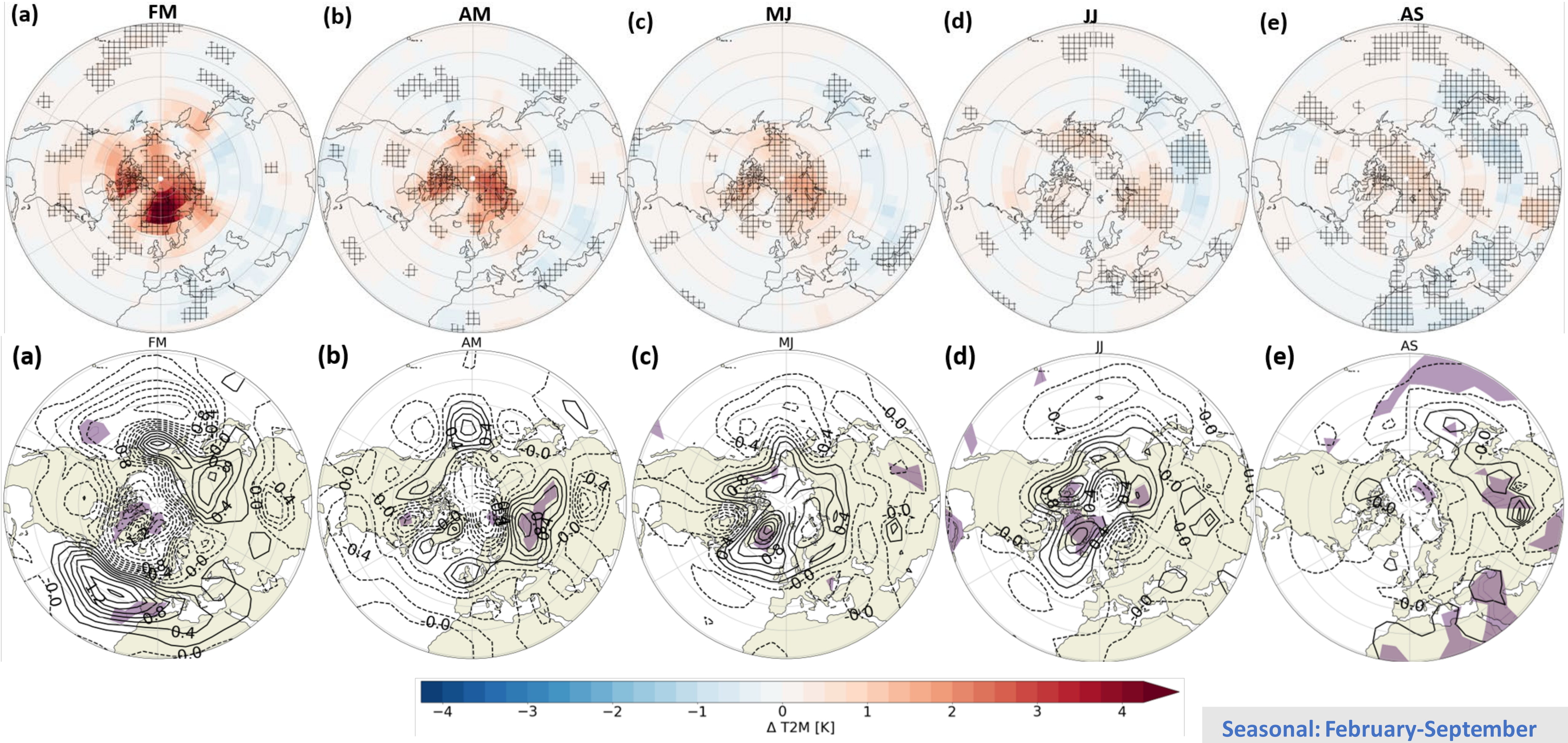


Pan-Arctic mean sea ice thickness [m]



Hatching and error bars:
Signif. at 5% level and 95 % confidence interval

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

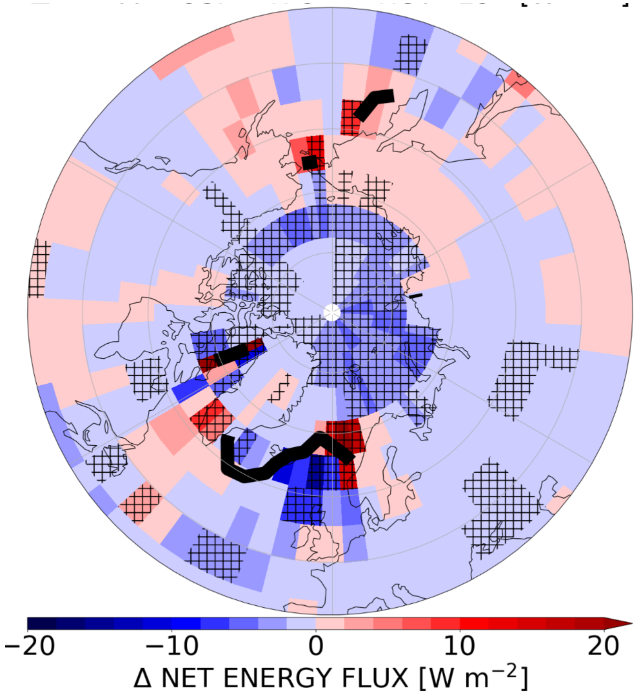


Seasonal: February-September

Hatching and shading: Significance at the 5% level

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

February-September mean
net energy fluxes



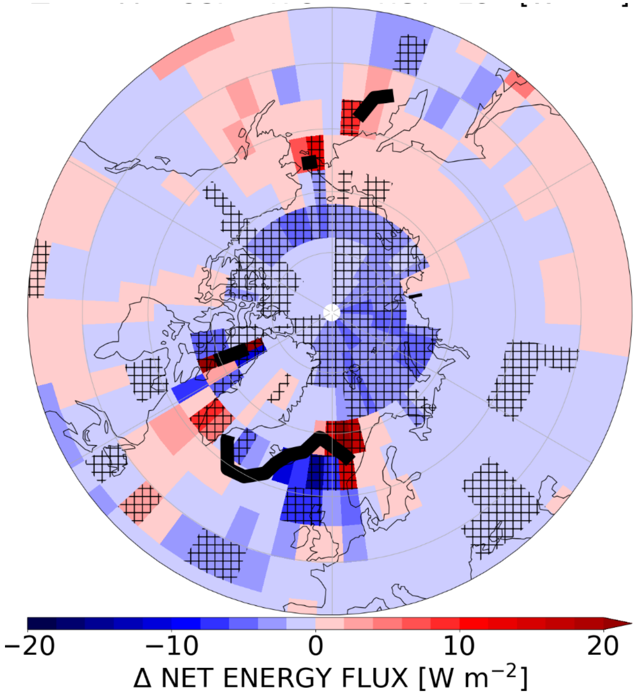
- Enhanced seasonal mean **net surface energy flux** from the atmosphere to sea ice-ocean

Seasonal: February-September

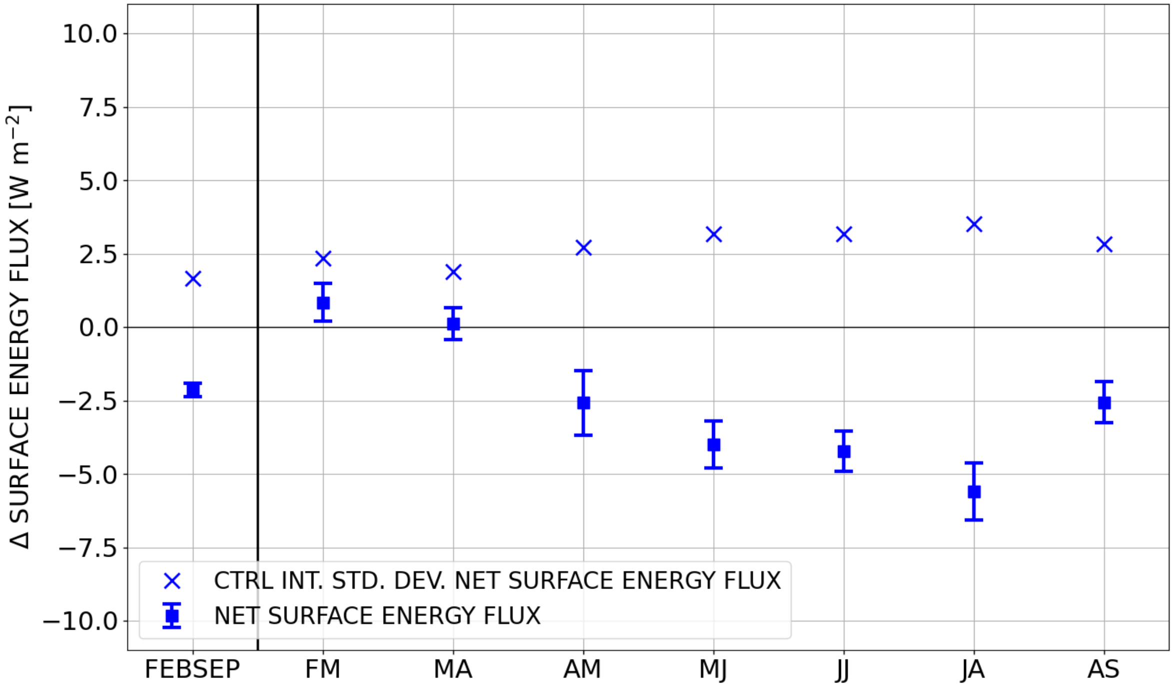
Hatching/Error bars: Significance at the 5% level/95% confidence interval

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

February-September mean net energy fluxes



Seasonal evolution of net energy fluxes



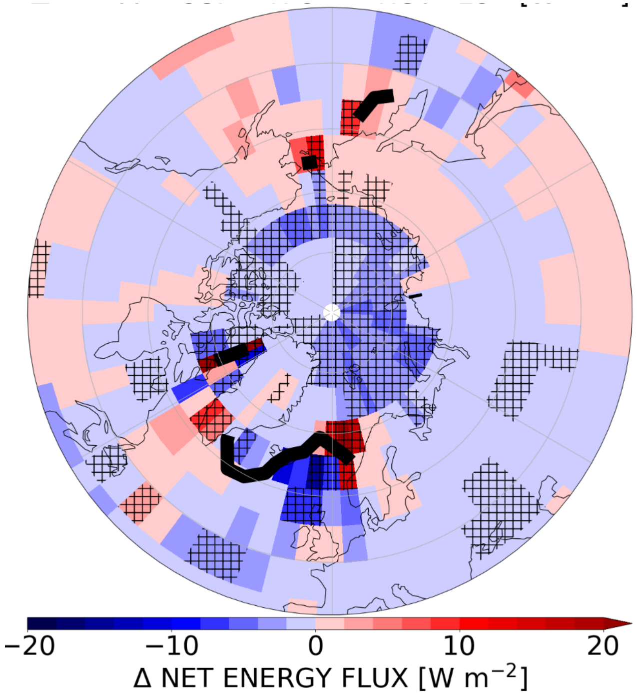
- Enhanced seasonal mean **net surface energy flux** from the atmosphere to sea ice-ocean
- Enhanced upward heat fluxes in winter and strongly enhanced downward fluxes from spring onwards

Seasonal: February-September

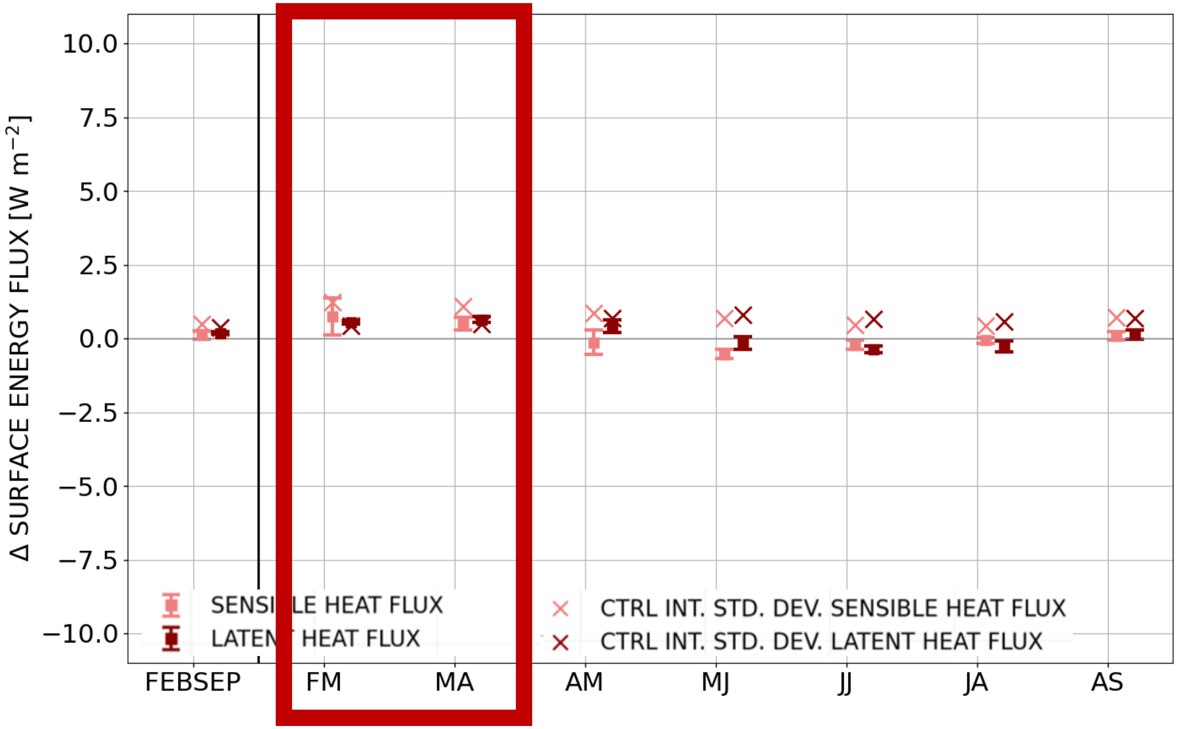
Hatching/Error bars: Significance at the 5% level/95% confidence interval

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

February-September mean net energy fluxes



Seasonal evolution of sensible and latent heat fluxes



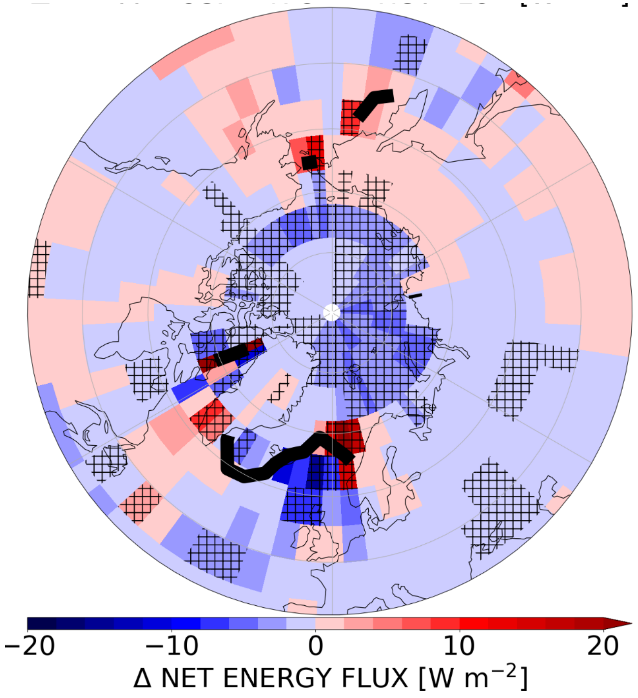
- Enhanced seasonal mean **net surface energy flux** from the atmosphere to sea ice-ocean
- **Enhanced upward sensible and latent heat flux in late winter**

Seasonal: February-September

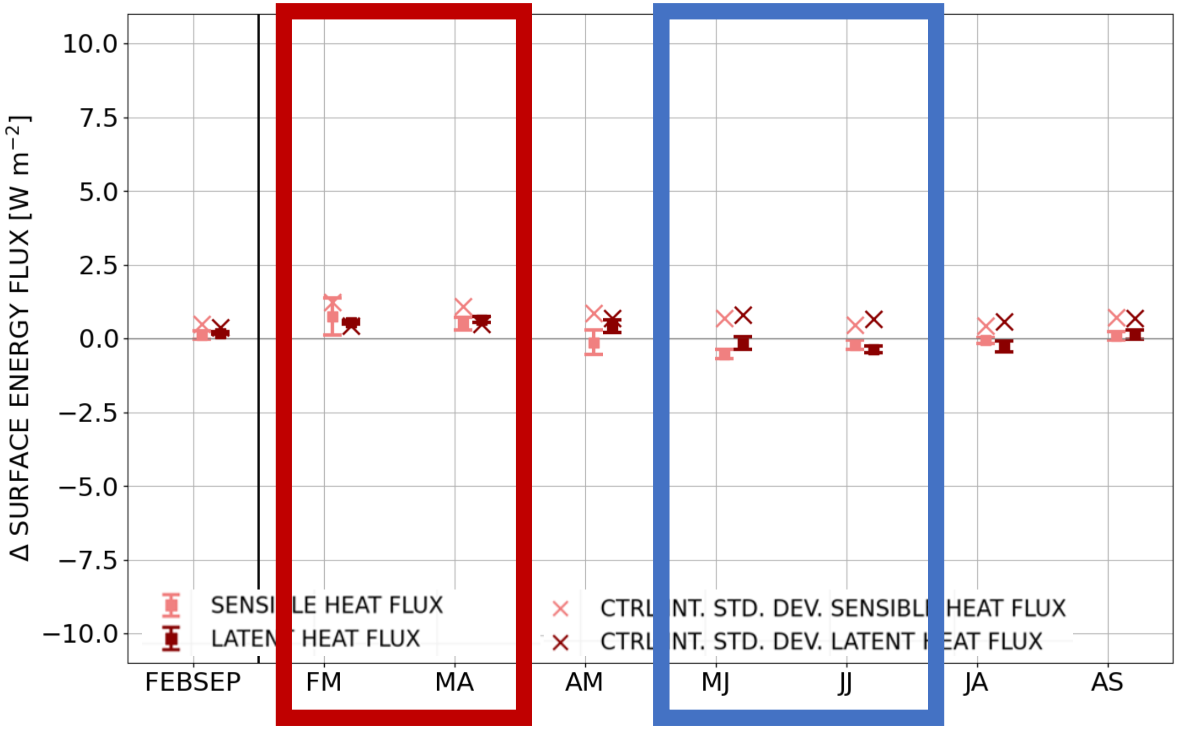
Hatching/Error bars: Significance at the 5% level/95% confidence interval

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

February-September mean net energy fluxes



Seasonal evolution of sensible and latent heat fluxes



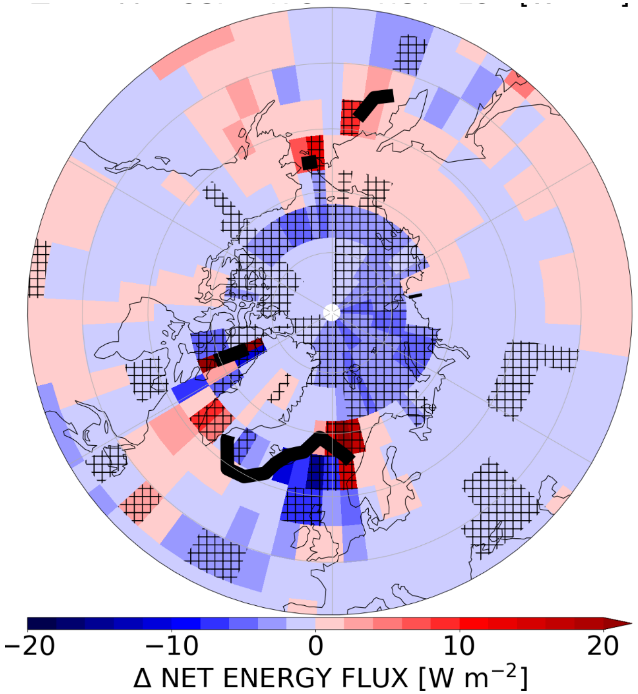
- Enhanced seasonal mean **net surface energy flux** from the atmosphere to sea ice-ocean
- **Enhanced upward sensible and latent heat flux in late winter**
- **Enhanced downward sensible heat fluxes** in May-June consistent with heat wave-like Z500 pattern

Seasonal: February-September

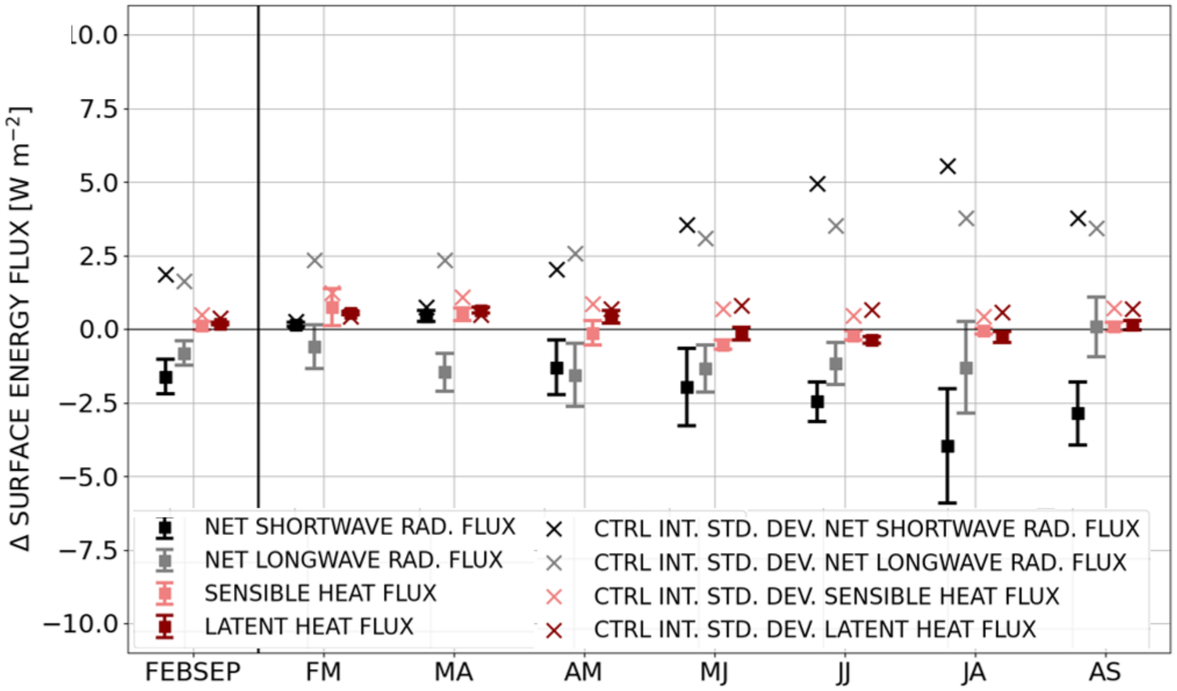
Hatching/Error bars: Significance at the 5% level/95% confidence interval

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

February-September mean net energy fluxes



Seasonal evolution of all flux components

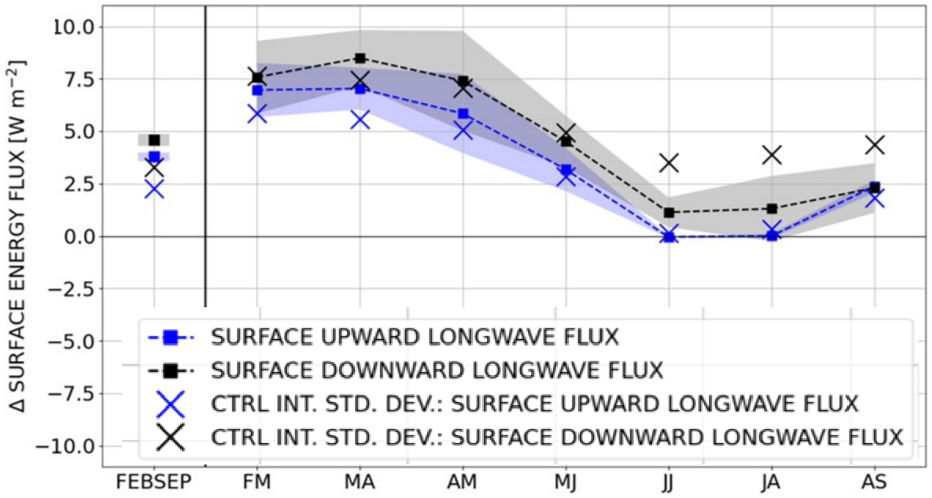


- Enhanced seasonal mean **net surface energy flux** from the atmosphere to sea ice-ocean
- **Enhanced upward sensible and latent heat flux in late winter**
- **Enhanced downward sensible heat fluxes** in May-June consistent with heat wave-like Z500 pattern
- **Radiative fluxes** dominate net surface flux anomalies
  -> **Longwave dominant in spring** – **shortwave dominant in summer**

Seasonal: February-September

Hatching/Error bars: Significance at the 5% level/95% confidence interval

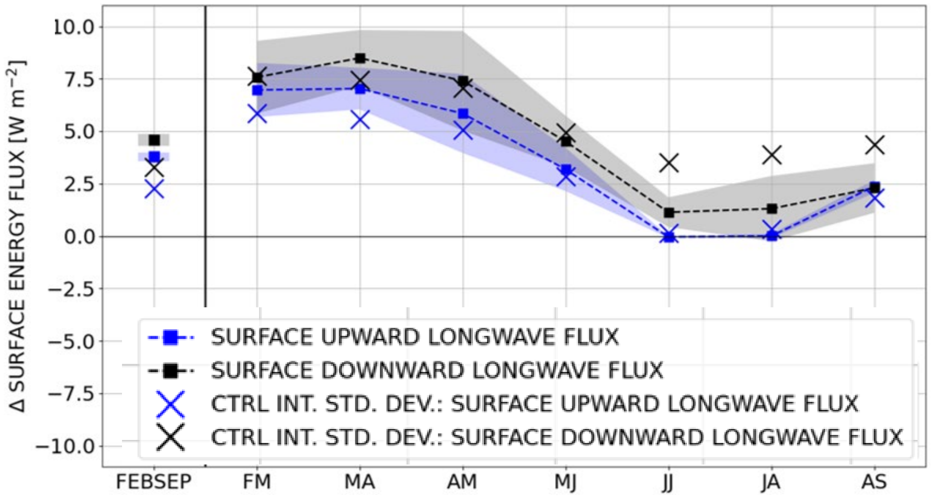
Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

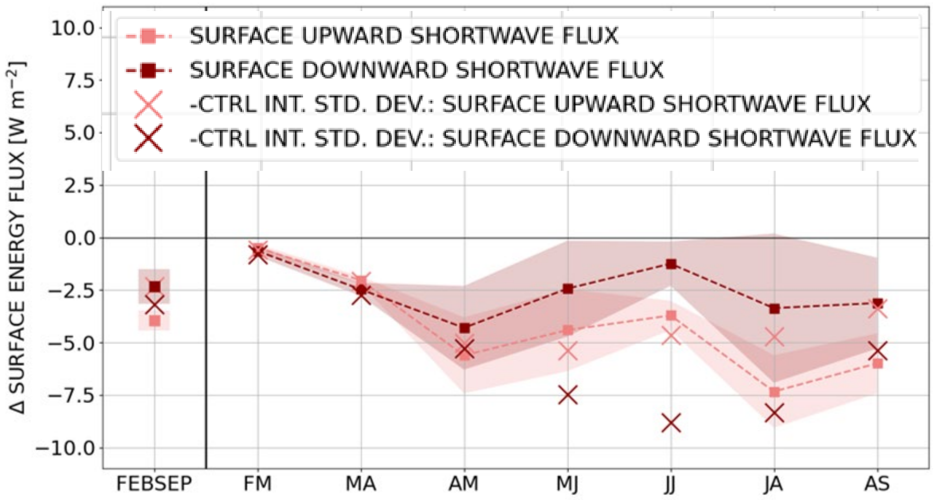


Seasonal: February-September

Shading: 95% confidence interval

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

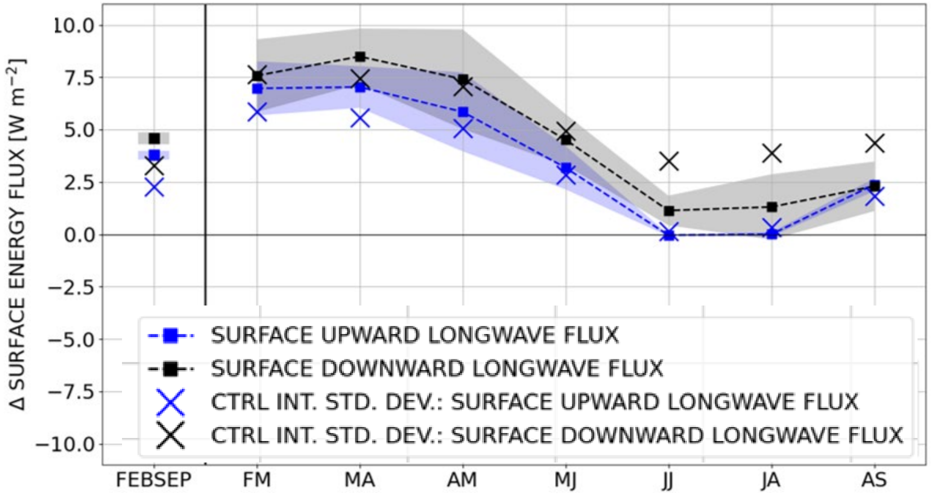


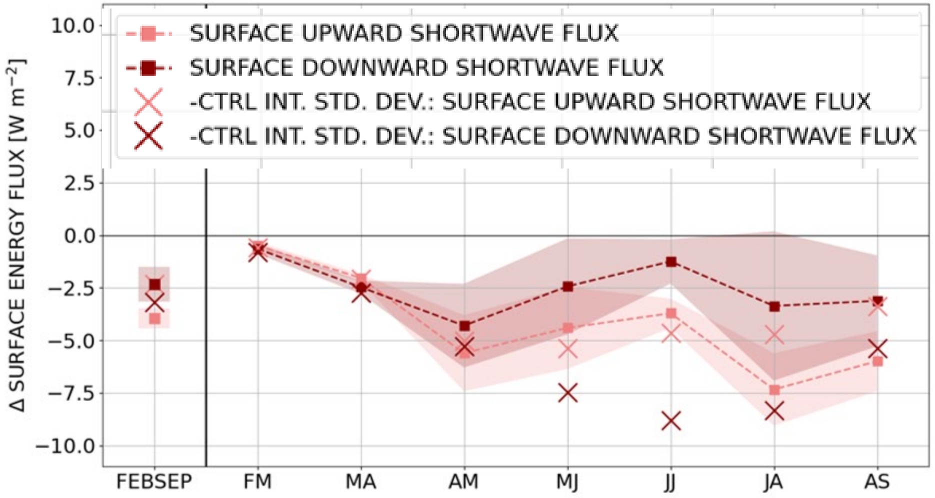


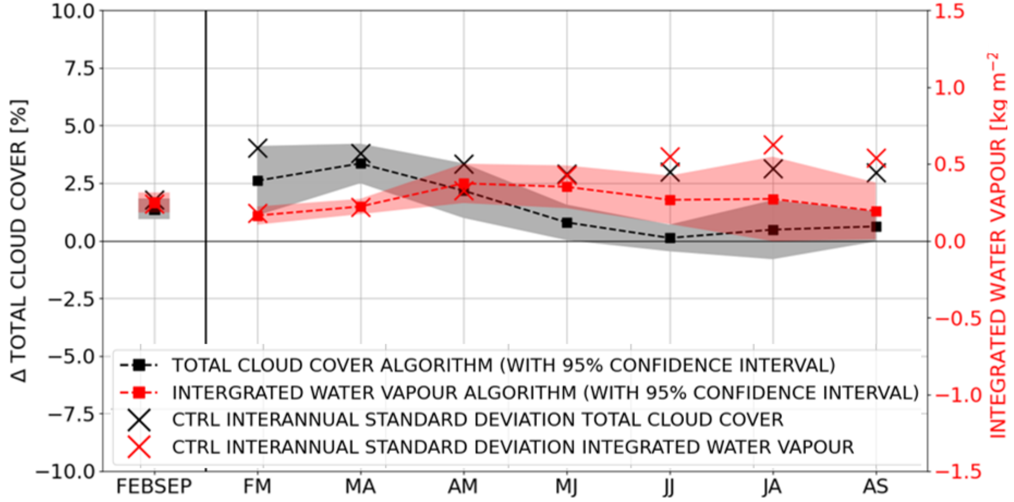
Seasonal: February-September

Shading: 95% confidence interval

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I







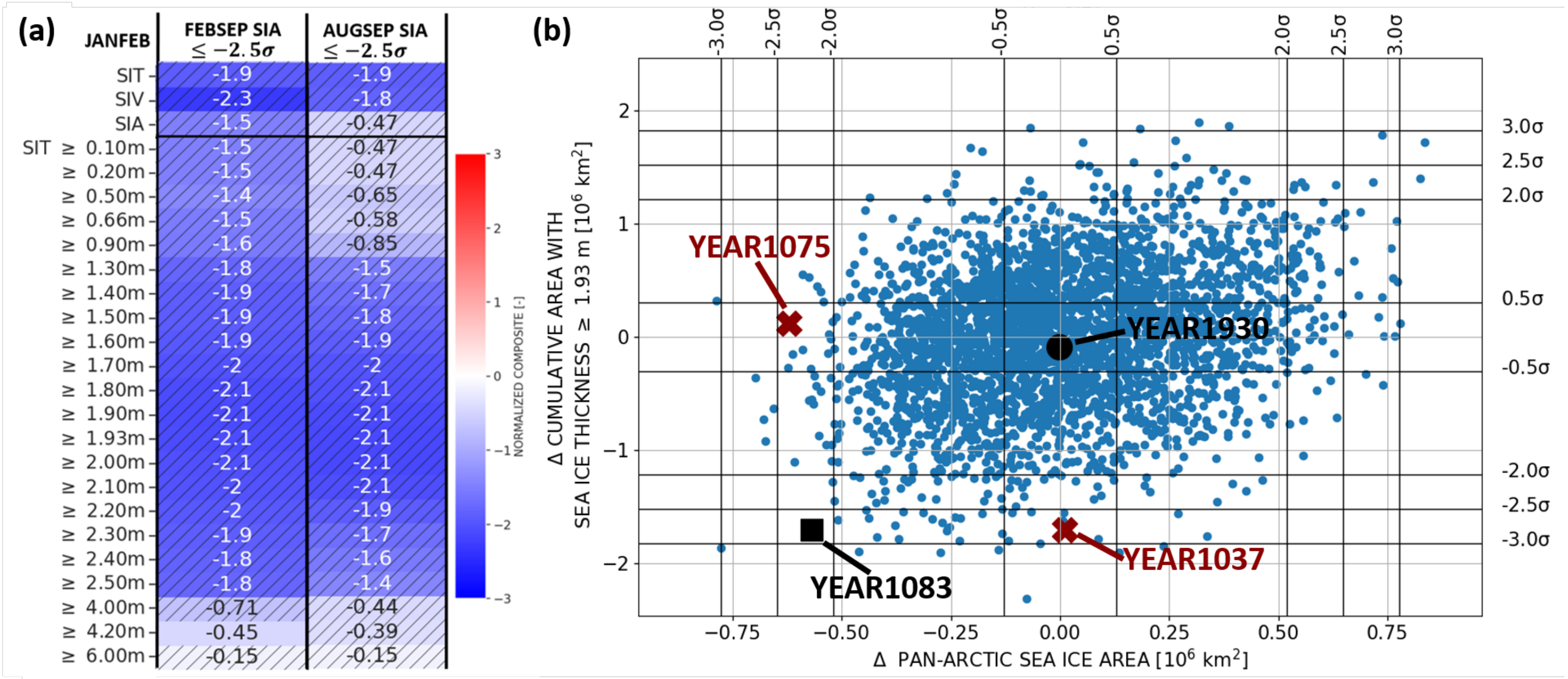
Seasonal: February-September

Shading: 95% confidence interval

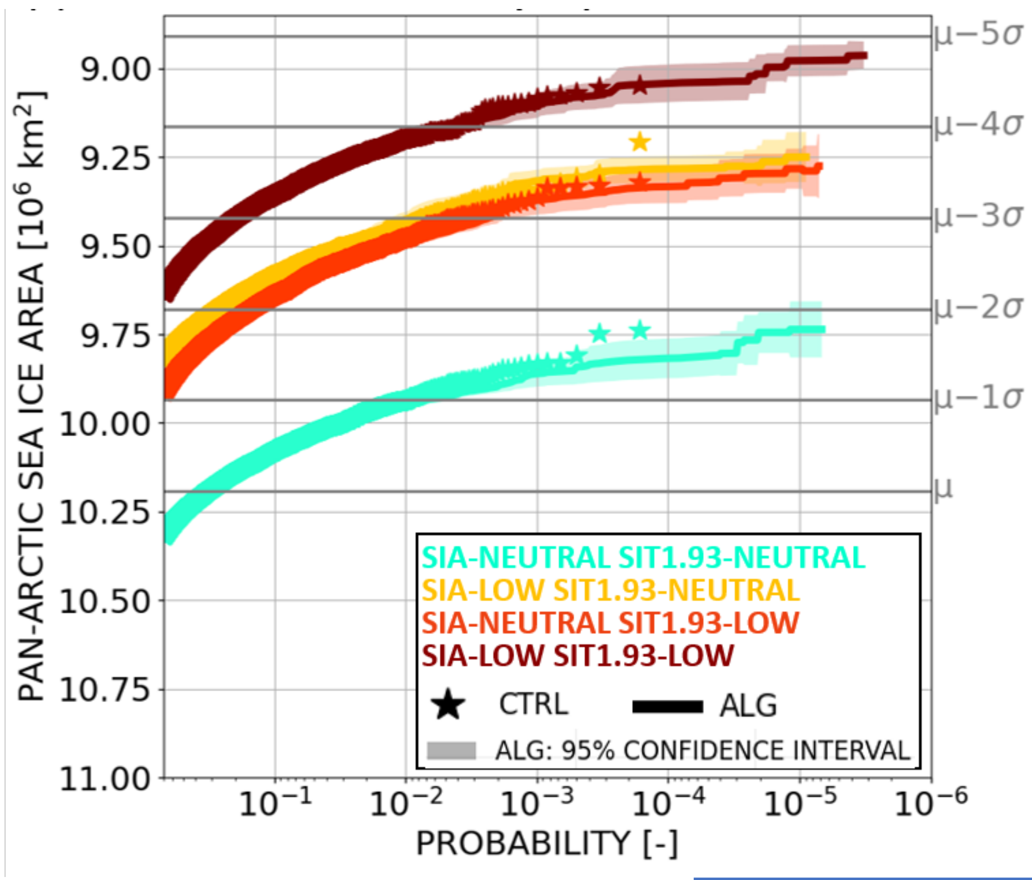
Importance of preconditioning *vs.* subseasonal-seasonal processes

January-February mean Arctic sea ice properties in PlaSim-T21-LSG 3000-year control run

Pan-Arctic sea ice area (x-axis) *vs.* cumulative area with sea ice thickness equal or larger than 1.93 metres (y-axis)



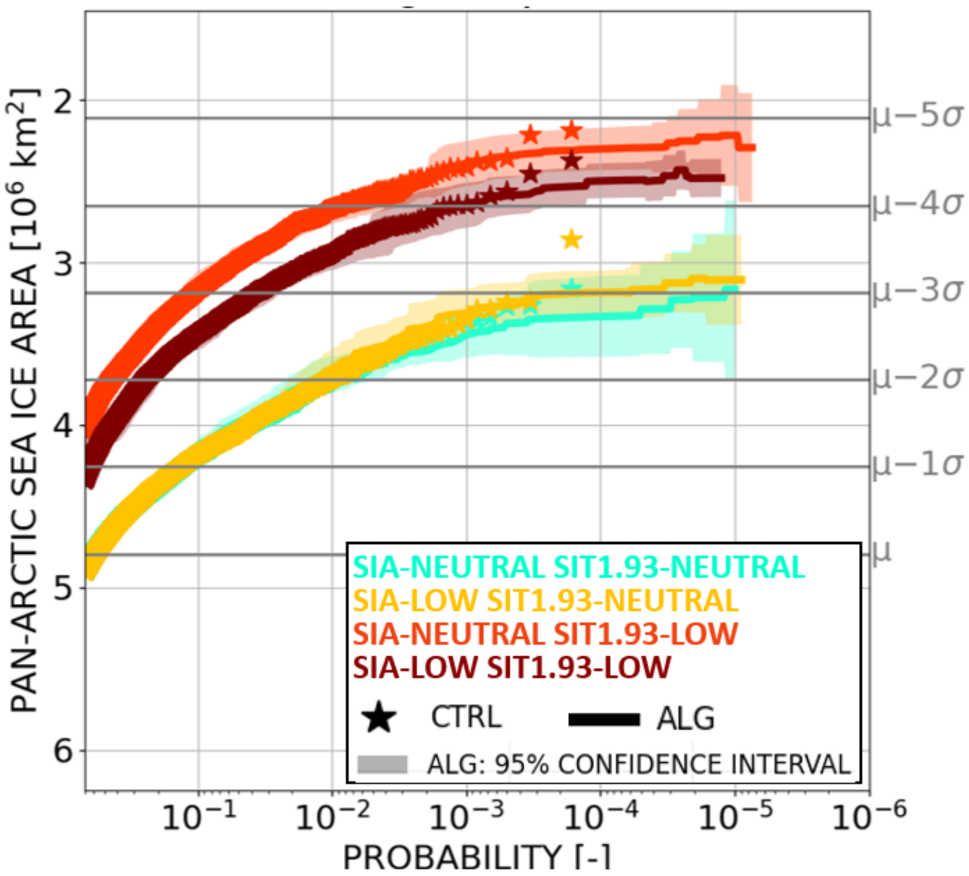
Importance of preconditioning *vs.* subseasonal-seasonal processes



February-September mean-Arctic sea ice area in PlaSim-T21-LSG

Initial condition	($SIA_{0.01}$ - μ) [$n\sigma_{CTRLRUN}$]	(μ_{ENS} - μ) [$n\sigma_{CTRLRUN}$]
SIA− SIT1.93−	−3.80	−2.49
SIA= SIT1.93−	−2.76	−1.39
SIA− SIT1.93=	−2.81	−1.71
SIA= SIT1.93=	−0.98	+0.22

Importance of preconditioning *vs.* subseasonal-seasonal processes



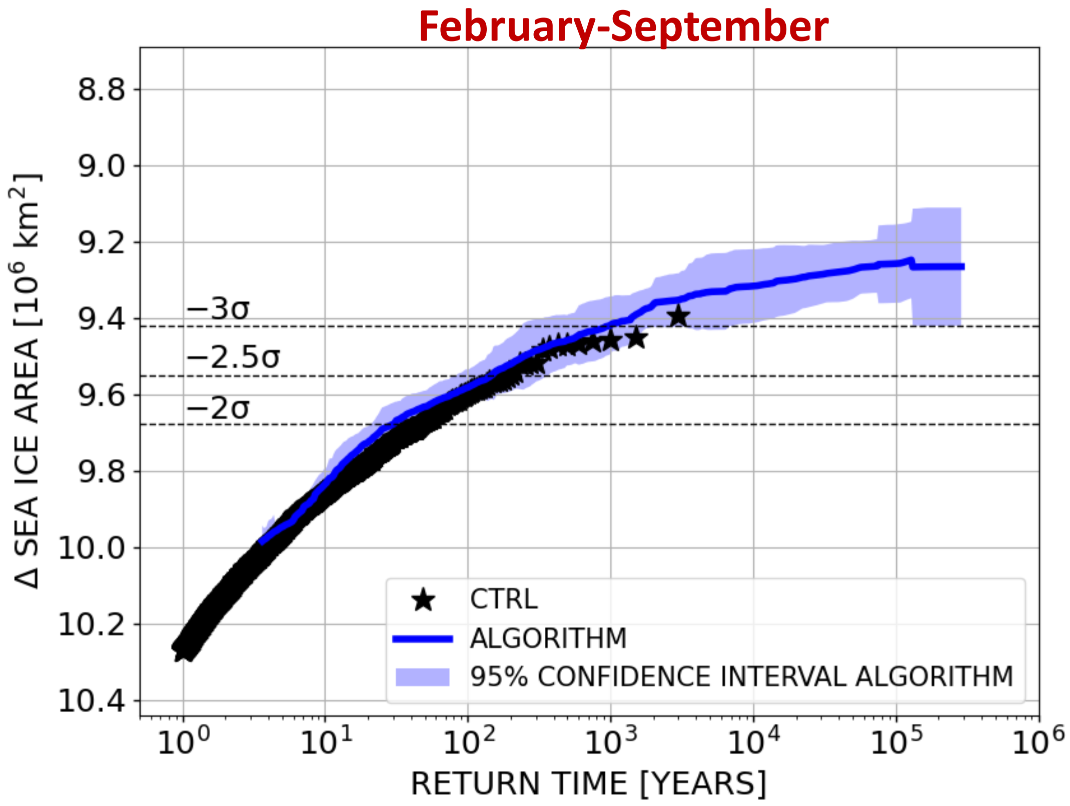
August-September mean-Arctic sea ice area in PlaSim-T21-LSG

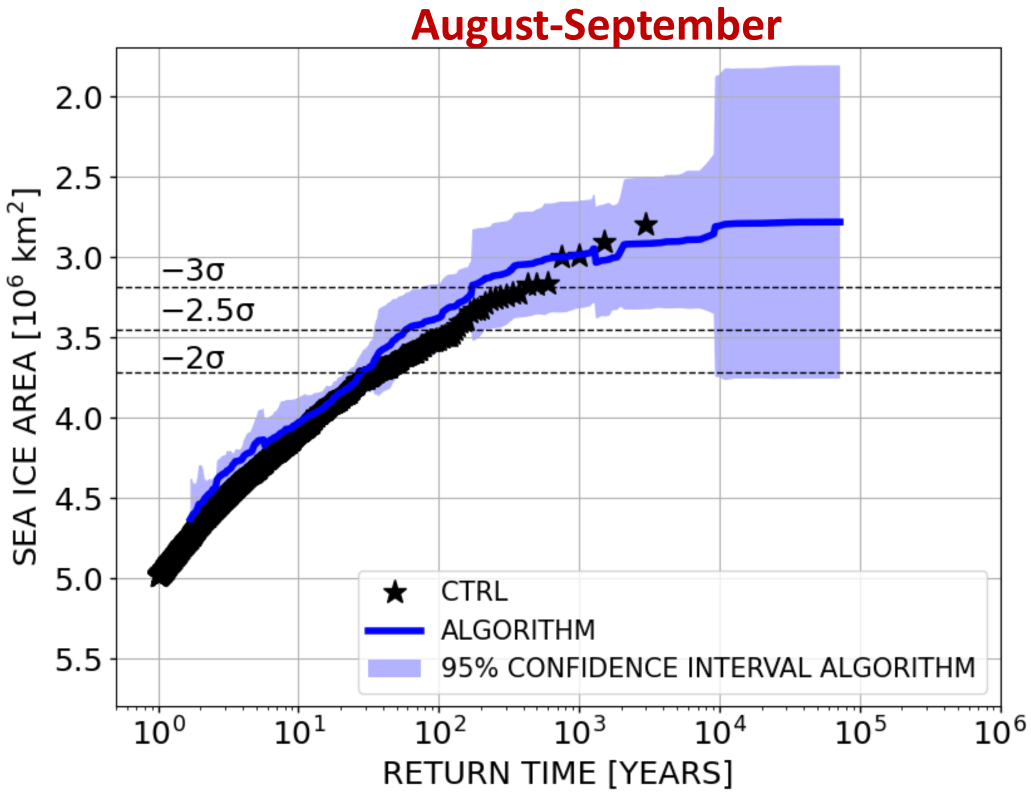
$$P(2012)_{PLASIM} \in [0.3 \cdot 10^{-4}, 7.5 \cdot 10^{-4}]$$

Initial condition	($SIA_{0.01}$ - μ) [$n\sigma_{CTRLRUN}$]	(μ_{ENS} - μ) [$n\sigma_{CTRLRUN}$]
SIA− SIT1.93−	−3.32	−1.36
SIA= SIT1.93−	−3.91	−1.89
SIA− SIT1.93=	−1.82	−0.19
SIA= SIT1.93=	−2.14	−0.19

Statistics of the pan-Arctic sea ice area in PlaSim-T21-LSG

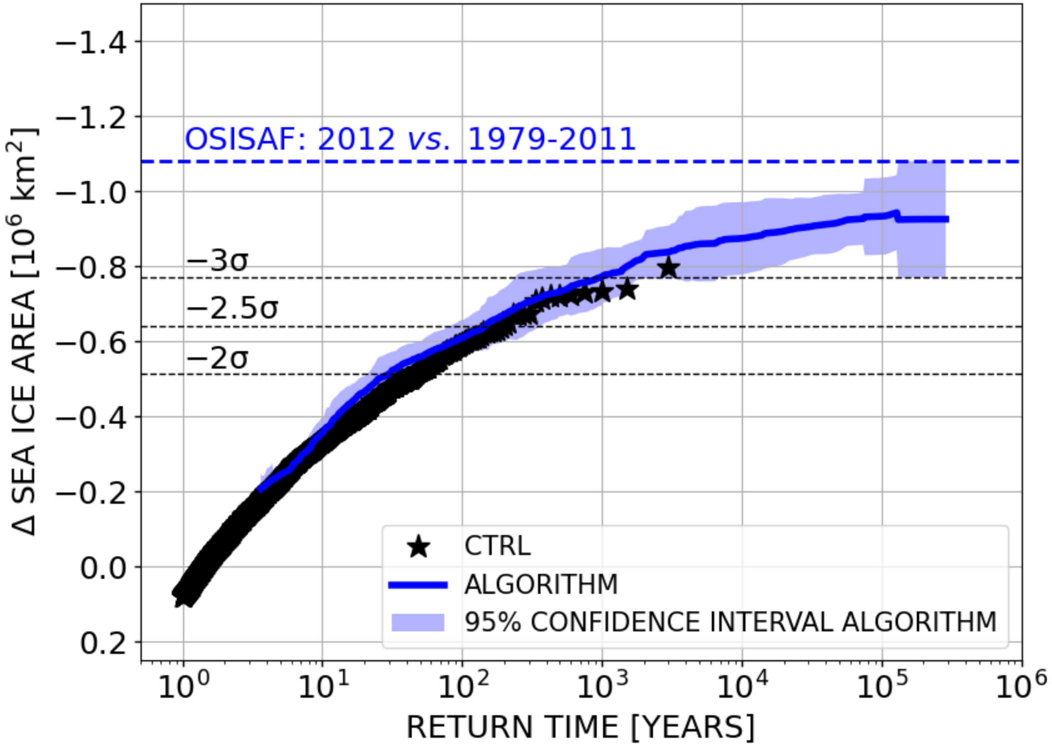
Pan-Arctic sea ice area in PlaSim-T21-LSG

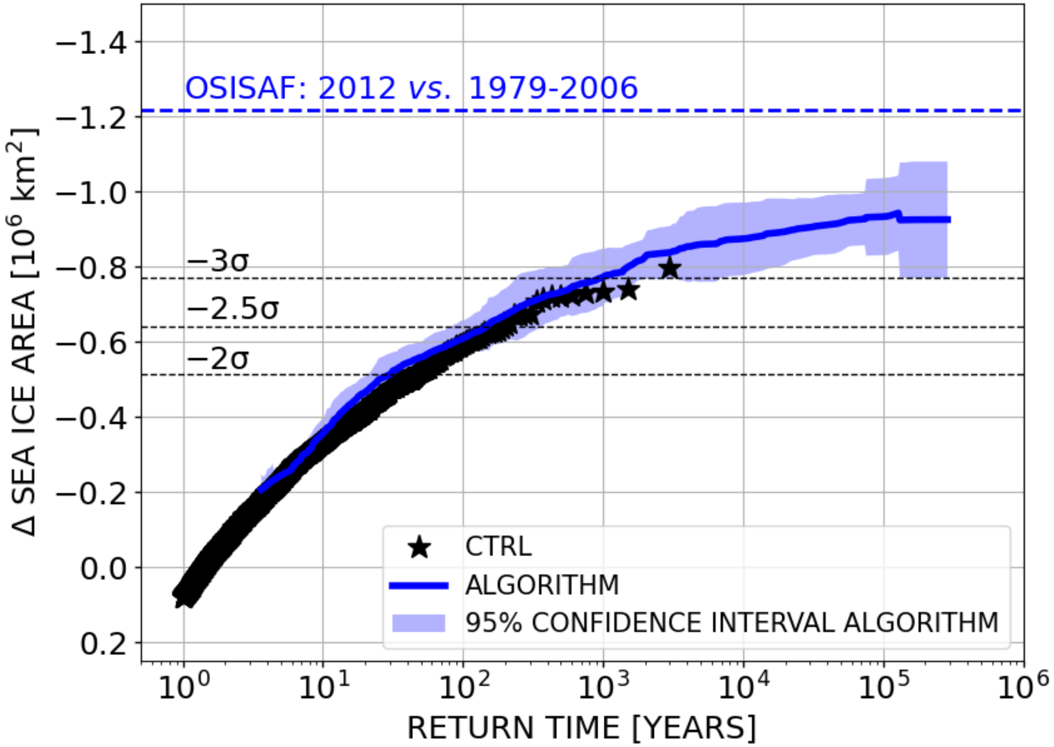




Probabilities of 2012-like Arctic sea ice area anomalies

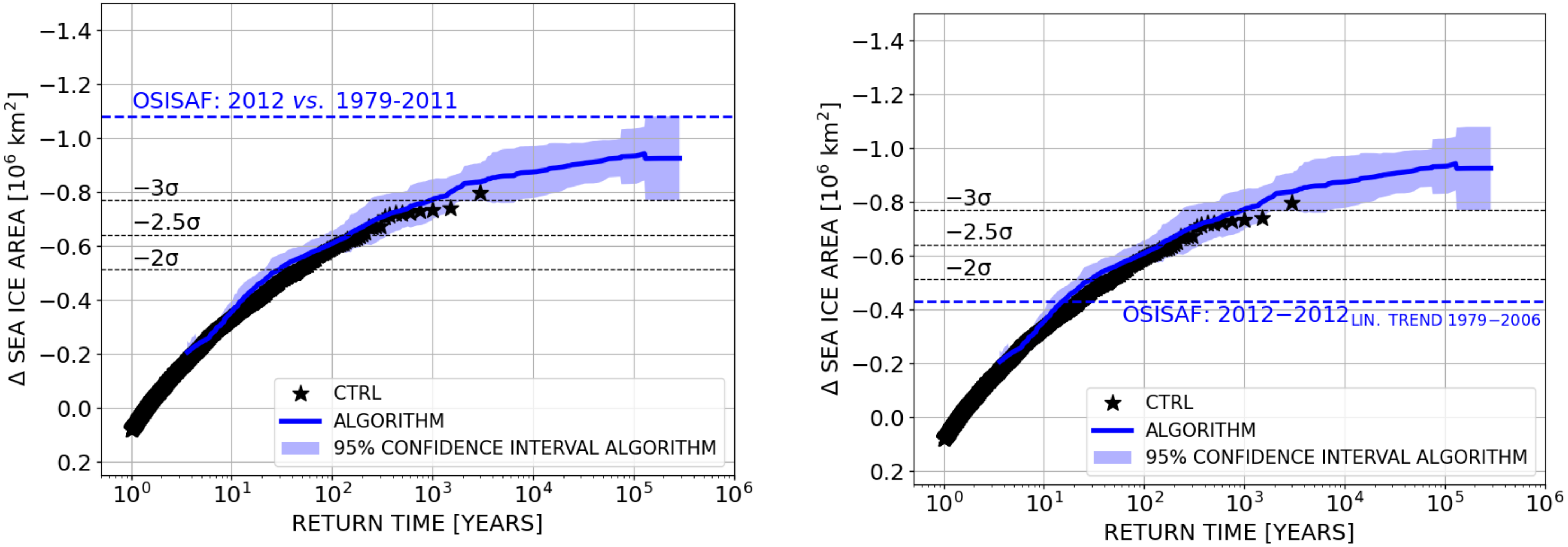
PlaSim-T21-LSG: February-September mean sea ice area anomalies





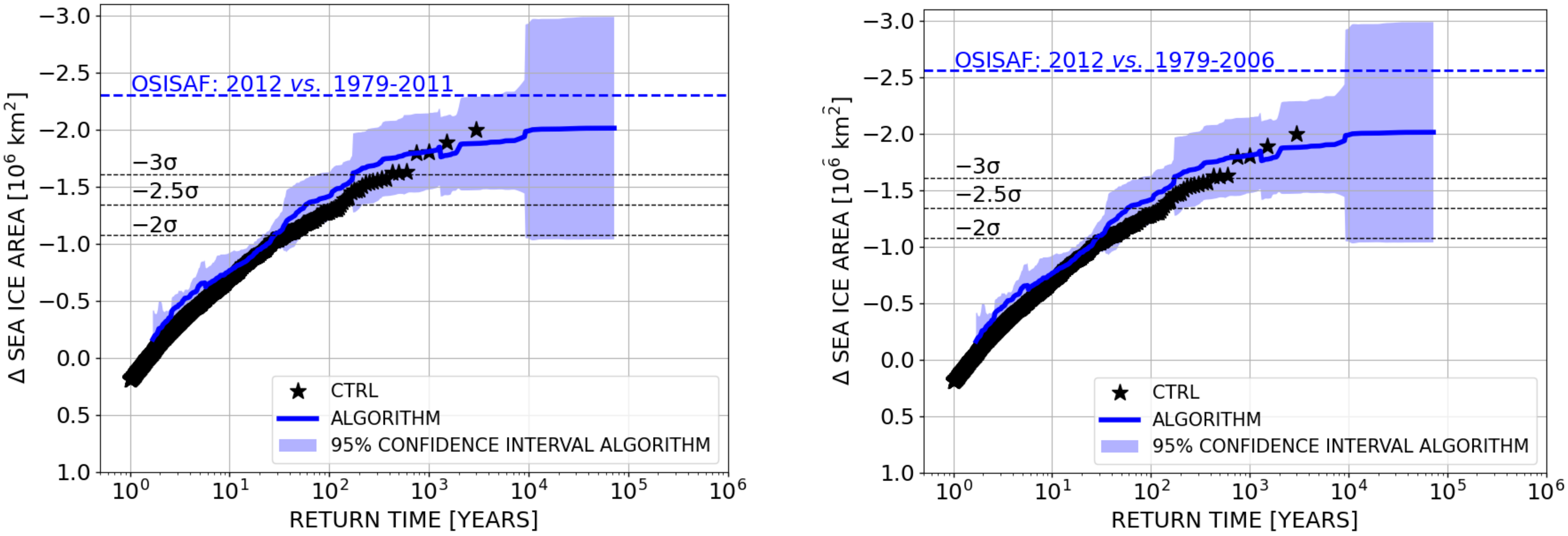
Probabilities of 2012-like Arctic sea ice area anomalies

PlaSim-T21-LSG: February-September mean sea ice area anomalies



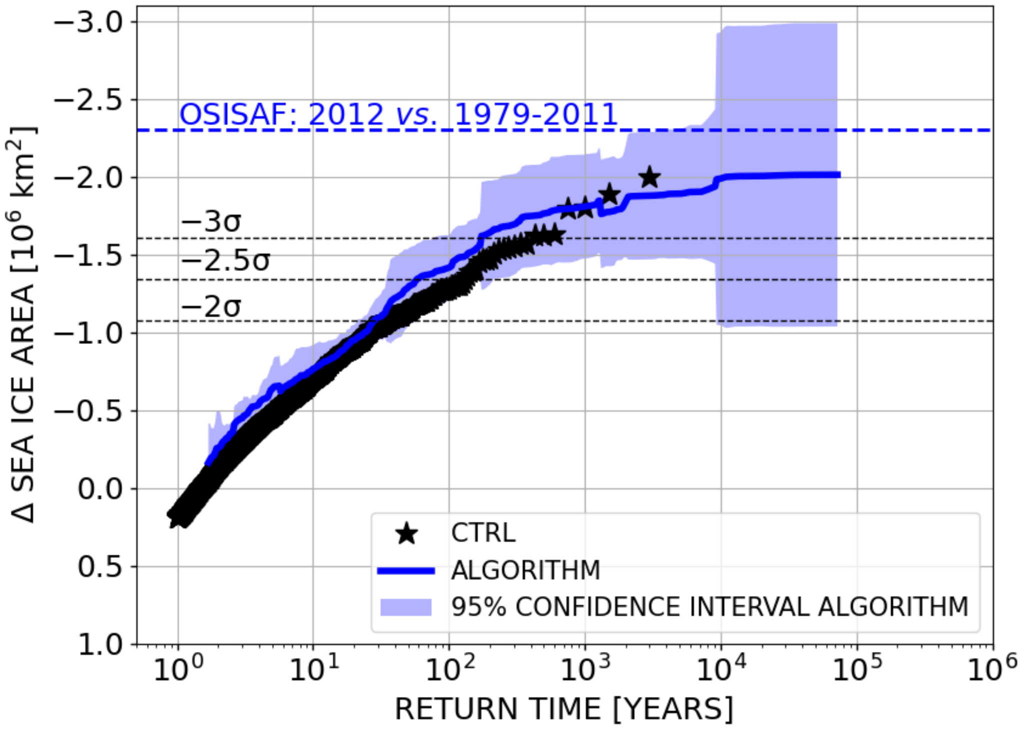
Probabilities of 2012-like Arctic sea ice area anomalies

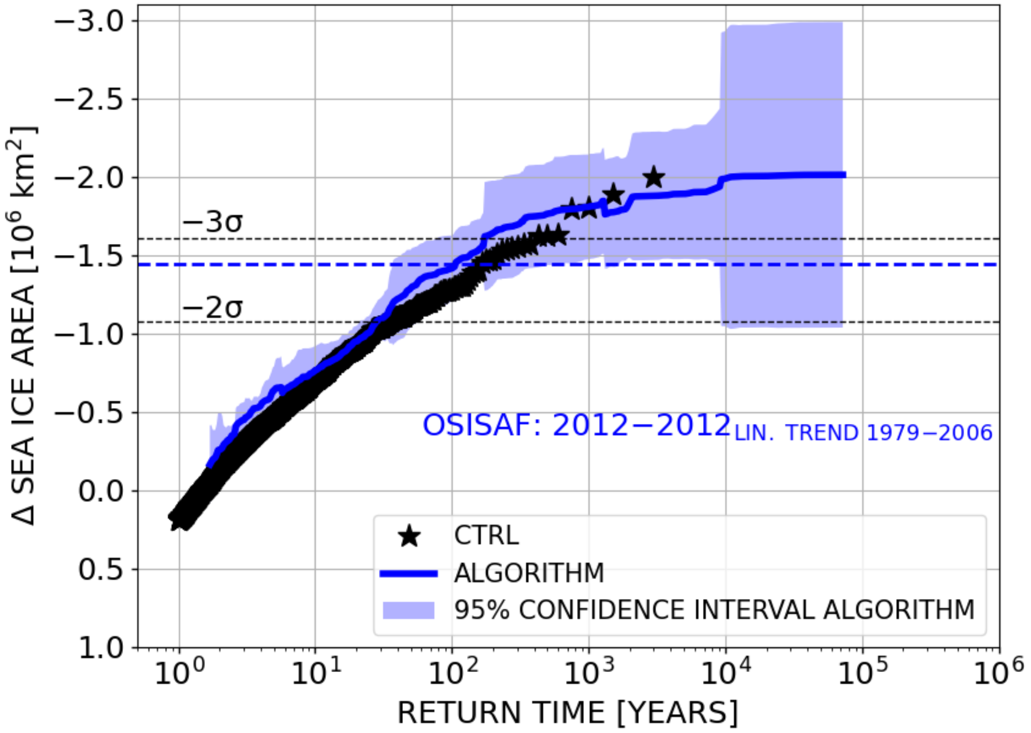
PlaSim-T21-LSG: August-September mean sea ice area anomalies



Probabilities of 2012-like Arctic sea ice area anomalies

PlaSim-T21-LSG: August-September mean sea ice area anomalies





Appendix

Methodology: Rare event algorithm

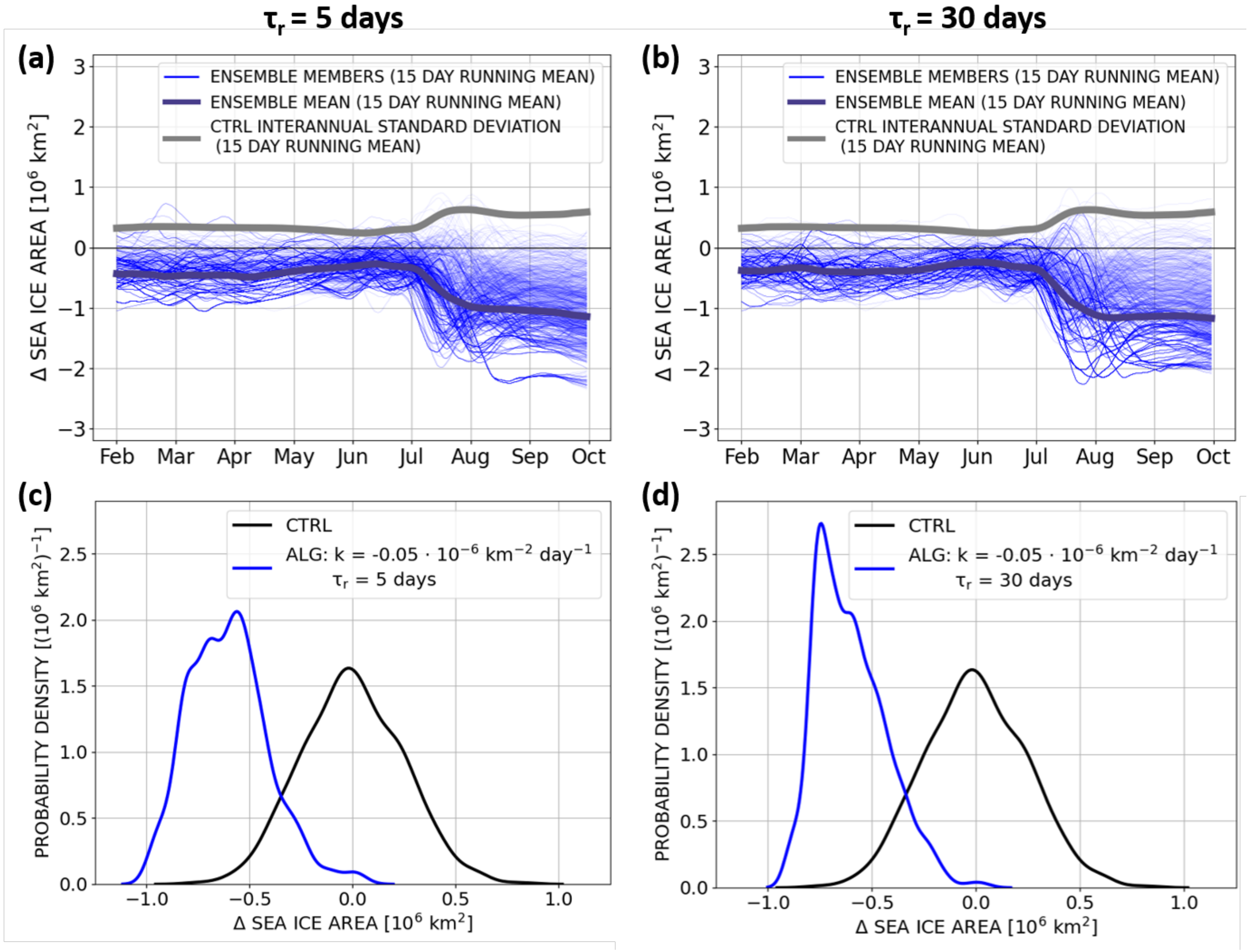
Consider N **trajectories** $\{X_n(t)\}$ $(n = 1, 2, \dots, N)$, an **observable** $A(\{X_n(t)\})$, a **total simulation time** $\mathbf{T_a}$ and a **resampling time** τ_r

At regular times $t_i = i\tau_r$ $\left(i = 1, \dots, \frac{T_a}{\tau_r}\right)$, trajectories are **killed or generate a number of replicates** depending on the **weights**

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

, with k **biasing parameter**

Results: Application of the rare event algorithm to PlaSim-T21-LSG – Phase I

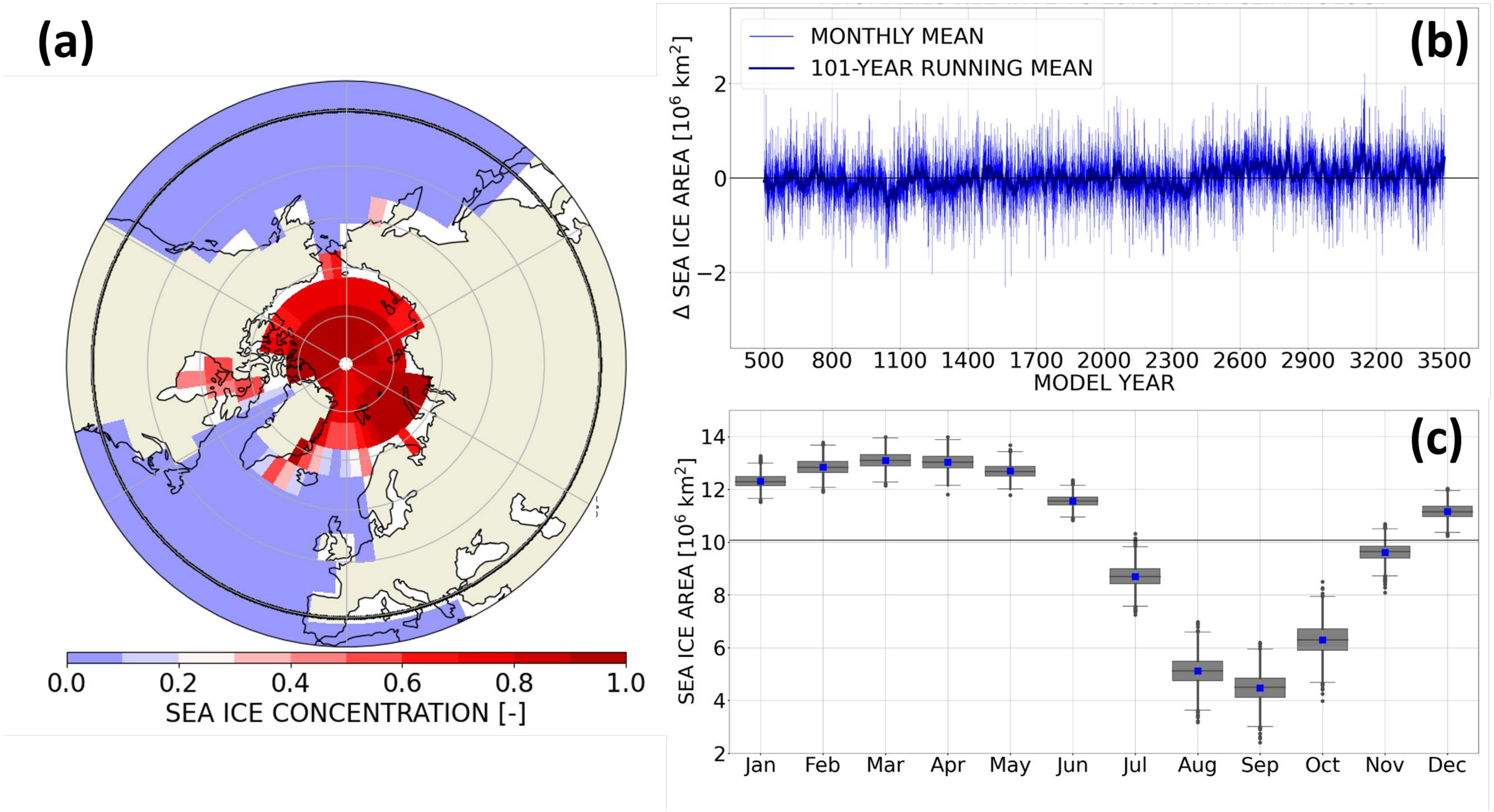


Pan-Arctic sea ice area [10^6 km^2]

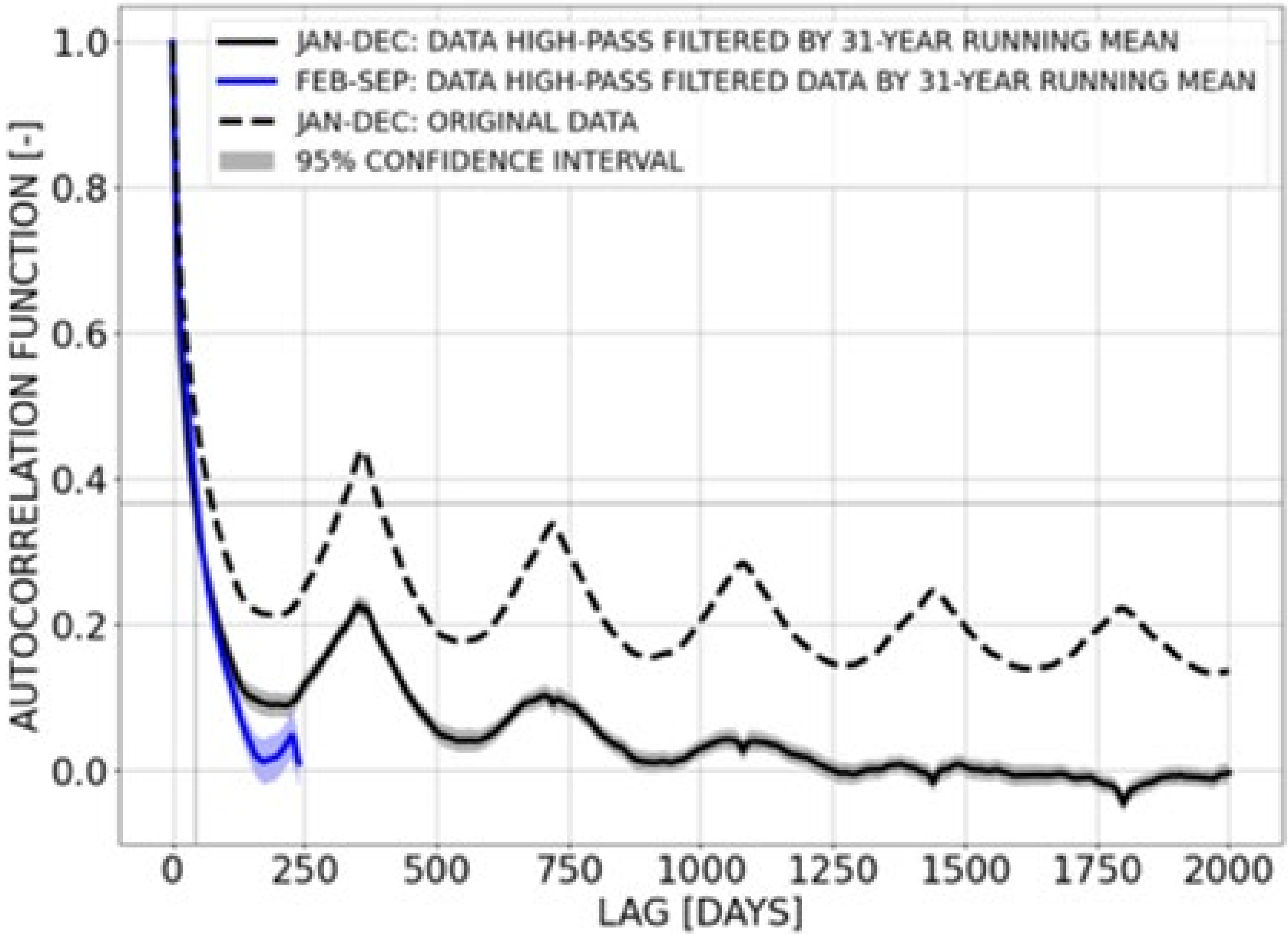
Daily mean

February-September mean

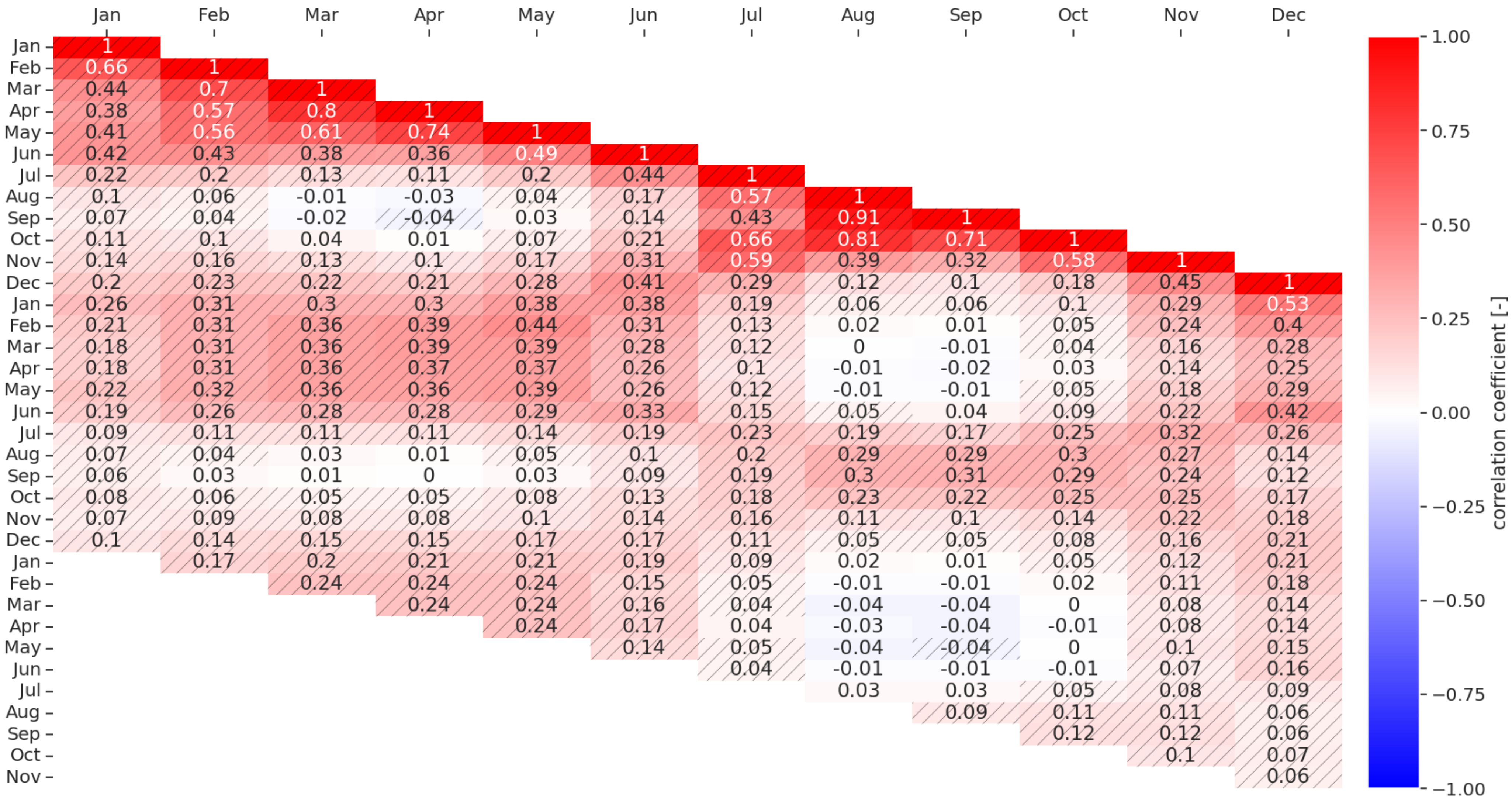
Results: Sea ice climatology in PlaSim-T21-LSG



Results: Sea ice persistence in PlaSim-T21-LSG



Results: Sea ice persistence in PlaSim-T21-LSG



Hatching: statistical significance at 5% level