



Faculty of Science
Earth and Climate Research Center
Earth and Life Institute



Royal Meteorological
Institute of Belgium

Extreme Arctic sea ice lows investigated with rare event sampling

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JEROME SAUER

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THESIS COMMITTEE:

Prof. François Massonnet (Supervisor)	UCLouvain, Belgium
Prof. Francesco Ragone (Supervisor)	University of Leicester, UK
Prof. Quizhen Yin	UCLouvain, Belgium
Prof. Hugues Goosse	UCLouvain, Belgium
Dr. Jeroen Wouters	University of Reading, UK
Dr. Steffen Tietsche	ECMWF, Bonn, Germany

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Résumé

Diverses études ont identifié les moteurs possibles des réductions extrêmes de la banquise arctique, comme observées pendant les étés 2007 et 2012. Ces moteurs incluent le préconditionnement, le transport de chaleur océanique, la variabilité de la circulation atmosphérique à grande échelle et les cyclones à échelle synoptique. Cependant, leur contributions relatives aux réductions extrêmes de la banquise arctique et les proportions spécifiques dans lesquelles ils causeront les futurs événements restent incertaines. Prévoir ces extrêmes à l'échelle saisonnière et comprendre l'impact du réchauffement climatique sur leur probabilité d'occurrence restent donc un défi.

Une difficulté majeure à l'étude des extrêmes climatiques est le petit échantillonnage statistique disponible par les observations et par les simulations numériques avec des modèles climatiques coûteux en calculs. Des études récentes ont abordé ce problème en utilisant des algorithmes d'événements rares, c'est-à-dire, des techniques de calcul issues de la physique statistique pour augmenter l'efficacité de l'échantillonnage des extrêmes dans les simulations numériques. Ces techniques présentent l'avantage de préserver la cohérence dynamique du modèle. Cependant, pour un coût de calcul fixe, ils permettent d'augmenter le nombre d'extrêmes simulé de plusieurs ordres de grandeur comparé aux simulations numériques directes. Ils permettent aussi de générer des événements ultra-rares qui sont pratiquement impossibles à étudier par échantillonnage direct.

Dans cette thèse, nous appliquons un algorithme d'événements rares aux simulations d'ensemble avec les modèles climatiques couplés Planet Simulator (PlaSim) et European community Earth-System-Model version 3 (EC-Earth3) pour étudier les réductions extrêmes de la banquise arctique sous un climat représentatif du début du XXI^e siècle. L'algorithme utilisé dans cette thèse est conçu pour améliorer l'efficacité de l'échantillonnage des valeurs extrêmes dont la dynamique se caractérise par une persistance temporelle supérieure aux cas déjà étudiés dans la littérature pour la dynamique atmosphérique. Nous mettons en œuvre cette technique selon deux approches.

Tout d'abord, nous initialisons les ensembles à partir des conditions statistiquement indépendantes issues d'une longue simulation de contrôle réalisée avec PlaSim. Cette approche permet de suréchantillonner les zones de l'espace de phase où se produisent des extrêmes dans un sens absolu. Nous simulons des étés caractérisés par une surface de glace de mer extrêmement réduite, avec des périodes de retour pouvant atteindre 100

000 ans, pour un coût de calcul équivalent à 1 000 ans. Nous calculons des cartes composites statistiquement significatives de grandeurs dynamiques, conditionnellement à des événements extrêmes dont la période de retour est supérieure à 200 ans. En utilisant PlaSim et EC-Earth3, la deuxième approche correspond à un dispositif de prévision climatique saisonnière dans lequel les ensembles sont initialisés à partir de conditions initiales identiques légèrement perturbées. Pour les deux modèles, nous obtenons des minima de la banquise en fin d'été dont l'amplitude est supérieure à celle de l'écart entre la surface observée de la banquise en fin d'été 2012 et la courbe de tendance. En utilisant EC-Earth3, nous calculons des cartes composites statistiquement significatives de grandeurs dynamiques lors des extrêmes de la réduction intra-saisonnière de la surface de la banquise dont les probabilités sont estimées à moins de 1% par an.

Nous réalisons une évaluation statistique quantitative des précurseurs des extrêmes de la réduction de la banquise arctique. Cela comprend des analyses du bilan du volume et de la surface de la glace de mer, ainsi que du bilan énergétique de surface. Le but de ces analyses de bilan est de distinguer les rôles respectifs des forçages dynamiques et thermodynamiques lors des extrêmes de réduction intra-saisonnière de la glace de mer. Les simulations d'ensemble initialisées nous permettent également d'évaluer les contributions respectives du préconditionnement préalable de la glace de mer et de l'océan en hiver, par rapport à la variabilité météorologique sub-saisonnière, aux amplitudes des anomalies extrêmement négatives de la surface de la glace de mer en fin d'été, calculées par rapport à une climatologie de référence fixe. Notre étude démontre que les facteurs permettant de prédire de manière probabiliste une superficie extrêmement réduite de la banquise en fin d'été sont, d'une part, la surface cumulée en fin d'hiver de la banquise dont l'épaisseur dépasse un certain seuil et, d'autre part, une perte de volume de la glace de mer systématiquement accrue entre mai et juillet, avant le minimum annuel de la banquise. Nous constatons que ce dernier phénomène est systématiquement associé à des anomalies négatives persistantes de la pression moyenne au niveau de la mer au-dessus de la partie centrale et eurasienne de l'océan Arctique. Le courant cyclonique associé favorise une accélération de la fonte de la banquise, tant sur le plan thermodynamique – en favorisant la convergence du transport de l'humidité et du chaleur sensible intégrée verticalement au-dessus de la partie pacifique et nord-américaine de l'océan Arctique – que sur le plan dynamique – en favorisant l'exportation de la glace de mer hors de la partie centrale de l'océan Arctique par le biais du transport induit par le vent.

Enfin, les avancées méthodologiques, techniques et scientifiques présentées dans cette thèse ouvrent de nombreuses perspectives pour l'avenir. Ces perspectives portent notamment sur les études d'attribution et l'amélioration des prévisions saisonnières concernant l'état de la banquise estivale, à l'aide de modèles statistiques basés sur des données, de prévisions basées sur l'apprentissage automatique et de prévisions initialisées issues d'ensembles de modèles climatiques. Bien que cette thèse porte exclusivement sur la surface de la banquise dans l'ensemble de l'Arctique, les stratégies élaborées peuvent être adaptées pour étudier les conditions anormales de la glace de mer dans des régions spécifiques de l'Arctique et en Antarctique.

Abstract

The Arctic sea ice cover and sea ice volume have been decreasing since at least the late 1970s, in large part due to anthropogenic emissions of greenhouse gases. Despite steadily increasing greenhouse gas concentrations, the sea ice decline is non-linear, and internal climate variability and feedback mechanisms modulate the downward trend of the sea ice. Accelerated sea ice decline occurred from the mid-2000s to 2012, including record reductions of the sea ice area compared to the trend line in 2007 and 2012.

The decline and extreme fluctuations of Arctic sea ice cover can impact the integrity of the permafrost, coastal erosion, mid- and high-latitude weather and climate, and have implications for Arctic Ocean accessibility. The latter concerns trans-Arctic and local shipping, the exploitation of natural resources, fishing, polar ecotourism and daily activities of local communities. Being able to predict summer sea ice conditions on seasonal time scales, in particular on a regional level, is therefore of potential interest for different users.

Various studies identified possible drivers of extremes of Arctic sea ice reduction, such as observed in the summers of 2007 and 2012, including sea ice-ocean preconditioning, oceanic heat transport, large-scale atmospheric circulation variability and synoptic-scale cyclones. However, a robust quantitative statistical analysis of extremes of sea ice reduction is hindered by the small number of rare events that can be sampled from observations and numerical simulations with computationally expensive climate models. A better understanding of the precursors of extreme sea ice lows and a more precise estimate of their probabilities are crucial to improve seasonal predictions of these events and to quantify their risk of occurrence under different climate change scenarios. The access to an improved statistics of extreme sea ice lows could also help to better assess their impacts.

Recent studies tackled the problem of sampling climate extremes by using rare event algorithms, i.e., computational techniques developed in statistical physics to reduce the computational cost required to sample rare events in numerical simulations. While preserving the dynamical consistency of the model, these techniques allow to increase the number of simulated extremes by several orders of magnitude compared to direct numerical simulations for a given computational cost, and to generate ultra-rare events that are almost impossible to study using direct sampling.

In this thesis, we apply a genealogical selection rare event algorithm to ensemble simulations with the coupled climate models Planet Simulator (PlaSim) and European community Earth-System-Model version 3 (EC-Earth3) to study extremes of summer pan-Arctic sea ice area reduction under present-day climate conditions. The specific algorithm used in this thesis is designed to improve the sampling of extremes whose dynamics is characterized by time-persistence. We apply this technique via two approaches.

Firstly, we initialize ensembles with the algorithm from statistically independent initial conditions taken from a long control run with PlaSim. This approach serves to oversample the areas of the phase space where extreme events in an absolute sense are. We simulate extremely low sea ice summers with return times up to 10^5 years for a computational cost of 10^3 years, and we compute statistically significant composite maps of dynamical quantities conditional on the occurrence of extremes with return times of more than 200 years. Using both PlaSim and EC-Earth3, the second approach corresponds to a seasonal climate prediction setup where ensembles are initialized from slightly perturbed identical initial conditions. For both models, we generate late summer sea ice lows with larger amplitudes compared to the deviation of the observed 2012 late summer sea ice area from the trend line. Using EC-Earth3, we also compute statistically significant composite maps of dynamical quantities during extremes of intra-seasonal pan-Arctic sea ice area reduction with estimates probabilities of less than 1% per year.

We exploit the improved statistics of extremes of sea ice reduction to perform a quantitative statistical analysis of their precursors. This includes sea ice volume, sea ice area and surface energy budget analyses to disentangle the roles of dynamic vs. thermodynamic forcing for these events. Initialized ensemble simulations also allow us to assess the relative contributions of winter sea ice-ocean preconditioning vs. sub-seasonal weather variability to the amplitudes of extremely negative late summer sea ice area anomalies computed relative to a fixed baseline climatology. Our manuscript demonstrates that sources of probabilistic predictability of extremely low late summer sea ice area are given by 1) the late winter cumulative area with sea ice thickness larger than a certain threshold and 2) by systematically enhanced May-July sea ice volume loss prior to the annual sea ice minimum. We find that the latter is systematically associated with persistent negative mean sea level pressure anomalies over the central and eastern Arctic Ocean. The associated cyclonic atmospheric flow promotes enhanced sea ice loss both thermodynamically due to convergence of vertically integrated moisture and sensible heat transport over the Pacific-North American part of the Arctic Ocean and dynamically by favoring Ekman drift of sea ice out of the central Arctic Ocean towards its marginal seas.

Finally, the methodological, technical and scientific achievements provided in this thesis open several future perspectives. These perspectives concern in particular attribution studies and the improvement of seasonal predictions of summer sea ice conditions using data-based statistical models, machine learning-based forecasts and climate model ensemble-based initialized forecasts. While this manuscript exclusively deals with the pan-Arctic sea ice area, the developed strategies can be adjusted to study anomalous sea ice conditions in specific regions of the Arctic and in Antarctica.

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Acronyms

AA	Arctic amplification
AD	Arctic Dipole
ADA	Arctic Dipole Anomaly
AMOC	Atlantic Meridional Overturning Circulation
AO	Arctic Oscillation
AS	August-September
AUGSEP	August-September
CanESM2	Second Generation Canadian Earth System Model
CMIP5	Coupled Model Intercomparison Project Phase 5
CMIP6	Coupled Model Intercomparison Project Phase 6
CNRM-CM3.3	Centre National de Recherches Météorologiques Coupled Global Climate Model version 3.3
EC-Earth3	European community Earth-System-Model version 3
ECMWF	European Centre for Medium-Range Weather Forecasts
EMICs	Earth system models of intermediate complexity
EOF	empirical orthogonal function
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
EVT	Extreme value theory
FEBMAR	February-March
FEBSEP	February-September
FM	February-March
GKLT	Giardina-Kurchan-Lecomte-Tailleur
H-TESEL	Tiled ECMWF Scheme for Surface Exchanges over Land with revised land surface hydrology
IFS	Integrated Forecast System
IWV	integrated water vapor
IPCC	Intergovernmental Panel on Climate Change
LIM3	Louvain-la-Neuve sea ice model version 3
LSG	Large-Scale Geostrophic
MJJ	May-June-July
JJA	June-July-August

Contents

NEMO	Nucleus for European Modelling of the Ocean
NEMO4.2.2	NEMO version 4.2.2
NEMO3.6	NEMO version 3.6
OSI SAF	Ocean and Sea Ice Satellite Application Facility
PIOMAS	Pan-Arctic Ice Ocean Modeling and Assimilation System
PlaSim	Planet Simulator
PlaSim-LSG	Planet Simulator coupled to LSG
RILEs	Rapid ice loss events
SEP	September
SIC	sea ice concentration
SIT1.80	cumulative area with sea ice thickness ≥ 1.80 m
SIT1.93	cumulative area with sea ice thickness ≥ 1.93 m
SIV	sea ice volume
SNV	snow volume
T2M	two metre temperature
TCC	total cloud cover
Z500	500 hPa geopotential height
TESSEL	Tiled ECMWF Scheme for Surface Exchanges over Land

Chapter 1

Introduction

1.1 The role of Arctic sea ice variability in the climate system and for society

1.1.1 The presence of sea ice on Earth

Sea ice is "any form of ice found at sea which has originated from the freezing of sea water" [WMO, 1989]. Compared to the ocean and the atmosphere, sea ice is a relatively thin layer with typical thickness of up to a few metres [Rothrock et al., 2008; Massonnet et al., 2026, p. 328]. Currently (e.g. during the early 21st century), sea ice can be found both around Antarctica and in the Arctic. On annual average and taking both polar regions together, sea ice covers approximately $25 \cdot 10^6 \text{ km}^2$ or about 4.5% of the Earth's surface [Cavalieri and Parkinson, 2012; Parkinson and Cavalieri, 2012].

1.1.2 Implications of sea ice variability and sea ice loss

The Arctic sea ice is a major player in the climate system with scientific and societal-political relevance. Sea ice area and sea ice volume have been decreasing since at least the late 1970s (cf. Figure 1.1, Notz and Marotzke [2012] and Stroeve and Notz [2018]) and climate models indicate a possible seasonal sea ice-free Arctic during the second half of the 21st century [Massonnet et al., 2012; Notz and Community, 2020; Jahn et al., 2024; Bonan et al., 2021]. Despite the steadily increasing greenhouse gas concentrations [Meinshausen et al., 2017], the decline of pan-Arctic sea ice area is not steady, and internal climate variability and feedback mechanisms have been shown to modulate the downward trend of the sea ice [Ding et al., 2017; Baxter et al., 2019; Ono et al., 2019; Francis and Wu, 2020; Tietsche et al., 2011; England et al., 2019]. Accelerated decline of the late summer pan-Arctic sea ice area occurred from the mid-2000s to 2012, resulting in record reductions of the sea ice area compared to the trend line in 2007 and 2012 (Figure 1.1). After 2012, the downward trend of the Arctic sea ice cover slowed substantially, and no statistically significant decline of September sea ice area occurred during the last two decades [England et al., 2025; Francis and Wu, 2020].

1. Introduction

While Arctic sea ice decline is an important indicator of global climate change [Notz and Marotzke, 2012; Stroeve and Notz, 2018; Gregory et al., 2002; Ding et al., 2017], the presence of sea ice vs. open water conditions, in turn, substantially affects the surface energy [e.g. Serreze and Barry, 2014, pp. 110-146], momentum [e.g. Martin et al., 2016] and water budget [e.g. Lohmann and Gerdes, 1998] and therefore also influences the climate system. The formation (melting) of sea ice is associated with an increase (decrease) of salt and water density in the upper layers of the ocean. On decadal and longer time-scales, variations of the sea ice edge may therefore affect the deep water formation and the thermohaline circulation [Guémas and Salas-Méla, 2008; Meccia et al., 2023; Lohmann and Gerdes, 1998].

Regarding the surface energy budget, sea ice and overlying snow have a substantially higher surface albedo than sea water and prevent a substantial fraction of solar radiation to penetrate into the ocean. The sea ice-snow layer acts as a thermal and physical insulator modulating the exchange of heat and moisture between the ocean and the atmosphere [Honda et al., 2009; Alexander et al., 2004]. As a consequence, sea ice decline contributes to the Arctic amplification (AA) of climate change although the precise relative contributions of different factors to AA are not fully understood [Screen and Simmonds, 2010; Previdi et al., 2020; Graversen and Wang, 2009]. Previdi et al. [2020] and Graversen and Wang [2009], for example, conclude from climate model sensitivity experiments with an instantaneous quadrupling of the CO₂ concentration [Previdi et al., 2020] and with a locked albedo [Graversen and Wang, 2009] that sea ice decline significantly contributes to amplified polar warming, but that AA can be triggered by fast atmospheric processes alone.

The decline of Arctic sea ice may impact the integrity of the permafrost [Lawrence et al., 2008] and causes an increase in coastal erosion by lengthening the open water season and by exposing coastlines to waves [Nielsen et al., 2022]. Although debated, sea ice retreat and variability potentially affects the atmospheric circulation in the mid-latitudes [Blackport and Screen, 2020; Blackport et al., 2019; Honda et al., 2009; Screen and Simmonds, 2010; Koenigk et al., 2016; Cohen et al., 2020]. Sea ice has a much larger memory than the atmosphere, typically a few months for pan-Arctic sea ice area and up to a few years for sea ice volume [Blanchard-Wrigglesworth et al., 2011; Massonnet et al., 2026, pp. 327-331]. The accurate representation and prediction of the state of Arctic sea ice within climate models is therefore relevant for seasonal climate forecast systems [Koenigk et al., 2016; Bunzel et al., 2016]. Being able to predict the summer state of the sea ice cover in the Arctic, in particular on a regional scale, is also of potential interest for stakeholders beyond the scientific community. Thus, the decline of the sea ice allows for increasing human activities in the Arctic Ocean, including trans-Arctic and local shipping, the exploitation of natural resources, fishing, polar ecotourism and daily activities of local communities [Eicken, 2013; Smith and Stephenson, 2013; Lloyd's, 2012].

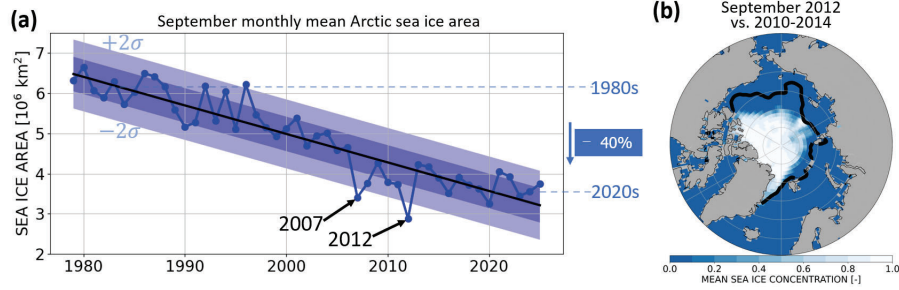


Figure 1.1: (a) September mean pan-Arctic sea ice area [10^6 km^2] from European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Ocean and Sea Ice Satellite Application Facility (OSI SAF) data (product ID: OSI-420) [EUMETSAT Ocean and Sea Ice Satellite Application Facility, 2024]. The black line shows a linear trend fitted to the period 1979–2025. The dark (light) blue shadings denote one and two standard deviations of the variability around the trend line. (b) (Shading) 2012 September mean sea ice concentration vs. (contour) the 15% sea ice concentration contour line of the 2010–2014 September mean sea ice concentration (product ID: OSI-450) [EUMETSAT Ocean and Sea Ice Satellite Application Facility, 2017].

1.2 Drivers of summer Arctic sea ice area variability and causes of the 2007 and 2012 extreme sea ice loss events

1.2.1 The bulk of the distribution of summer Arctic sea ice area

The mechanisms driving the variability in the bulk of the distribution of the summer Arctic sea ice area are comprehensively documented in the literature [e.g. Guémas et al., 2016; Blanchard-Wrigglesworth et al., 2011; Chevallier and Salas-Mélia, 2012; Massonnet et al., 2026]. In general, the factors governing seasonal to inter-annual sea ice area variability and predictability are the persistence and reemergence of sea ice area anomalies, the preconditioning through the winter-spring sea ice-ocean state, the oceanic and atmospheric circulations and involved feedback mechanisms.

The memory properties of the sea ice-ocean system are key in determining persistence and preconditioning. Observational and model studies indicate season-dependent characteristic e-folding time scales of pan-Arctic sea ice area anomalies in the order of 1–5 months [Blanchard-Wrigglesworth et al., 2011; Massonnet et al., 2026, pp. 327–331]. These persistence time scales are smallest in spring and sharply increase in summer, which is partly due to the sea ice-albedo feedback [Blanchard-Wrigglesworth et al., 2011; Bushuk et al., 2020]. Growth-to-melt season reemergence has been proposed as a mechanism through which persistent sea ice thickness anomalies provide a bridge between autumn-winter and subsequent summer sea ice area anomalies [Blanchard-Wrigglesworth et al., 2011]. Expanding on the idea of the preconditioning of summer sea ice area, Chevallier and Salas-Mélia [2012] and Goosse et al. [2009] emphasize the role of sea ice thickness for the probability of winter sea ice to survive the melting season. Apart from the sea ice thickness, another source of preconditioning of late summer sea ice area is given by the spring-summer melt pond fraction which substantially alters the surface albedo prior to the formation of open water [Liu et al., 2015a; Massonnet et al., 2026, pp. 332–334].

1. Introduction

1.2.2 Knowns and unknowns about extremes of sea ice reduction

Since by definition extreme sea ice reductions are rare in the observational sample, a relatively low number of studies addressed the mechanisms driving these extreme states compared to studies investigating the average conditions. Several studies attributed the 2007 and 2012 drastic sea ice loss events both to internal climate variability via particular weather and climate events during the melt season and to sea ice-ocean preconditioning [Lindsay et al., 2009; Kauker et al., 2009; Zhang et al., 2008, 2013; Parkinson and Comiso, 2013; Kirchmeier-Young et al., 2017]. Sea ice-ocean preconditioning occurs on different time-scales, including long-term sea ice thinning related to global warming and low-frequency variability in the ocean heat content and meridional ocean heat transport [Cai and Chen, 2025; Parkinson and Comiso, 2013; Holland et al., 2006; Döscher and Koenigk, 2013]. While progress has been made in quantifying the relative contributions of anthropogenically forced vs. internal climate variability to the observed downward trend of the sea ice cover [Ding et al., 2017; England et al., 2019], their relative contributions to extreme sea ice loss events such as observed in 2007 and 2012 remain uncertain. Notably, despite ongoing global warming, summer sea ice conditions are still above the 2012 minimum, highlighting a substantial contribution of internal climate variability to the 2007 and 2012 events [Baxter et al., 2019; Francis and Wu, 2020; England et al., 2025].

Different atmospheric and oceanic drivers of anomalously low summer Arctic sea ice area were discussed in the literature. These include enhanced North Atlantic and Pacific oceanic heat transport [Årthun et al., 2012; Woodgate et al., 2010], the positive and negative phases of the winter and summer Arctic Oscillation (AO) [Rigor et al., 2002; Ogi et al., 2016], and reduced cloudiness during summer [Schweiger et al., 2008]. In contrast, Kapsch et al. [2019], Horvath et al. [2021a] and Liang et al. [2022] attributed negative summer sea ice anomalies to persistent episodes of two types of atmospheric circulation during spring-summer: 1) negative geopotential height anomalies over the central Arctic resembling the positive phase of the AO and favoring cyclonic flow from Eurasia into the Pacific side of the Arctic Ocean and 2) a positive phase of the Arctic Dipole (AD) pattern promoting enhanced heat and moisture transport from the Pacific into the Arctic. In 2007, extreme sea ice reduction was favored by enhanced inflow of warm Pacific water through Bering Strait [Woodgate et al., 2010] and by anomalously persistent southerly winds in the Pacific sector associated with the AD pattern. In 2012, a summer storm contributed to enhanced sea ice reduction by leading to increased bottom melt via anomalously strong vertical mixing in the oceanic boundary layer [Guemas et al., 2013; Zhang et al., 2013; Parkinson and Comiso, 2013; Simmonds and Rudeva, 2012].

As is the case with the study of climate extremes in general, a quantitative statistical analysis of extremes of Arctic sea ice reduction is hindered by the poor statistics in observations and in conventional numerical simulations. Going beyond individual case studies, a quantitative analysis of the relative importance of different atmospheric and oceanic precursors of extreme sea ice lows is therefore lacking. Likewise, it is the small number of extreme events in the lower tail of the distribution of sea ice area that makes it challenging to quantify the probability of a 2012-like sea ice low for a given background climate and initial condition. A better understanding of precursors of extremes of summer

Arctic sea ice reduction and a more precise estimate of their probabilities are crucial to improve seasonal predictions of these events, to quantify their risk of occurrence under different climate change scenarios and to better assess their impacts.

1.3 Importance sampling and the rare event algorithm

Statistical and dynamical studies of climate extremes are hampered by two overarching problems: 1) climate model biases due to parameterized subgrid-scale processes, inexact boundary conditions (forcings) or the lack of representation of processes (e.g. interactions with land ice) and 2) by the lack of robust statistics available from observations and numerical simulations. The record of satellite-based sea ice observations includes only a few annual sea ice minima with orders of magnitude comparable to the ones in September 2007 and 2012 [Fetterer et al., 2017] (Figure 1.1). The large computational cost of comprehensive climate models, in turn, makes it unrealistic to run ensembles with a few thousands of trajectories for a simulation length of one year and to quantitatively study extreme events with probabilities of less than 1% per year. Multi-model analyses would increase the computational cost even further.

A possible solution to the problem of computational cost limitations are rare event algorithms, i.e., computational techniques from statistical physics designed to increase the sampling efficiency of rare events in numerical simulations. These techniques allow to reduce the uncertainty of probability (return time) estimates and of conditional statistics on extremes (e.g. composites) compared to conventional simulation strategies, and to generate ultra-rare events that are very unlikely to occur using direct sampling.

Rare event algorithms have been introduced in the 1950s and have been used since for a wide range of applications (for an overview and the mathematical analysis see e.g. Del Moral [2004]; Giardina et al. [2011]; Grafke and Vanden-Eijnden [2019]). Different types of rare event algorithms are appropriate to study different problems, as the underlying design mechanisms are tailored to target extremes with specific properties. In general, two main classes of rare event algorithms exist [Lestang et al., 2018]: 1) those that operate in state space forming replicates of the system according to selection rules favoring the appearance of the desired extremes [Giardina et al., 2011; Del Moral and Garnier, 2005; Ragone et al., 2018; Ragone and Bouchet, 2020, 2021] and 2) rare event algorithms that search directly in path space the histories of the system which show the desired properties of interest [Grafke et al., 2015; Laurie and Bouchet, 2015]. In this context, both methods using static importance sampling and dynamic importance sampling exist [Moral and Salmerón, 2003]. The goal behind both approaches is to approximate expectation values with respect to a certain target distribution by a weighted average over random samples drawn from a shifted distribution (a detailed description of static importance sampling is given in section 1.3.1). The particularity of dynamic importance sampling is thereby that the choice of the biasing distribution is adapted over the course of the simulation. Static importance sampling, instead, uses a fixed biasing distribution. Recently, some of these techniques have been applied in climate science and in fluid dynamics to study heat waves [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021], midlatitude precipitation [Wouters et al., 2023], tropical storms [Plotkin et al., 2019; Webber et al., 2019], weakening and collapse of the Atlantic meridional overturning circulation [Cini et al., 2024],

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turbulence [Bouchet et al., 2018; Grafke et al., 2015; Lestang et al., 2020], and extremes of Arctic sea ice reduction [Sauer et al., 2024, 2025] (Chapters 2-3).

Apart from rare event algorithms, extreme value theory (EVT) [Coles, 2001] and ensemble boosting [Fischer et al., 2023; Gessner et al., 2023] provide techniques that allow to investigate extreme events with amplitudes beyond the range of available data. Depending on the purpose of the desired analysis, each method has its advantages and disadvantages. In climate science, extreme value theory is often used for attribution studies as it provides an efficient way to extrapolate return times of anomaly values unavailable from the data set [Coles, 2001; Parey et al., 2010]. However, EVT does not allow to study the dynamics driving the extrapolated extreme events. Ensemble boosting, instead, constitutes an approach to focus the computational power in climate model simulations on trajectories that lead to extreme events of interest [Fischer et al., 2023; Gessner et al., 2023]. In this approach, ensemble simulations are re-initialized days to weeks before the peak of an extreme event allowing to generate physically plausible ultra-rare events with unprecedented amplitude. While ensemble boosting therefore allows to study the dynamics of unprecedented extreme events, it does not deliver the probabilities of these events and is thus suitable only in story-line sense. Another limitation of ensemble boosting is that this method is only designed to study processes that act on short lead times (up to a few weeks). For example, preconditioning of an extreme event through processes acting on seasonal to interannual time scales cannot be studied within the re-initialized ensemble. In contrast to ensemble boosting and in contrast to extreme value theory, rare event algorithms give both the dynamical trajectories that lead to the extreme events of interest, even for lead times substantially larger than a few weeks, and enable to estimate their probabilities of occurrence. Rare event algorithms therefore allow to better identify relevant covariates for the targeted extremes without the need of assumptions on the underlying distributions.

1.3.1 The concept of importance sampling

First, we use a synthetic example to illustrate importance sampling (cf. Ragone et al. [2018]; Rubino et al. [2009]; Wouters et al. [2023]; Plotkin et al. [2019]). Importance sampling is a key probabilistic concept behind many rare event algorithms. We consider the probability density function $\rho(X)$ of a random variable X and we wish to compute $\gamma_B = \mathbb{P}\{X \in B\}$, the small probability that X takes a value in the set B in the upper tail of the distribution of $\rho(X)$ (Figure 1.2). The random variable X could represent a climate variable such as spatially-averaged two metre temperatures or the pan-Arctic sea ice area. In this synthetic example, γ_B can be computed analytically with

$$\gamma_B = \int \mathbb{1}_B(X) \cdot \rho(X) dX. \quad (1.1)$$

where $\mathbb{1}_B(X)$ is the indicator function

$$\mathbb{1}_B(X) = \begin{cases} 1, & \text{if } X \in B \\ 0, & \text{if } X \notin B. \end{cases} \quad (1.2)$$

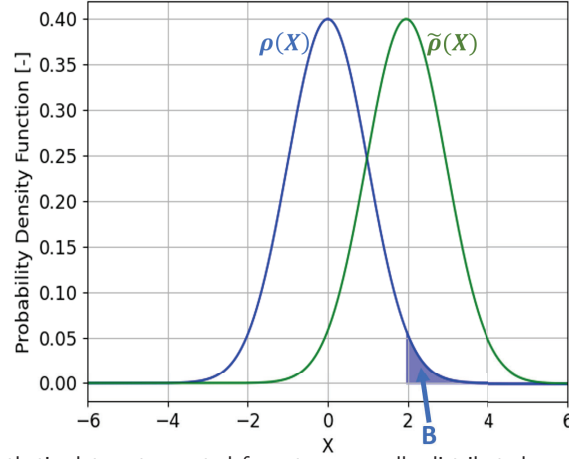


Figure 1.2: Synthetic data sets created from two normally distributed random variables $\rho(X)$ and $\tilde{\rho}(X)$ to illustrate the concept of importance sampling. The sampling uncertainty of the estimate of the probability to be in the set B can be substantially reduced by drawing data from $\tilde{\rho}(X)$ instead of $\rho(X)$

In real applications, the probability density function of an observable of interest is often unknown and parameters of its distribution need to be estimated using Monte-Carlo sampling. In the present synthetic example, Monte-Carlo sampling means that we draw a sufficiently large number of N independent realizations $\{x_i : i = 1, 2, \dots, N\}$ from $\rho(X)$ and approximate the integral in Equation (1.1) using the estimator

$$\hat{\gamma}_B = \frac{1}{N} \sum_{i=1}^N \mathbb{1}_B(x_i), \quad (1.3)$$

The sampling uncertainty of $\hat{\gamma}_B$ can be quantified via the empirical variance. In this thought experiment, the empirical variance of $\hat{\gamma}_B$ can be derived analytically from the central limit theorem [von Storch and Zwiers, 1999, p. 35] and is given by

$$\begin{aligned} \text{VAR}[\hat{\gamma}_B] &= \sigma_{\mathbb{1}_B(X)}^2 / N \\ &= \frac{1}{N} \int (\mathbb{1}_B(X) - \gamma_B)^2 \rho(X) dX \\ &= \frac{1}{N} \gamma_B (1 - \gamma_B), \end{aligned} \quad (1.4)$$

where $\sigma_{\mathbb{1}_B(X)}^2$ is the variance of the indicator function and Equation (1.1) is used to substitute the integral in Equation (1.4). While the empirical variance and hence the absolute error become very small for rare events (i.e. $\gamma_B \ll 1$; Equation (1.4)), the relative error

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$$\text{RE}[\hat{\gamma}_B] = \frac{\sqrt{\text{VAR}[\hat{\gamma}_B]}}{\gamma_B} = \frac{\sqrt{\gamma_B(1-\gamma_B)/N}}{\gamma_B} = \frac{\sqrt{1-\gamma_B}}{\sqrt{N}\gamma_B} \underset{\gamma_B \ll 1}{\sim} \frac{1}{\sqrt{N_B}}, \quad (1.5)$$

scales with the inverse square root of the number of expected events in the set B , computed as $N_B = \sqrt{N}\gamma_B$, and may become large (cf. Rubino et al. [2009]; Wouters et al. [2023]; Ragone et al. [2018]; Rubinstein and Kroese [2017]). To illustrate the practical implication of Equation (1.5), we consider an event with $\gamma_B \approx 1\%$ per year, which corresponds to an event with a return time of about 100 years. Assume we wish to estimate γ_B with a relative error of 10% (10^{-1}). According to Equation (1.5), such a level of statistical accuracy requires a sample size of order 10^4 years. This is hardly possible to be obtained from observations or with comprehensive climate models.

The purpose of importance sampling is to draw N realizations $\{\tilde{x}_i : i = 1, 2, \dots, N\}$ from the shifted distribution $\tilde{\rho}(X)$ with $\rho(X) = L(X)\tilde{\rho}(X)$, where $L(X)$, i.e., the ratio between the original distribution and the shifted one, is known. One can choose L such that the extreme event of interest may become common, and the computational cost required to estimate rare event probabilities with a certain accuracy may be reduced compared to direct sampling. In the case of importance sampling, Equations (1.1) and (1.3) become

$$\begin{aligned} \gamma_B &= \int \mathbb{1}_B(X) \cdot \frac{\rho(X)}{\tilde{\rho}(X)} \cdot \tilde{\rho}(X) dX \\ &\approx \frac{1}{N} \sum_{i=1}^N \mathbb{1}_B(\tilde{x}_i) \cdot \frac{\rho(\tilde{x}_i)}{\tilde{\rho}(\tilde{x}_i)} \end{aligned} \quad (1.6)$$

As documented in Rubino et al. [2009] and Ragone et al. [2018], the relative error of $\hat{\gamma}_B$ scales with $1/\sqrt{N}$ instead of $1/\sqrt{N_B}$ if one finds the optimal L for which the desired rare event is common. Therefore, in order to estimate γ_B with a relative error of 10%, the required sample size is in the order of 10^2 years, a gain of a factor 100 compared to the direct sampling approach.

1.3.2 Description of the rare event algorithm

Importance sampling (section 1.3.1) is simple if one knows the analytical distribution of a certain target observable. If its statistics, however, is generated by a chaotic or stochastic dynamic system, one needs a rare event algorithm to perform importance sampling at the level of the trajectories of the system. In this project, we use a genealogical selection algorithm [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021; Sauer et al., 2024, 2025] adapted from Del Moral and Garnier [2005] and Giardina et al. [2011], that is designed to study persistent, long-lasting extreme events. In the present manuscript, this method is referred to as Giardina-Kurchan-Lecomte-Tailleur (GKLT) rare event algorithm. The GKLT algorithm is applied on top of an ensemble simulation and is designed to perform importance sampling of rare dynamical trajectories populating the tail of the

distribution of the time-average of a target observable over the entire simulation period. In this context, the application of this method is reasonable when the length of the full simulation and thus the averaging time is longer than the typical decorrelation time of the observable.

The procedure of the algorithm works as follows: instead of letting the trajectories of an ensemble evolve independently, at constant intervals of a resampling time τ_r , some trajectories are killed, while others are replicated, depending on the values of weights defined on the past evolution of the trajectories. The weights are exponential functions of the time-average of the target observable during the past interval of duration τ_r . Denoting T_a the total simulation time, the weights are defined as

$$w_n^i = \frac{e^{k \int_{t_{i-1}}^{t_i} A(\{X_n(t)\}) dt}}{R_i} \text{ with } R_i = \frac{1}{N} \sum_{n=1}^N e^{k \int_{t_{i-1}}^{t_i} A(\{X_n(t)\}) dt}, \quad (1.7)$$

where $X(t)$ is the vector of all model variables at time t , $t_i = i \cdot \tau_r$ ($i = 1, 2, \dots, \frac{T_a}{\tau_r}$) are the time steps where the resampling is conducted, $\{X_n(t)\} (n = 1, 2, \dots, N)$ denotes an ensemble of N trajectories, $A(\{X_n(t)\})$ is the target observable (i.e., a function that maps for each trajectory the state vector to a single scalar), R_i is a normalization term and k is a biasing parameter that controls the strength of the selection. The sign of k determines whether trajectories with extremely positive or extremely negative anomalies are oversampled. The case $k = 0$ would be close to a regular simulation, i.e., neither positive nor negative anomalies of an observable would be systematically oversampled. The killing-cloning procedure is performed in such the way that the total ensemble size remains constant after each cloning event. After the resampling, each trajectory is slightly perturbed by adding a small random noise field just before running the next resampling time, in order to allow the clones to evolve differently. When the final time of the simulation is reached, one last resampling is performed and an effective ensemble is reconstructed by attaching at each resampling event from the end to the beginning of the simulations the ancestors to the pieces of surviving trajectories. All trajectories that did not survive until the end of the simulation are discarded. The rationale behind this method is that if τ_r is not larger than the decorrelation time of the observable, then the selection will favor the survival of trajectories leading to extreme anomalies of the time-average of the target observable.

As described in Ragone et al. [2018] and Ragone and Bouchet [2020], one obtains for a large ensemble size N the importance sampling formula

$$\mathbb{P}_k(\{X_n(t)\}_{0 \leq t \leq T_a}) \underset{N \rightarrow \infty}{\sim} \frac{e^{k \int_0^{T_a} A(\{X_n(t)\}) dt}}{\mathbb{E}_0[e^{k \int_0^{T_a} A(\{X_n(t)\}) dt}] \mathbb{P}_0(\{X_n(t)\}_{0 \leq t \leq T_a})}, \quad (1.8)$$

where $\mathbb{P}_0(\{X_n(t)\}_{0 \leq t \leq T_a})$ and $\mathbb{P}_k(\{X_n(t)\}_{0 \leq t \leq T_a})$ are the probability densities of trajectories in the standard ensemble simulation and in an ensemble simulation generated with the algorithm and $\mathbb{E}_0$ is the expectation value with respect to $\mathbb{P}_0$. Thanks to Equation (1.8), the expectation value according to $\mathbb{P}_0$ (the real statistics of the system) of a generic

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quantity $O(\{X_n(t)\}_{0 \leq t \leq T_a})$ can be estimated from data generated with the algorithm (which are instead distributed according to $\mathbb{P}_k$) as

$$\mathbb{E}_0[O(\{X_n(t)\}_{0 \leq t \leq T_a})] \underset{N \rightarrow \infty}{\sim} \frac{1}{N} \sum_{n=1}^N Z_k e^{-k \int_0^{T_a} A(\{X_n(t)\}) dt} \cdot O(\{X_n(t)\}_{0 \leq t \leq T_a}), \quad (1.9)$$

where the constant factor $Z_k = \prod_{i=1}^{T_a/\tau_r} R_i$ converges in the limit of large N ($N \rightarrow \infty$) to the denominator of Equation (1.8) as explained in the Supplementary Information of Ragone et al. [2018] and Ragone and Bouchet [2021]. Equation (1.9) shows that statistical quantities like composites, probabilities or return times with respect to the real model statistics can be estimated with data generated by the algorithm by weighting the contribution of each trajectory to sample averages by the inverse of the exponential factor which appears in the importance sampling formula. We refer to the Chapters 2-4 for a detailed description of the computation of composites, return times, probabilities and the construction of confidence intervals around statistical estimates.

1.3.3 Pseudocode description of the rare event algorithm

We here provide a pseudocode description of how we apply the Giardina-Kurchan-Lecomte-Tailleur rare event algorithm to climate model ensemble simulations. As an example, we illustrate in the following the implementation of the rare event algorithm into the environment of the European community Earth-System-Model version 3 (Döscher et al. [2022]; see section 1.4 for more details about the models used for this thesis):

```
#####
#### 1. PARALLELIZATION OF THE SIMULATIONS AND ALLOCATED COMPUTING RESOURCES ####
#####

#!/bin/bash

#SBATCH --job-name=ANV2
#SBATCH --time=24:00:00
#SBATCH --nodes=12
#SBATCH --ntasks=1440
#SBATCH --ntasks-per-node=120
#SBATCH --qos=np
#SBATCH --account=spberago
#SBATCH --mem=0
#SBATCH --output=ANV2_BX1_BX2.out
#SBATCH --error=ANV2_BX1_BX2_err.out

## We run each EC-Earth3 model trajectory on 360 CPUs:
## IFS: 240 CPUs - NEMO: 118 CPUs - RUNOFF-MAPPER: 1 CPU - XIOS: 1 CPU

## We run 4 trajectories in parallel. This means that one "batch" consisting
## out of 4 trajectories requires at least 360 CPUS/traj * 4 traj = 1440 CPUs.
## One node on "Atos" typically contains 128 or 256 CPUs/cores. Therefore,
## reserving 12 nodes implies reserving up to 3072 CPUs even though the model
## itself is run on 1440 CPUs. This is, however, necessary to avoid memory issues.

## We run a total of N = 300 trajectories per ensemble. Consequently, one ensemble
## experiment requires to run 75 batches with 4 trajectories per batch.

#####
#### 2. INITIALIZATION OF THE ENSEMBLE AT THE BEGINNING OF THE SIMULATION ####
#####

PROGRAM create_inits(expname)

  GET restart_ice.nc restart_oce.nc (NEMO restart files)
  GET rstas.nc rstos.nc (OASIS restart files)
  GET ICMGG${expname}INIT ICMGG${expname}INIUA ICMH${expname}INIT
    (IFS initial condition files)

  FOR traj = 1 TO ${ntrajs} DO
    PERTURB amplitudes of the spherical harmonics of natural logarithm of
      surface pressure in ICMH${expname}INIT
    SAVE ICMH${expname}INIT_PERTURBED_${traj}
  END FOR
```

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```
#####
#### 3. SEQUENTIALLY RUN THE MODEL FOR BLOCKS OF THE LENGTH OF THE RESAMPLING ####
#### TIME AND APPLY THE RESAMPLING OF THE GKLT ALGORITHM AFTER EACH BLOCK ####
#####

PROGRAM run_model(k,dt,taur,observable,ntrajs=300,endblock=43,
                 endbatch=75,ntrajspersbatch=4,ntasks=360,nodes=3)

  WHILE block <= ${endblock}

    FOR traj = 1 TO ${ntrajs} DO
      PERTURB amplitudes of the spherical harmonics of natural logarithm of
              surface pressure in ICMSH${expname}INIT_${traj}.${block}
    END FOR

    SET batch = 1
    WHILE batch <= ${endbatch}

      CALCULATE starttraj = ${batch} - 1
      CALCULATE starttraj = ${starttraj} * ${ntrajspersbatch} + 1
      CALCULATE endtraj = ${batch} * ${ntrajspersbatch}

      SET traj = ${starttraj}
      WHILE traj <= ${endtraj}

        RUN the model for all four trajectories within the given batch:
        /usr/bin/time srun --mem=0 --kill-on-bad-exit=1 --ntasks=${ntasks}
                        --nodes=${nodes} -l --multi-prog conf.txt &

      END WHILE

      MOVE all files related to the current four runs
        (e.g. output, restart and log files) into desired directories
    END WHILE

    CALCULATE nc = CALL REA_WEIGHTS(${ntrajs},${k},${dt},${taur},${observable})
    CALCULATE nc = CALL REA_NUM_REPLICATES(${ntrajs},${nc})
    CALL REA_PREPARE_NEXTINITS(${ntrajs},${nc})

  END WHILE
```

```
#####
#### 4. FUNCTION TO COMPUTE THE WEIGHTS FOR THE RARE EVENT ALGORITHM ####
#####

FUNCTION REA_WEIGHTS(ntrajs,k,dt,taur,obs)

  ## INITIALIZE ARRAYS
  DECLARE ARRAY obs[ntrajs,taur] ## observable
  DECLARE ARRAY obsint[ntrajs] ## time-integral of observable
  DECLARE ARRAY W[ntrajs] ## weights
  DECLARE ARRAY w[ntrajs] ## normalized weights
  DECLARE ARRAY nc[ntrajs] ## integer version of normalized weights

  ## COMPUTATION OF EXPONENTIAL WEIGHTS
  for traj = 1 TO ntrajs DO
    CALCULATE obsint[traj] = SUM(obs[traj,:]*dt)
    CALCULATE W[traj] = EXP(k*obsint[traj])
  END FOR
  CALCULATE R = SUM(W)/ntrajs
  CALCULATE w = W/R

  ## TAKE THE INTEGER OF THE EXPONENTIAL WEIGHTS
  FOR traj = 1 TO ntrajs DO
    CALCULATE nc[traj] = INTEGER( w[traj] + RANDOM_UNIFORM(0,1) )
  END FOR

  RETURN nc
```

```
#####
#### 5. FUNCTION TO ADJUST THE NUMBER OF REPLICATED TRAJECTORIES IN SUCH A #####
#### WAY THAT THE ENSEMBLE SIZE REMAINS CONSTANT AFTER A RESAMPLING EVENT #####
#####

FUNCTION REA_NUM_REPLICATES(ntrajs,nc)

  ## COMPUTE THE THEORETICAL ENSEMBLE SIZE (Nc) AFTER A RESAMPLING EVENT
  CALCULATE Nc = SUM(nc)
  CALCULATE dN = Nc - ntrajs

  DECLARE ARRAY label[ntrajs]
  FOR traj = 1 TO ntrajs DO
    SET label[traj] = traj
  END FOR

  ## IF ENSEMBLE SIZE SMALLER THAN ntrajs: RE-CLONE SURVING TRAJECTORIES UNTIL
  ## THE ORIGINAL ENSEMBLE SIZE IS REACHED
  IF dN < 0 THEN
    DECLARE ARRAY traj2clone[INTEGER(-dN)]
    CALCULATE p = nc/SUM(nc)
    FOR traj = 1 TO INTEGER(-dN) DO
      traj2clone[traj] = RANDOM_CHOICE(label,p)
    END FOR
    FOR traj = 1 TO INTEGER(-dN) DO
      CALCULATE nc[INTEGER(traj2clone[traj])] = nc[INTEGER(traj2clone[traj])] + 1
    END FOR
  END IF

  ## IF ENSEMBLE SIZE LARGER THAN ntrajs: KILL SURVING TRAJECTORIES UNTIL
  ## THE ORIGINAL ENSEMBLE SIZE IS REACHED
  IF dN > 0 THEN
    DECLARE ARRAY traj2kill[INTEGER(dN)]
    FOR traj = 1 TO INTEGER(dN) DO
      CALCULATE p = nc/SUM(nc)
      traj2kill[traj] = RANDOM_CHOICE(label,p)
      CALCULATE nc[int(traj2kill[traj])] = nc[int(traj2kill[traj])] - 1
    END DO
  END IF
  RETURN nc
#####

#### 6. FUNCTION TO ASSIGN THE POST-RESAMPLING INITIAL CONDITIONS FOR #####
#### THE SIMULATION OF THE NEXT BLOCK #####
#####

FUNCTION REA_PREPARE_NEXTINITS(ntrajs,nc)

  DECLARE ARRAY killedlabel[ntrajs]
  FOR traj = 1 TO ntrajs DO
    IF nc[traj] > 0 THEN
      SET killedlabel[traj] = 0
    ELSE
      SET killedlabel[traj] = 1
    END IF
  END DO

  DECLARE ARRAY initlabel[ntrajs]
  DECLARE ARRAY udkilledlabel[ntrajs]
  SET udkilledlabel = killedlabel
  FOR traj = 1 TO ntrajs DO
    SET initlabel[traj] = traj
  END DO

  FOR traj = 1 TO ntrajs DO
    IF nc[traj] > 1:
      FOR n = 1 TO INTEGER(nc[traj]) DO
        SET p = udkilledlabel/SUM(udkilledlabel)
        SET traj2substitute = RANDOM_CHOICE(label,p)
        SET initlabel[INTEGER(traj2substitute)] = traj
        SET udkilledlabel[int(traj2substitute)] = 0
      END FOR
    END IF
  END FOR

  FOR traj = 1 TO ntrajs DO
    COPY restart/initial condition file for a given trajectory into
    desired trajectory
  END FOR
#####
```

1.4 The Planet Simulator and the European community Earth-System-Model version 3

Weather and climate models numerically represent the dynamics and physical processes that occur in the climate system. Their applications are versatile, including deterministic and probabilistic weather forecasts and climate predictions, climate projections and the reconstruction of past climate states, e.g. for paleoclimate studies or for the development of reanalysis products. Weather and climate models are also used for attribution studies, process understanding through dedicated sensitivity experiments (prescribed forcings and/or variables) and by providing substantially larger data sets than available from observations, i.e., through large ensembles and long stationary control runs. In general, models of different complexity are used for different scientific purposes [Claussen et al., 2002; Goosse, 2015, pp. 73-133]. The model hierarchy ranges from conceptual models, such as energy balance and box models, over Earth system models of intermediate complexity (EMICs) to comprehensive general circulation and Earth system models. The term "complexity" thereby refers to the number and detail of description of processes included in the model and to the number of interacting components of the climate system that are explicitly described in the model.

In this project, we work both with an intermediate complexity climate model, the Planet Simulator [Fraedrich et al., 2005] coupled to a dynamic Large-Scale Geostrophic ocean [Maier-Reimer et al., 1993] (referred to as "PlaSim-LSG"), a mixed-layer ocean model and a zero-layer thermodynamic sea ice model [Semtner, 1976], and with the comprehensive CMIP6-generation European community Earth-System-Model version 3 (EC-Earth3) [Döscher et al., 2022] (repository tag 3.3.1 in the EC-Earth development portal for members of the consortium: <https://www.ec-earth.org>). PlaSim-LSG is suitable of the first part of this thesis as its intermediate complexity allows to run large ensembles within a reasonable amount of time and computational cost. It is therefore an efficient tool to develop appropriate strategies to apply the rare event algorithm to study extremes of Arctic sea ice reduction. Despite its intermediate complexity, PlaSim-LSG produces a reasonably realistic present-day climate, especially in the northern hemisphere [Angeloni, 2022]. This model therefore allows to gain an understanding of the most relevant thermodynamic processes and time scales governing the sea ice lows. Further applications for which PlaSim-LSG has been used include aquaplanet and paleoclimate studies [Hertwig et al., 2014; Andres and Tarasov, 2019], a study on the linkage between high-latitude precipitation and low-frequency variability of the Atlantic Meridional Overturning Circulation (AMOC) [Mehling et al., 2023], a study on weakening and collapse of the AMOC [Cini et al., 2024], and a study on extreme European winter rainfall [Wouters et al., 2023].

In the following, we give a short summary of the model set-ups used in the project and discuss the basic climate states produced by the two models. We refer to section 2.2.1 of Chapter 2 for more technical details about the PlaSim-LSG climate model and to section 4.2.1 of Chapter 4 for more details about the EC-Earth3 climate model.

1.4.1 Set-up of the PlaSim-LSG and EC-Earth3 climate models

Set-up of PlaSim-LSG: The atmosphere is run with a horizontal spectral resolution of T21 (triangular truncation at wavenumber 21 $\sim 5.625^\circ \times 5.625^\circ$ on the corresponding Gaussian grid), ten non-equally spaced sigma-levels up to about 40 hPa in the vertical and a numerical time step of 45 minutes. The LSG is run with a $2.5^\circ \times 5^\circ$ staggered E-type grid [Arakawa and Lamb, 1977] in the horizontal, with 22 levels in vertical and with a numerical time step of 5 days. The computational time steps of the mixed-layer ocean and sea ice models are one day. The thermodynamic sea ice model is based on the zero-layer model of Semtner [1976] and computes the evolution of the sea ice thickness and surface temperature from the energy balances at the top and bottom of a sea ice-snow layer. The sea ice-snow layer is assumed to have a linear temperature gradient and to have no capacity to store heat. The sea ice concentration is binary, i.e., either a grid cell is fully sea ice covered or open water.

As described in Angeloni [2022], a vertical oceanic diffusion coefficient, Av , is used to parameterize turbulent motions in LSG. Following Bryan and Lewis [1979], Av is computed as

$$Av(z) = a^* + a_{range} \arctan[\lambda(z - z^*)], \quad (1.10)$$

where the vertical diffusion coefficient at a reference depth z^* is given by a^* , the considered depth range from the surface to the bottom is described by a_{range} , and λ is the rate at which the vertical diffusion coefficient varies with depth near z^* . The chosen values of these parameters substantially impact the Atlantic Meridional Overturning Circulation [Angeloni, 2022] and, consequently, are highly relevant for the representation of Arctic climate and sea ice. For our simulations, we set $a^* = 0.8714 \cdot 10^{-4} \text{ m}^2 \text{ s}^{-1}$, $a_{range} = 0.2843 \cdot 10^{-4} \text{ m}^2 \text{ s}^{-1}$, $\lambda = 4.5 \cdot 10^{-3} \text{ m}^{-1}$ and $z^* = 2500 \text{ m}$.

Set-up of EC-Earth3: We run EC-Earth3 in the basic atmosphere-ocean physical model configuration. The atmospheric component consists of the cycle 36r4 Integrated Forecast System (IFS, [European Center for Medium Range Forecast, 2010]) and includes the H-TESSEL land-surface scheme [Balsamo et al., 2009]. The ocean is given by the Nucleus for European Modelling of the Ocean (NEMO; [Madec et al., 2008]) version 3.6, including the Louvain-la-Neuve (LIM3; [Vancoppenolle et al., 2012]) sea ice model. Field exchanges between the ocean and the atmosphere are governed by the OASIS3-MCT [Valcke, 2013] coupler version 3.0. The atmosphere is run with a horizontal resolution of T255 (i.e. triangular truncation at wavenumber 255 in spectral space, corresponding to a spacing of about 80 km), 91 levels up to 0.01 hPa in the vertical and a numerical time step of 45 minutes. The sea ice-ocean is configured on the tripolar ORCA1L75 grid, corresponding to an average horizontal resolution of $1^\circ \times 1^\circ$ and 75 vertical levels. The numerical time step of the sea ice-ocean is 45 minutes. The LIM3 model applies an sea ice thickness distribution framework to represent metre-scale variations in the sea ice thickness [Rousset

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et al., 2015]. This allows to account for the non-linear dependence of sea ice processes, in particular growth and melt, on the sea ice thickness. The present set-up includes five sea ice thickness categories with upper sea ice thickness boundaries at 0.454, 1.129, 2.141, 3.671 and 99 metres.

Forcing, pan-Arctic sea ice area and available simulations: All simulations with PlaSim-LSG and EC-Earth3 are run with constant greenhouse gas conditions and solar forcing as we are interested in the statistics and dynamics of Arctic sea ice lows related to internal climate variability under a stationary climate. This choice allows to avoid mixing signals from externally forced variability and internally generated variability. For PlaSim-LSG, we prescribe a fixed pre-industrial effective CO₂ volume mixing ratio of 280 ppmv. In EC-Earth3, year-2000 greenhouse gas conditions are prescribed (CO₂ volume mixing ratio of 369 ppmv). We choose these two values of greenhouse gas concentrations since we are interested in studying the drivers of present-day sea ice lows. For these two selected greenhouse gas forcings, both models produce a basic large-scale Arctic sea ice state that is representative of present-day conditions (see section 1.4.2). In the project, we produce a stationary 3000-year control run with PlaSim-LSG (Figure 2.1), a 250-year stationary control run with EC-Earth3 (Figure 4.1) and a set of control and rare event algorithm ensemble simulations with both of these two models (Chapters 2-4). We consider the statistics of the pan-Arctic sea ice area

$$A(t) = \sum_{\phi \geq \phi_{min}} \sum_{\lambda} SIC_{\phi,\lambda}(t) \cdot G_{\phi,\lambda}, \quad (1.11)$$

where $SIC_{\phi,\lambda}(t)$ is the sea ice concentration at time t in a grid cell centered at latitude ϕ and longitude λ . In EC-Earth3, the grid cell area $G_{\phi,\lambda}$ is provided by the architecture of the model. In PlaSim-LSG, instead, we compute the grid cell area as $G_{\phi,\lambda} = \int_{\phi-\frac{\Delta\phi}{2}}^{\phi+\frac{\Delta\phi}{2}} \int_{\lambda-\frac{\Delta\lambda}{2}}^{\lambda+\frac{\Delta\lambda}{2}} R^2 \cos(\phi') d\lambda' d\phi'$, where R is the earth radius, $\Delta\phi$ and $\Delta\lambda$ are the angular distances between two grid points in the meridional and zonal direction. The summation in Equation (1.10) includes all ocean grid boxes north of 40°N. The land-sea mask is binary (i.e. a grid cell is either completely ocean or land) in both models.

1.4.2 Representative climate conditions in PlaSim-LSG and EC-Earth3

Pan-Arctic sea ice area, sea ice concentration and sea ice thickness: For the above-mentioned greenhouse gas forcings, both the PlaSim-LSG and EC-Earth3 annual mean and late summer pan-Arctic sea ice area are representative of the observed 1979-2015 mean Arctic sea ice climatology (cf. Figure 2.1(a,c), Figure 4.1, Figure A1). In terms of spatial distribution, EC-Earth3 reasonably represents the observed 1979-2015 average late summer sea ice concentration (Figure 1.3(b,c)) and the 1979-2015 average late winter mean and annual mean sea ice thickness fields available from the Pan-Arctic Ice Ocean Modeling and Assimilation System [Zhang and Rothrock, 2003] (PIOMAS; cf. Figure 1.3(e-f), Figure 4.1, page 207 of Chevallier et al. [2019] and page 328 of Massonnet et al.

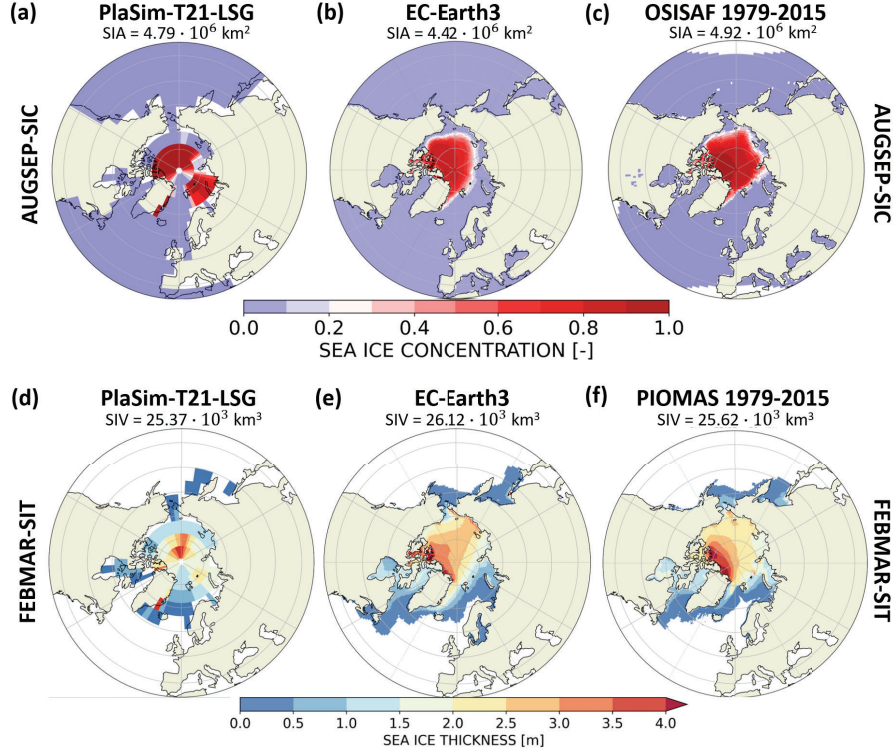


Figure 1.3: (a-c) August-September mean sea ice concentration and (d-f) February-March mean sea ice thickness for (a,d) the 3000-year PlaSim-LSG control run, (b-e) the 250-year EC-Earth3 control run and (c) OSI SAF for the period 1979-2015 (product ID: OSI-450) [EUMETSAT Ocean and Sea Ice Satellite Application Facility, 2017] and (f) PIOMAS for the period 1979-2015 [Zhang and Rothrock, 2003].

[2026]). Differences in the representation of gridded sea ice in PlaSim-LSG compared to observations and PIOMAS include a positive late summer sea ice concentration (SIC) bias from the Greenland to the Kara Sea, a negative late summer SIC bias western of Greenland, and positive late winter sea ice thickness biases around the North Pole and from the Greenland to Kara seas (Figure 1.3(a,c,d,f)). While overall the differences between the pan-Arctic sea ice area in PlaSim-LSG and in observational data are small compared to the range of sea ice area values available from the Coupled Model Intercomparison Project 6 (CMIP6) models [Notz and Community, 2020], the regional sea ice thickness and sea ice concentration biases of PlaSim-LSG compared to the derived 1979-2015 climatologies may impact the interpretation of the results. This point is discussed in section 3.4 of Chapter 3 and in Chapter 5.

Persistence and reemergence of pan-Arctic sea ice area anomalies: As described in section 1.2.1, the memory properties of the sea ice provide one key source of predictability

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of the sea ice area in the Arctic. The persistence of the anomalies of a certain target observable, e.g. the pan-Arctic sea ice area, is also a crucial property required for the reasonable application of the Giardina-Kurchan-Lecomte-Tailleur rare event algorithm. To illustrate this, let us assume that the memory of the target observable was lost for all non-zero time lags (e.g. a white noise process), or at least that the decorrelation time of the target observable was substantially smaller than the chosen resampling time τ_r used with the algorithm. Under these circumstances, the desired property of replicated trajectories to favor the development of extreme anomalies of the time-average of the observable would get lost within the period between two consecutive resampling events. Consequently, the rare event algorithm would not shift the distribution of the time-averaged observable towards the extremes.

We apply an autocorrelation function analysis to the pan-Arctic sea ice area of the PlaSim-LSG control run to verify whether this model, despite its intermediate complexity, captures the main sea ice memory properties known from observations and from comprehensive climate models (cf. Figure 1.5 and Blanchard-Wrigglesworth et al. [2011]; Day et al. [2014]). For a stationary stochastic process $\{X_t : t \in \mathbb{Z}\}$ with time t , the autocorrelation function can be defined as

$$r(\tau) = \frac{\mathbf{E}[(X_t - \mu) \cdot (X_{t+\tau} - \mu)]}{\mathbf{E}[(X_t - \mu)^2]}, \quad (1.12)$$

where $\tau \in \mathbb{Z}$ is time lag, $\mathbf{E}[\cdot]$ is the expectation operator and $\mu = \mathbf{E}[X_t]$ the mean value of X_t that does not depend on t under the assumption of a stationary process [von Storch and Zwiers, 1999, p. 217]. In the application to the pan-Arctic sea ice area, however, the assumption on stationarity is not valid as both the mean and the standard deviation of the sea ice area and also the persistence of sea ice area anomalies itself depend on the timing during the year [Chevallier et al., 2019]. We therefore compute the autocorrelation function as

$$r_t(\tau) = \frac{\mathbf{E}[(X_t - \mu_t) \cdot (X_{t+\tau} - \mu_{t+\tau})]}{\sqrt{\mathbf{E}[(X_t - \mu_t)^2]} \sqrt{\mathbf{E}[(X_{t+\tau} - \mu_{t+\tau})^2]}}, \quad (1.13)$$

where the parameter μ is computed for each calendar day (for daily data) or calendar month (for monthly data) of the year and r_t depends on the initialization time of the autocorrelation function.

We present in Figure 1.4(a) an average estimate of the autocorrelation function over all initialization times during the year (daily data) to obtain a generic estimate of the persistence of sea ice area anomalies in PlaSim-LSG. To account for a potential effect of low-frequency variability on this estimate, we thereby apply the autocorrelation function both to sea ice area anomalies relative to a fixed day-of-year dependent mean ("ORIGINAL DATA" in Figure 1.4(a)) and to sea ice area anomalies that are computed relative to a day-of-year dependent 31-year running mean ("DATA HIGH-PASS FILTERED BY 31-YEAR RUNNING MEAN"). For the unfiltered data, the autocorrelation function drops for the first time below $1/e$ after about 75 days, whereas the e-folding time for the high-pass filtered data is approximately 45 days (Figure 1.4(a)). Consequently, the decorrelation

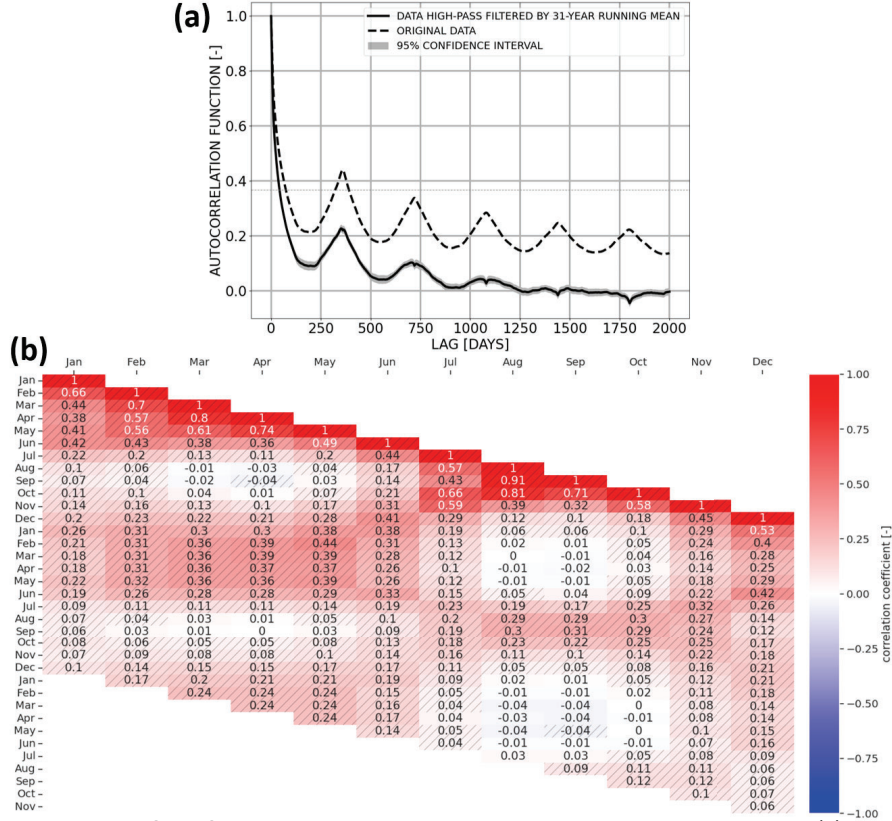


Figure 1.4: PlasiSim-LSG 3000-year control run: autocorrelation function applied to (a) daily pan-Arctic sea ice area anomalies relative to (dashed black line) a fixed climatology and (solid) a 31-year running mean. (b) Lagged correlations applied to monthly mean pan-sea ice area anomalies relative to a 31-year running mean with increasing lag from top to bottom up to a lag of 23 months. (a) Shading shows the 95% confidence interval and (b) hatching denotes statistical significance at the 5% level. To obtain the error bars, we subdivide the 3000-year control run into 100 blocks of 30 years and use the central limit theorem to derive the 95% confidence interval from 100 estimates of the autocorrelation function (i.e. $\pm 1.96 \cdot \sigma / \sqrt{N}$ with $N = 100$ and σ denoting the standard deviation over the 100 estimates).

time of pan-Arctic sea ice area anomalies in PlasiSim-LSG is consistent with the lower range of persistence time scales obtained from observations and comprehensive climate models [Blanchard-Wrigglesworth et al., 2011; Day et al., 2014; Massonnet et al., 2026, pp. 327-331]. It is therefore sufficiently well represented for the purpose of the first part of the project. According to Figure 1.4(a), the memory of sea ice area is largely lost after a time lag of about five years. This information is relevant for the selection of independent initial conditions for the construction of the ensembles in Chapter 2.

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Figure 1.4(b) shows for each initialization month of the year the values of the autocorrelation function applied to high-pass filtered (31-year running mean) monthly mean sea ice area anomalies for a lag of up to 23 months (from top to bottom; note that exactly the same analysis as in Figure 1.4(b), but applied to data without high-pass filtering, can be found in the Supplementary Figure B1). PlaSim-LSG captures the main properties of sea ice memory known from comprehensive climate models, including a spring predictability barrier-like structure in the persistence of pan-Arctic sea ice area anomalies and a growth-to-melt season reemergence of sea ice area anomalies (cf. Figure 1.4(b), Blanchard-Wrigglesworth et al. [2011] and Day et al. [2014]). While the former is evident from the fact that July sea ice area anomalies are substantially more persistent than the ones in May, the latter manifests by the fact that September (August, July) sea ice area anomalies are more connected to September (October, November) sea ice area anomalies one year before than to the ones at lead times of only a few months (Figure 1.4(b)). Apart from the growth-to-melt season reemergence, PlaSim-LSG displays a melt-to-growth season reemergence of sea ice area anomalies. This is manifested by the fact that sea ice area anomalies in March (April, May, June) are significantly correlated with the sea ice area anomalies during the subsequent autumn-winter, but not with the ones in September of the same year (Figure 1.4(b)). Figure 1.4(b) indicates that the secondary maximum of lagged correlations is particularly pronounced between two consecutive annual sea ice maxima (around March) and between two consecutive annual sea ice minima (around September), substantially contributing to the re-emerging peaks in the values of the autocorrelation function for time lags of about 360 days in Figure 1.4(a).

1.5 Thesis goals, methods and research questions

Possible drivers of extremes of Arctic sea ice reduction, such as observed in the summers of 2007 and 2012, have been suggested in the literature [e.g. Lindsay et al., 2009; Kauker et al., 2009; Zhang et al., 2008, 2013; Parkinson and Comiso, 2013; Kirchmeier-Young et al., 2017]. These drivers are, like many compound climate extremes [Zscheischler et al., 2018], multi-factorial and include sea ice-ocean preconditioning, oceanic heat transport, large-scale atmospheric circulation variability and synoptic-scale storms. However, the precise relative contributions of these different factors to extremes of sea ice reduction and the seasonal predictability of these events remain elusive, in large part due the lack of robust statistics of rare events in observations and simulations with complex numerical models. A better understanding of the precursors of extremes of summer Arctic sea ice reduction and a more precise estimate of their probabilities are crucial to improve seasonal predictions of these events and to assess their risk of occurrence under different climate change scenarios. Likewise, access to an improved statistics of extremes of sea ice reduction can help to better investigate the impacts of these events.

In this project, we apply the Giardina-Kurchan-Lecomte-Tailleur (GKLT) rare event algorithm [Del Moral and Garnier, 2005; Giardina et al., 2011; Ragone et al., 2018; Ragone and Bouchet, 2020, 2021] (introduced in section 1.3.2) to ensemble simulations with the

coupled climate models Planet Simulator (PlaSim) [Fraedrich et al., 2005] and the European community Earth-System-Model version 3 (EC-Earth3) [Döscher et al., 2022] to investigate extremely negative summer and late-summer pan-Arctic sea ice area anomalies under present-day climate conditions. The GKL algorithm is designed to improve the sampling of time-persistent extremes [Ragone and Bouchet, 2020] and is therefore suited to study extremes of Arctic sea ice reduction. Taking advantage of the improved statistics provided by the algorithm, we estimate the probabilities of extreme sea ice lows and we perform a quantitative statistical analysis of the physical drivers of these events. The aim is to better understand the relative importance of winter-spring sea ice-ocean preconditioning vs. spring-summer thermodynamic and dynamic processes in favoring extremely low late summer sea ice states. Finally, we are interested in the probability of ultra-rare but high impact events, including sea ice area anomalies larger in magnitude than observed in 2012 and events with a total disappearance of Arctic sea ice for one year under current climate conditions.

The substantially different model complexities between PlaSim and EC-Earth3 defines two consecutive project phases that structure the manuscript accordingly. PlaSim, including a dynamic Large-Scale Geostrophic (LSG) ocean, a mixed-layer ocean model and a zero-layer thermodynamic sea ice model, is suitable for the first project phase as its intermediate complexity allows to conduct large ensemble simulations at reasonable computational cost and time. On the one hand, this model produces a climate state that is realistic enough to gain a general understanding of the large-scale thermodynamic processes and time scales being relevant for extreme Arctic sea ice reduction (see section 1.4). On the other hand, it provides an efficient tool to investigate different rare event algorithm parameters with respect to the increase in the sampling efficiency of events with extremely low pan-Arctic sea ice area. Setting-up ensemble simulations with the rare event algorithm requires the choice of the following parameters and quantities:

- The value of the **biasing parameter** k can be chosen to improve the sampling efficiency of rare dynamical trajectories leading to a certain range of extreme event amplitudes. A reasonable order of magnitude of this value can be derived from the (instantaneous) standard deviation and decorrelation time of the target observable using a scaling argument presented in Ragone and Bouchet [2020] and in the Supplement of Ragone and Bouchet [2021]. The precise value of k , however, is chosen empirically.
- The precise value of the **resampling time** τ_r is chosen empirically, but a reasonable order of magnitude of this parameter is given by the decorrelation time of the dynamics that cause the extremes of the target observable. If τ_r is not larger than the decorrelation time of the dynamics, the resampling will favor the survival of trajectories leading to extreme events characterized by time-persistence of large anomalies of the target observable.
- The empirically chosen **ensemble size** N requires a trade-off between avoiding too large computational resources and avoiding a large level of degeneracy. A large level of degeneracy means that the effective ensemble is effectively shrunk to one or a very few ensemble members that are only distinguishable in a small last part of a simulation [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021]. In that case, the very few independent ensemble members would not allow for a quantitative statistical

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analysis of the drivers of extreme sea ice lows. While the rare event simulations with PlaSim-LSG presented in Chapters 2 and 3 are performed with $N = 600$ trajectories, the rare event simulations with EC-Earth3 presented in Chapter 4 demonstrate that an ensemble size of $N = 300$ trajectories is sufficient to quantitatively study extremes of Arctic sea ice reduction.

- The aim of this project is to study extremely negative anomalies of the pan-Arctic sea ice area. Consequently, an intuitive choice of the **target observable** is to use the pan-Arctic sea ice area itself. Chapter 4, however, suggests that using the pan-Arctic sea ice volume as an observable is likely more efficient in sampling low states of the late summer sea ice area than using the sea ice area as the observable itself.

The project addresses two complementary approaches of using the rare event algorithm. In Chapter 2, ensemble simulations with the rare event algorithm are initialized from statistically independent initial conditions sampled from a 3000-year control run using PlaSim-LSG. This approach allows to oversample the areas of the phase space where extreme events in an absolute sense are. Extremes are therefore sampled from unconditional probability distributions and probabilities can be interpreted as absolute probabilities. In this Chapter 2, we investigate extremely negative anomalies of the pan-Arctic sea ice area on average over the entire simulation period between February and September (i.e. seasonally averaged over the melting or extended summer season between February and September). For this specific application, the February-September time-averaged sea ice area corresponds to the target quantity for which the rare event algorithm is specifically designed to improve the sampling of the extremes [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021]. In this context, we compare the statistics of extremely negative sea ice area anomalies between rare event simulations performed with a resampling time of $\tau_r = 5$ days vs. a resampling time of $\tau_r = 30$ days. In contrast to the latter, the former is not larger than the persistence time scale of the large-scale atmospheric circulation and is only slightly larger than the typical persistence of synoptic-scale atmospheric fluctuations [Hoven, 1957]. The ensembles with a resampling time of $\tau_r = 5$ days are therefore designed to efficiently sample extremely low sea ice states both due to anomalies in the oceanic thermal state and due to anomalies in the atmospheric circulation that are in the order of or larger than the upper range of the synoptic time scale. In contrast, the experiments with a resampling time of $\tau_r = 30$ days are primarily designed to improve the sampling efficiency of extremely low sea ice states related to 1) oceanic drivers and 2) anomalously persistent atmospheric drivers such as for example an one month long persistent negative phase of the summer Arctic Oscillation.

In Chapter 3, the ensemble simulations with the rare event algorithm are initialized from slightly perturbed identical initial conditions selected from the PlaSim-LSG 3000-year control run. This approach allows to oversample areas of the phase space populated by extreme events conditional on starting from that initial state. As in Chapter 2, the ensembles are initialized on 01 February and run until the end of September. The algorithm is therefore again designed to improve the sampling of extremely negative February-September mean sea ice area anomalies. The high correlation (in the order of 0.9) between the February-September and late summer (August-September) mean sea

ice area values in the single initial condition control ensembles, however, imply that this approach also allows to improve the sampling of extremely negative sea ice area anomalies during the annual sea ice minimum.

The approach used in Chapter 3 corresponds to a seasonal climate prediction setup, allowing to quantify the probability of observing an extreme late summer sea ice low as a function of a given initial winter sea ice-ocean state, and to study the physical processes and conditions favoring an extreme pan-Arctic sea ice area reduction within one single melting season. While the choice of the initial condition may impact the variance of late summer sea ice area and therefore the amplitudes of the extremes [Goosse et al., 2009], the triggers of extremes of sea ice area reduction are entirely attributable to processes acting on time scales of less than one melting season. This is different compared to the approach used in Chapter 2 where both multi-annual variability, including a possible feedback of the atmosphere to long oceanic time scales, and sub-seasonal weather variability may contribute to anomalously low sea ice states.

Regarding Chapter 4, we implement the rare event algorithm into the EC-Earth3 environment and apply the seasonal climate prediction setup approach to this model. In this context, we consider two sets of control and rare event algorithm ensemble simulations initialized from two different initial sea ice-ocean states (simulation period 01 March - 01 October; ensemble size $N = 300$ trajectories). In one of these two experiments, called "SI-NEUTRAL", the ensembles are initialized from a winter state where the sea ice thickness is approximately representative of the 1979-2015 mean winter sea ice thickness available from PIOMAS. As described in Chapter 4, the standard deviation of late summer sea ice area in the SI-NEUTRAL control ensemble is representative of the observed late summer sea ice area variability around a linear trend both fitted to the period 1979-2015 and to the period 1979-2025. Regarding the second experiment, called "SI-LOW", we use "anomaly initialization" [Tian et al., 2021] to add to the initial condition of the SI-NEUTRAL experiment on a grid point level the observed differences of selected snow-sea ice-ocean variables between 2012 and the 1995-2005 climatology (" $2012 - \text{AVG} < 1995-2005 >$ "). Comparing the statistics of extremely negative late summer sea ice area anomalies between the SI-LOW and SI-NEUTRAL experiments serves to assess the relative contributions of sea ice-ocean preconditioning ("slow drivers") vs. (sub)seasonal weather variability ("fast drivers") to the risk and amplitudes of these extremes. In this context, we discuss a response of the mean vs. variance of the distribution of late summer sea ice area to the changing initial condition. We also provide an estimate of the probability of occurrence of a negative August-September mean sea ice area anomaly larger in magnitude than the observed 2012 August-September mean sea ice area deviation from a linear trend fitted to the period 1979-2025. Finally, we conduct a sea ice volume and sea ice area budget analysis [Holland and Kwok, 2012] to disentangle the roles of thermodynamic vs. dynamic forcing for extremes of intra-seasonal sea ice reduction. The simulations with EC-Earth3 are performed using two different target observables, one is the pan-Arctic sea ice area and the other one is the pan-Arctic sea ice volume.

In summary, we address in this thesis the following three scientific questions:

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- How likely (in a statistical sense) is a 2012-like event under present-day conditions, and what are the physical bounds to the most extreme sea ice reduction in one single melting season?
- What are the precursors of extreme Arctic sea ice lows and how does an extreme become an ultra-rare event?
- What is the relative importance of preconditioning through the winter sea ice-ocean state vs. thermodynamical and dynamical processes during spring-summer?

1.6 Four contributions of the present thesis

In response to the research questions defined in section 1.5, the thesis provides four contributions to better study and understand the drivers, predictability and probabilities of extremes of Arctic sea ice reduction using coupled climate model ensemble simulations:

- We developed appropriate strategies to use the Giardina-Kurchan-Lecomte-Tailleur rare event algorithm to improve the sampling of trajectories leading to extremely low sea ice cover in climate model ensemble simulations. From the technical point of view, we implemented the algorithm into the environment of the EC-Earth3 climate model.
- For the first time and using a comprehensive climate model, we have performed a quantitative statistical analysis of the physical processes and conditions favoring extremely low states of late summer sea ice cover. This helps to better understand the sources and limits of predictability of extreme Arctic sea ice lows.
- Both using PlaSim-LSG and EC-Earth3, we managed to provide an estimate of the probability of a 2012-like intra-seasonal sea ice area reduction under present-day climate conditions. This implies that the method can be useful for attribution studies in the future, i.e., to better quantify the relative contributions of a changing climate vs. internal climate variability to extremes of sea ice reduction. The ability of simulating ultra-rare but high impact events may also be of interest for policy-makers. In contrast to conventional simulation strategies, rare event simulations may help to anticipate the worst-case scenarios that are possible conditional on starting from a known initial state.
- Using two initialized ensemble simulations with EC-Earth3, we provide an order of magnitude of the relative importance of winter sea ice-ocean preconditioning vs. sub-seasonal weather variability for the development of extreme Arctic sea ice lows. This includes a discussion on a possible response of the late summer sea ice area variance to a changing winter sea ice-ocean initial condition. In addition, we perform a sea ice area and sea ice volume budget analysis to assess the relative contributions of thermodynamic vs. dynamic forcing to extremes of intra-seasonal sea ice reduction.

These four contributions are documented in Chapters 2-4. A synthesis of the most relevant results and a description of future perspectives is given in Chapter 5.

Chapter 2

Sampling extremes of seasonally averaged sea ice area from the full phase space using PlaSim-LSG

This chapter is based on the following paper, published in *Climate Dynamics*:

Sauer, J., Demaeyer, J., Zappa, G., Massonnet, F., Ragone, F.: Extremes of summer Arctic sea ice reduction investigated with a rare event algorithm, *Climate Dynamics*, 62, 5219–5237, <https://doi.org/10.1007/s00382-024-07160-y>, 2024.

Abstract

Various studies identified possible drivers of extremes of Arctic sea ice reduction, such as observed in the summers of 2007 and 2012, including preconditioning, local feedback mechanisms, oceanic heat transport and the synoptic- and large-scale atmospheric circulations. However, a robust quantitative statistical analysis of extremes of sea ice reduction is hindered by the small number of events that can be sampled in observations and numerical simulations with computationally expensive climate models. Recent studies tackled the problem of sampling climate extremes by using rare event algorithms, i.e., computational techniques developed in statistical physics to

2. Sampling extremes from unconditional probability distributions using PlaSim-LSG

reduce the computational cost required to sample rare events in numerical simulations. Here we apply a rare event algorithm to ensemble simulations with the intermediate complexity coupled climate model PlaSim-LSG to investigate extreme negative summer pan-Arctic sea ice area anomalies under pre-industrial greenhouse gas conditions. Owing to the algorithm, we estimate return times of extremes orders of magnitude larger than feasible with direct sampling, and we compute statistically significant composite maps of dynamical quantities conditional on the occurrence of these extremes. We find that extremely low sea ice summers in PlaSim-LSG are associated with preconditioning through the winter sea ice-ocean state, with enhanced downward longwave radiation due to an anomalously moist and warm spring Arctic atmosphere and with enhanced downward sensible heat fluxes during the spring-summer transition. As a consequence of these three processes, the sea ice-albedo feedback becomes active in spring and leads to an amplification of pre-existing sea ice area anomalies during summer.

2.1 Introduction

The Arctic sea ice cover has been shrinking since at least the late 1970s [Notz and Marotzke, 2012; Stroeve and Notz, 2018], in large part due to anthropogenic emissions of greenhouse gases [Gregory et al., 2002; Notz and Marotzke, 2012; Stroeve and Notz, 2018; Ding et al., 2017]. On top of the downward trend, internal climate variability contributes to the year-to-year variations and associated extreme events of the annual sea ice minimum in September [Francis and Wu, 2020; Ono et al., 2019].

Extreme Arctic sea ice reduction, such as observed in the summers of 2007 and 2012, may have impacts outside the Arctic Ocean. Studies have suggested a possible influence of sea ice loss on the integrity of the permafrost [Lawrence et al., 2008] and on weather patterns and climate in the mid to high latitudes [Petoukhov and Semenov, 2010; Francis et al., 2009; Francis and Vavrus, 2012; Screen et al., 2018; Petrie et al., 2015; Chripko et al., 2021; Delhayé et al., 2022]. Apart from its effect on the climate system, Arctic sea ice decline leads to increased marine accessibility. This has implications for the opening of trans-Arctic shipping routes, offshore industries, polar ecotourism and the daily life of local communities [Eicken, 2013; Smith and Stephenson, 2013; Lloyd's, 2012].

Possible drivers of extreme summer Arctic sea ice reduction have been suggested in the literature. Both the extreme sea ice lows in 2007 and 2012 were attributed to climate change via preconditioning through the ongoing winter sea ice thinning and to the occurrence of particular weather and climate events [Lindsay et al., 2009; Kauker et al., 2009; Zhang et al., 2008, 2013; Parkinson and Comiso, 2013]. In 2007, sea ice reduction was favoured by enhanced inflow of warm Pacific water through Bering Strait [Woodgate et al., 2010] and by anomalously persistent southerly winds in the Pacific sector associated with the Arctic Dipole (AD) pattern [Wang et al., 2009; Lindsay et al., 2009; Overland et al., 2012; Kauker et al., 2009]. In 2012, a summer storm contributed to enhanced sea ice reduction by leading to increased bottom melt via anomalously strong vertical mixing in the oceanic boundary layer [Guemas et al., 2013; Zhang et al., 2013]. Further possible triggers of anomalously low summer Arctic sea ice area include enhanced North

Atlantic oceanic heat transport [Årthun et al., 2012], the positive and negative phases of the winter and summer Arctic Oscillation (AO) [e.g. Rigor et al., 2002; Ogi et al., 2016], reduced cloudiness during summer [Schweiger et al., 2008], and increased surface downward longwave radiation related to enhanced poleward atmospheric moisture transport during spring [Kapsch et al., 2013, 2019].

Even though different physical drivers have been suggested to contribute to individual extremes of Arctic sea ice reduction, a quantitative statistical analysis of their physical drivers is hindered by the poor sampling of extreme events in observations and in numerical simulations. The record of satellite-based sea ice observations includes only a few annual sea ice minima with orders of magnitude comparable to the ones in September 2007 and 2012 [Fetterer et al., 2017]. Moreover, the large computational cost of state-of-the-art general circulation models makes it unrealistic to run them longer than a few thousands of years and to quantitatively study sea ice extremes with return times of longer than order 10^2 years. Going beyond individual case studies, a generalized analysis of the relative importance of different atmospheric and oceanic precursors of extremes of sea ice reduction remains therefore a challenge. A better understanding of the precursors of extremes of summer Arctic sea ice reduction and a more precise estimate of their probabilities are in turn crucial to improve seasonal predictions of these events and to assess their risk of occurrence under different climate change scenarios.

In this work, we address the problem of computational cost limitations by using a rare event algorithm. Rare event algorithms are computational techniques developed in statistical physics to improve the sampling efficiency of rare events in numerical simulations [e.g. Ragone et al., 2018; Ragone and Bouchet, 2020, 2021]. Compared to conventional numerical simulations with the same computational cost, rare event algorithms enable to increase the number of simulated extreme events by several orders of magnitude. In this way, these techniques allow to reduce the uncertainty of return time estimates and of conditional statistics on extreme events (e.g. composites) compared to conventional simulation strategies, and to generate ultra-rare events that are very unlikely to be observed using direct sampling. Rare event algorithms have been introduced in the 1950s [Kahn and Harris, 1951] and have been used since for a wide range of applications (for an overview and the mathematical analysis see e.g. Del Moral [2004]; Giardina et al. [2011]; Grafke and Vanden-Eijnden [2019]). Recently, some of these techniques have been applied in climate science and in fluid dynamics to study heat waves [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021], midlatitude precipitation [Wouters et al., 2023], tropical storms [Plotkin et al., 2019; Webber et al., 2019], weakening and collapse of the Atlantic meridional overturning circulation (AMOC) [Cini et al., 2024], and turbulence [Bouchet et al., 2018; Grafke et al., 2015; Lestang et al., 2020].

Apart from rare event algorithms, other techniques exist that allow to study extreme events with return times beyond the range of available data. For example, extreme value theory can be used to extrapolate return times for anomaly values unavailable from the data set [Coles, 2001; Parey et al., 2010]. EVT is used in climate science in particular for attribution studies, as it is an efficient way to estimate probabilities of events outside the range of observational data. However, one of the drawbacks is that it does not provide the dynamics that leads to the extrapolated extreme events. Moreover, a recently published

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approach to focus the computational power in climate model simulations on trajectories that lead to extreme events is ensemble boosting [Fischer et al., 2023; Gessner et al., 2023]. In this approach, ensemble simulations are re-initialized days to weeks before the peak of an extreme event allowing to generate physically plausible ultra-rare events with unprecedented amplitude. Ensemble boosting thus allows to study the dynamics of unprecedented extreme events, but it does not provide the probabilities of these events and can therefore be used only in a story-line sense. Rare event algorithms instead deliver both the dynamical trajectories that lead to the extreme events of interest and enable to estimate their probabilities of occurrence. This allows for example to explore covariates of an observable of interest without the need of assumptions on the underlying distributions.

Different types of rare event algorithms are suited to study different problems, as the underlying design mechanisms are tailored to target extremes with specific properties. Here we use a genealogical selection algorithm [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021] adapted from Del Moral and Garnier [2005]; Giardina et al. [2011], that is appropriate to study persistent, long lasting events. We apply this rare event algorithm to the intermediate complexity coupled climate model PlaSim-LSG [Fraedrich et al., 2005; Drijfhout et al., 1996; Maier-Reimer et al., 1993] to investigate extreme negative summer pan-Arctic sea ice area anomalies under fixed pre-industrial greenhouse gas conditions. Owing to the algorithm, we compute return times two to three orders of magnitude larger than feasible with direct sampling and we obtain statistically significant composite maps of dynamical quantities conditional on the occurrence of extremely low sea ice summers with return times of more than 200 years. Finally, we elaborate possible physical drivers of these events. The paper is structured as follows. In section 2.2, we present the set-up of the model and the control run and we describe the methodology of the rare event algorithm and the design of the rare event algorithm experiments. In section 2.3, we show that the rare event algorithm performs importance sampling of summer seasons with extremely low pan-Arctic sea ice area and we discuss possible physical drivers of these events. In this context, we describe the average states of the atmosphere and of the sea ice during extremely low sea ice summers, we discuss the relative contribution of winter preconditioning vs. intra-seasonal sea ice reduction to extreme negative summer pan-Arctic sea ice area anomalies and we perform a surface energy budget analysis in order to trace back extremely low sea ice conditions to anomalous atmospheric conditions. In section 2.4, we present our conclusions and we discuss possible future lines of research.

2.2 Materials and methods

2.2.1 The Planet Simulator with a Large-Scale Geostrophic ocean circulation model

All the following simulations are conducted with the intermediate complexity climate model Planet Simulator (PlaSim) version 17 [Fraedrich et al., 2005]. To account for the importance of oceanic processes for Arctic sea ice variability, we use a coupled version of PlaSim that includes a dynamic Large-Scale Geostrophic (LSG) ocean [Maier-Reimer et al., 1993; Drijfhout et al., 1996] in addition to a mixed-layer ocean model and to a

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thermodynamic sea ice model (PlaSim coupled to LSG is referred to as "PlaSim-LSG" in this work). PlaSim-LSG is computationally less demanding than Earth system models used in the assessments of the Intergovernmental Panel on Climate Change (IPCC). It allows to conduct large ensemble simulations at reasonable computational cost, which is suitable for the aim of this work to investigate the applicability of a rare event algorithm to study extremes of Arctic sea ice reduction with a numerical climate model. Despite its intermediate complexity, PlaSim-LSG produces a reasonably realistic present-day climate, especially in the northern hemisphere [Angeloni, 2022]. Further applications for which PlaSim-LSG has been used include aquaplanet and paleoclimate studies [Hertwig et al., 2014; Andres and Tarasov, 2019] and a study on the linkage between high-latitude precipitation and low-frequency variability of the AMOC [Mehling et al., 2023].

The PlaSim-LSG atmosphere includes a wet primitive equation dynamical core governing the conservation of momentum, mass, energy, the specific humidity and the equation of state with hydrostatic approximation [Fraedrich et al., 2005; Lunkeit et al., 2012]. The equations are solved on a terrain following σ -coordinate system (pressure divided by surface pressure) with a spectral transform method [Orszag, 1970; Eliassen et al., 1970]. Parameterizations of unresolved subgrid scale processes include moist and dry convection [Kuo, 1965, 1974], clouds [Slingo and Slingo, 1991; Stephens et al., 1978, 1984], large-scale precipitation, boundary fluxes of sensible and latent heat and of momentum, long-wave and short-wave radiation [Sasamori, 1968; Lacis and Hansen, 1974], vertical and horizontal diffusion [Laursen and Eliassen, 1989; Louis, 1979; Louis et al., 1981] and a land surface scheme with five diffusive layers for temperature and a bucket model for soil hydrology.

The LSG is a three-dimensional global ocean general circulation model based on primitive equations under the assumption of large spatial and temporal scales, using the Boussinesq and hydrostatic approximations and neglecting vertical friction [Maier-Reimer et al., 1993; Maier-Reimer and Mikolajewicz, 1992]. Turbulent motions are parameterized by a vertical oceanic diffusion coefficient. The LSG model is used to calculate the heat flux from the deep ocean to the mixed-layer due to advective and convective processes, i.e., advection, horizontal diffusion, vertical transport, vertical diffusion, convective adjustments. In contrast, the mixed-layer ocean model is used to compute the temperature tendencies of the mixed-layer due to heat exchanges with the atmosphere.

The thermodynamic sea ice model is based on the zero-layer model of Semtner [1976]. This model computes the evolution of the sea ice thickness and surface temperature from the energy balances at the top and bottom of a sea ice-snow layer. The sea ice-snow layer is assumed to have a linear temperature gradient and to have no capacity to store heat. The sea ice concentration is binary, i.e., either a grid cell is fully sea ice covered or open water.

We run the PlaSim-LSG simulations at statistically stationary state with a fixed pre-industrial effective CO₂ volume mixing ratio of 280 ppmv. We perform the runs without diurnal cycle and with seasonal cycle of the solar radiation and each year has 360 days. For the atmosphere, we use a horizontal spectral resolution of T21 (triangular truncation at wavenumber 21 $\sim 5.625^\circ \times 5.625^\circ$ on the corresponding Gaussian grid), ten non-equally spaced sigma-levels up to about 40 hPa in the vertical, a computational time step of 45

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minutes and an output time step of one day. The computational and output time steps of the mixed-layer ocean and sea ice models are one day. The LSG is run on a $2.5^\circ \times 5^\circ$ staggered E-type grid [Arakawa and Lamb, 1977] in the horizontal, with 22 levels in the vertical and with computational and output time steps of five days.

2.2.2 Pan-Arctic sea ice area in the control run

We consider a control run (CTRL) of 3000 years at equilibrium state (Figure 2.1; labeled as model years 501-3500; model years 1-500 are discarded as spin-up). From the control run, we derive several experiments with the rare event algorithm (see section 2.2.3.2). We consider the statistics of the pan-Arctic sea ice area

$$A(t) = \sum_{\phi \geq \phi_{min}} \sum_{\lambda} SIC_{\phi,\lambda}(t) \cdot G_{\phi,\lambda}, \quad (2.1)$$

where $SIC_{\phi,\lambda}(t)$ is the sea ice concentration at time t in a grid cell centered at latitude ϕ and longitude λ , $G_{\phi,\lambda} = \int_{\phi-\frac{\Delta\phi}{2}}^{\phi+\frac{\Delta\phi}{2}} \int_{\lambda-\frac{\Delta\lambda}{2}}^{\lambda+\frac{\Delta\lambda}{2}} R^2 \cos(\phi') d\lambda' d\phi'$ is the grid cell area, R is the earth radius, $\Delta\phi$ and $\Delta\lambda$ are the angular distances between two grid points in the meridional and zonal direction. The summation in (2.1) includes all ocean grid boxes north of 40°N (i.e. $\phi_{min} \cdot \frac{180^\circ}{\pi} = 40^\circ$; the black circle in Figure 2.1(a) shows the southern boundary of the domain over which the pan-Arctic sea ice area is computed). The land-sea mask is binary (i.e. a grid cell is either completely ocean or land).

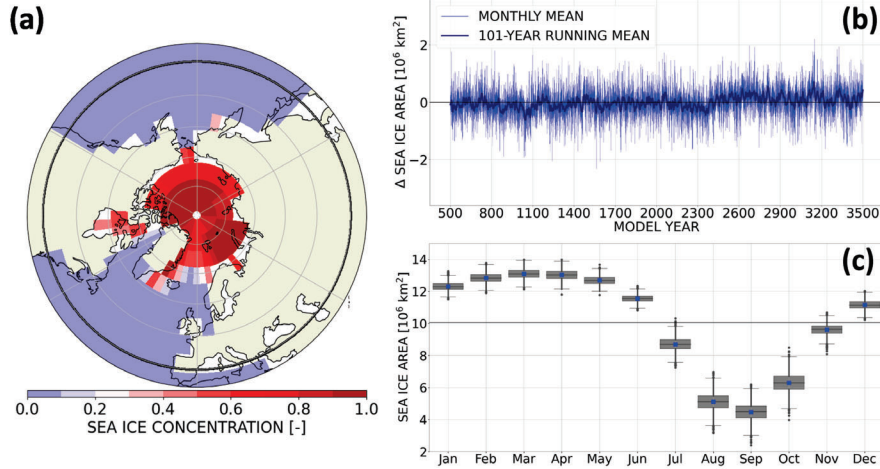


Figure 2.1: PlaSim-LSG control run (model years 501-3500): (a) Black circle shows the southern boundary of the domain over which the pan-Arctic sea ice area is computed. Shading shows the climatological annual mean sea ice concentration [-] field. (b) Time series of monthly mean pan-Arctic sea ice area anomalies [10^6 km^2] relative to the climatology of the control run for (blue) the original monthly values and (darkblue) the 101-year running mean. (c) Distributions of monthly mean pan-Arctic sea ice area [10^6 km^2] with respect to the 3000 model years. The averages and medians are given by the blue squares and the horizontal lines in the boxes. The boxes denote interquartile ranges and the maximum whisker length is defined as 1.5 times the interquartile range. The horizontal gray line shows the annual mean pan-Arctic sea ice area.

The monthly mean pan-Arctic sea ice area anomalies show interannual variability superimposed on weak fluctuations on multi-year to centennial time scales (Figure 2.1(b)). For example, the sea ice area tends towards positive anomalies between model years 2500 and 2700 and towards negative anomalies around model year 1000 (Figure 2.1(b)). The annual average, the amplitude of the seasonal cycle and the timing of the annual minimum and maximum of the pan-Arctic sea ice area are representative of the observed Arctic sea ice climatology between 1979 and 2015 (cf. Figures 2.1(a,c) and Supplementary Figure A1(a,b); we used data from EUMETSAT Ocean and Sea Ice Satellite Application Facility [2017, 2023] to compare the representation of sea ice in PlaSim-LSG with observations (Supplementary Figure A1)). Nevertheless, compared to observations, PlaSim-LSG has a delayed melting period, a positive sea ice concentration (SIC) bias from the Greenland to the Kara Sea and a negative SIC bias western of Greenland (cf. Figures 2.1(a,c) and Supplementary Figure A1(a,b)). Despite this, the representation of sea ice dynamics and statistics in PlaSim-LSG is sufficient for the purpose of this study.

We study extreme negative anomalies of February-September (FEBSEP) averaged pan-Arctic sea ice area. We classify a sea ice area anomaly $I'(t)$ as extremely negative if $I'(t) \leq -n\sigma_{CTRL}$, where σ_{CTRL} is the standard deviation of the control run and n is a real-valued number being defined in section 2.3. The choice of studying extreme anomalies of February-September averaged sea ice area instead of extreme annual sea ice minima has methodological reasons. As described in section 2.2.3., the rare event algorithm is primarily designed to improve the sampling of extreme anomalies of a target observable on average over the full simulation length. In Chapter 3 and Chapter 4, however, we will show how experiments with the rare event algorithm can be adjusted to study extreme annual sea ice minima in the Arctic.

2.2.3 Rare event algorithm

2.2.3.1 Description of the method

In climate modeling and weather forecast, ensemble simulations provide a distribution of possible trajectories of the state of the atmosphere or of the climate system. In a conventional ensemble simulation, most of these trajectories correspond to typical fluctuations of an observable, e.g. the pan-Arctic sea ice area. Only a few trajectories lead to extreme states of the observable, which hampers robust statistical and dynamical studies on events that correspond to the tail of the distribution. The genealogical selection algorithm presented in Giardina et al. [2011]; Ragone et al. [2018]; Ragone and Bouchet [2020, 2021] is designed to guide ensemble simulations to oversample rare dynamical trajectories that lead to extreme anomalies of the time-average of an observable where the averaging time is longer than the typical decorrelation time of the observable. This algorithm is therefore well suited to study the statistics of the seasonally averaged pan-Arctic sea ice area.

We describe the main steps of the algorithm in the following and refer to Ragone et al. [2018] and Ragone and Bouchet [2020, 2021] for more details. We denote $X(t)$ the vector of all model variables at time t . We consider an ensemble of N trajectories $\{X_n(t)\}$ ($n = 1, 2, \dots, N$), an observable $A(\{X_n(t)\})$ (i.e., a function that maps for each trajectory the state vector to a single scalar), a total simulation time T_a and a resampling

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time τ_r . We start the ensemble simulation from statistically independent initial conditions. We perform at regular times $t_i = i \cdot \tau_r$ ($i = 1, 2, \dots, \frac{T_a}{\tau_r}$) a resampling procedure in which trajectories are killed or generate a random number of replicates depending on weights that are related to the magnitude of the time-average of the observable during the past interval. The weights are defined as

$$w_n^i = \frac{e^{k \int_{t_{i-1}}^{t_i} A(\{X_n(t)\}) dt}}{R_i} \text{ with } R_i = \frac{1}{N} \sum_{n=1}^N e^{k \int_{t_{i-1}}^{t_i} A(\{X_n(t)\}) dt}, \quad (2.2)$$

where R_i is a normalization term and k is a biasing parameter. With a positive (negative) k , the weights favour the replication of trajectories leading to large (small) values of the time-average of the observable during the past interval, while trajectories leading to small (large) values of the time-average of the observable are likely to be killed. The absolute value of k controls the strength of the selection. As described in Ragone et al. [2018], each resampling is performed in such a way that the ensemble size remains constant and equal to N . After the resampling, we slightly perturb the surface pressure field of each trajectory to enable copies of the same trajectory to separate from each other during the subsequent simulation interval (the perturbation is performed as described in the Supporting Information of Ragone et al. [2018]). When the final time T_a is reached, we perform one last resampling and reconstruct an effective ensemble by attaching at each resampling event from the end to the beginning of the simulation the ancestors to the pieces of surviving trajectories. All trajectories that did not survive until the end of the simulation are discarded.

As described in Ragone et al. [2018] and Ragone and Bouchet [2020], one obtains for a large ensemble size N the importance sampling formula

$$\mathbb{P}_k(\{X_n(t)\}_{0 \leq t \leq T_a}) \underset{N \rightarrow \infty}{\sim} \frac{e^{k \int_0^{T_a} A(\{X_n(t)\}) dt}}{\mathbb{E}_0[e^{k \int_0^{T_a} A(\{X_n(t)\}) dt}] \mathbb{P}_0(\{X_n(t)\}_{0 \leq t \leq T_a})}, \quad (2.3)$$

where $\mathbb{P}_0$ and $\mathbb{P}_k$ are the probability densities of trajectories in the standard ensemble simulation and in an ensemble generated with the algorithm and $\mathbb{E}_0$ is the expectation value with respect to $\mathbb{P}_0$. The importance sampling formula describes the ratio of probability densities of trajectories in a simulation obtained with the rare event algorithm to the probability density of trajectories according to the real model statistics. Consequently, expectation values (e.g. composites, return times) with respect to the real model statistics can be computed from the data obtained with the rare event algorithm by weighting the contribution of each trajectory to sample averages by the inverse of the exponential factor in (2.3) (see Ragone et al., 2018; Ragone and Bouchet, 2020; Supporting Information of Ragone and Bouchet, 2021 for more details).

2.2.3.2 Set-up of the rare event algorithm experiments

We use as target observable $A(\{X_n(t)\})$ the pan-Arctic sea ice area and perform two sets of experiments with the rare event algorithm. One set is performed with a resampling time of $\tau_r = 30$ days, the other with a resampling time of $\tau_r = 5$ days. Both resampling times are chosen to be smaller than the decorrelation time of the pan-Arctic sea ice area (the autocorrelation function of sea ice area anomalies drops for the first time below $1/e$ after about 75 days). In this way, the selection favours the survival of trajectories characterized by large negative time-persistent sea ice area anomalies during the interval prior to a resampling event. In contrast to the resampling time of $\tau_r = 30$ days, the resampling time of $\tau_r = 5$ days is not larger than the persistence time scale of the large-scale atmospheric circulation [Baldwin et al., 2003] and is only slightly larger than the typical persistence of synoptic-scale atmospheric fluctuations [Hoven, 1957]. We therefore expect that the experiments with a resampling time of $\tau_r = 5$ days efficiently sample extremely low sea ice states both due to anomalies in the oceanic thermal state and due to anomalies in the atmospheric circulation that are in the order of or larger than the upper range of the synoptic time scale. In contrast, the experiments with a resampling time of $\tau_r = 30$ days are primarily designed to increase the sampling efficiency of oceanic drivers of low sea ice states. In this case, we expect atmospheric drivers of sea ice reduction to be sampled only if they are characterized by an anomalously large persistence (e.g. an one month long persistent negative phase of the summer AO).

Both sets of experiments include $M = 5$ ensemble simulations labelled with $m = 1, \dots, M$ (Table 1). Each ensemble has $N = 600$ trajectories and a total simulation time of $T_a = 240$ days between February 1st and September 30th. We take different values of the biasing parameter for the different experiments: $k = -0.06 \cdot 10^{-6} \text{ km}^{-2} \text{ day}^{-1}$ for ensemble $m = 1$, $k = -0.05 \cdot 10^{-6} \text{ km}^{-2} \text{ day}^{-1}$ for ensembles $m = 2$ and $m = 4$ and $k = -0.04 \cdot 10^{-6} \text{ km}^{-2} \text{ day}^{-1}$ for ensembles $m = 3$ and $m = 5$. While the precise values of k is chosen empirically, a reasonable order of magnitude of the parameter can be derived using a scaling argument presented in Ragone and Bouchet [2020] and in the Supporting Information of Ragone and Bouchet [2021]. According to this scaling argument, the selected k -values correspond to a shift of the peak of the distribution of February-September mean pan-Arctic sea ice area anomalies to values between $-0.5 \cdot 10^6 \text{ km}^2$ and $-0.75 \cdot 10^6 \text{ km}^2$, which corresponds to a range of estimated return times between 100 and 1000 years (see section 2.3.1).

For each ensemble, the initial condition for trajectory $n = 1, \dots, N$ is taken from February 1st in year $500 + m + 5(n - 1)$ of the control run (Table 2.1). In order to have a baseline for the statistics, we also subdivide the 3000-year control run into five 600-member control ensembles such that the rare event algorithm ensemble m has exactly the same initial conditions as the control ensemble m . Sampling the initial conditions with a gap of five years ensures that sea ice area anomalies in the different trajectories within an ensemble are relatively independent from each other.

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Table 2.1: 600-member rare event algorithm ensemble simulations running between February 1st and September 30th. This set-up applies both to the experiments with a resampling time of $\tau_r = 5$ days and to the experiments with a resampling time of $\tau_r = 30$ days.

m	Model years for initial condition	Biasing parameter k [$10^{-6} \text{ km}^{-2} \text{ day}^{-1}$]
1	501, 506,..., 3496	-0.06
2	502, 507,..., 3497	-0.05
3	503, 508,..., 3498	-0.04
4	504, 509,..., 3499	-0.05
5	505, 510,..., 3500	-0.04

2.3 Results

2.3.1 Importance sampling of summer seasons with extremely low pan-Arctic sea ice area

Our goal of using the rare event algorithm is to improve the sampling efficiency of extreme negative pan-Arctic sea ice area anomalies on average over the extended summer season between February and September. We show the seasonal evolution of daily pan-Arctic sea ice area anomalies merged over the two rare event algorithm experiments with $k = -0.05 \cdot 10^{-6} \text{ km}^{-2} \text{ day}^{-1}$ (Figure 2.2(a,b)). Throughout the season, trajectories generated with the rare event algorithm show a systematic shift towards lower sea ice area values compared to the control run. The amplitude of this shift does not differ between the 5-days and the 30-days resampling time experiments and is more than twice as large after July than between February and June. The amplification of the shift during July coincides with an increase in the climatological sea ice area variability of the control run (cf. Figures 2.2(a,b) and Figure 2.1(c)).

The systematic biasing towards negative sea ice area anomalies both in the 5-days and 30-days resampling time experiments emerges from the trajectory resampling at intervals shorter than the decorrelation time of the sea ice area. During each resampling event, trajectories characterized by large negative time-persistent sea ice area anomalies form replicas at the expense of trajectories with less negative sea ice area anomalies. After the simulation, the surviving pieces of trajectories are reconstructed into an effective ensemble. As a consequence, the rare event algorithm efficiently performs importance sampling of trajectories that lead to extreme negative February-September time-averaged sea ice area anomalies (Figure 2.2). The control distribution of February-September mean sea ice area anomalies has a standard deviation of about $0.25 \cdot 10^6 \text{ km}^2$ and a minimum value of $-0.80 \cdot 10^6 \text{ km}^2$. In contrast, the sea ice area anomalies obtained with the rare event algorithm fluctuate around a mean value of $-0.6 \cdot 10^6 \text{ km}^2$ and have minima at $-0.89 \cdot 10^6 \text{ km}^2$ (30-days resampling time experiments) and at $-0.99 \cdot 10^6 \text{ km}^2$ (5-days resampling time experiments). The simulations with the rare event algorithm require the same computational cost as the control run, but strongly populate the lower tail of the distribution of FEBSEP mean pan-Arctic sea ice area anomalies (Figure 2.2(c,d); we refer to the Supplementary Information A2 and Supplementary Figures A5 and A6 for more details about the adequacy of the rare event simulations used in this work, i.e., of the extent to which the effective ensembles contain sufficiently enough different initial-time

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ancestors with a non-zero number of final-time descendants to gather robust statistics).

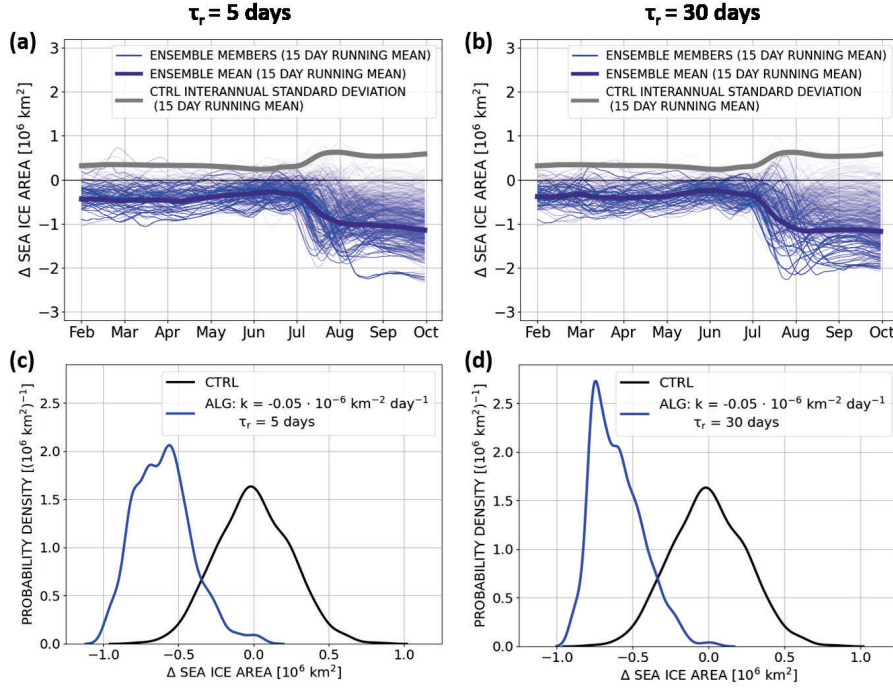


Figure 2.2: (a-b) Trajectories (thin blue lines) and ensemble mean (thick blue line) of daily pan-Arctic sea ice area anomalies in rare event algorithm ensemble simulations two and four, i.e. with $k = -0.05 \cdot 10^{-6} \text{ km}^{-2} \text{ day}^{-1}$, for (a) a resampling time of 5 days and (b) a resampling time of 30 days. The anomalies are evaluated relative to the daily climatology of the control ensembles two and four. Only the trajectories that survived until the final simulation time are plotted and are used for the computation of the ensemble mean. The gray lines show the climatological standard deviation of daily sea ice area anomalies in the control ensembles $m=2$ and $m=4$. (c-d) Probability distribution functions of February-September mean pan-Arctic sea ice area anomalies relative to the control climatology for (c) a resampling time of 5 days and (d) a resampling time of 30 days. (Black) Anomalies of the control run itself merged over ensembles $m=2$ and $m=4$ and (blue) anomalies in the rare event algorithm experiments corresponding to ensembles $m=2$ and $m=4$, i.e. with $k = -0.05 \cdot 10^{-6} \text{ km}^{-2} \text{ day}^{-1}$ (exclusively based on the trajectories that survived until the end of the simulation).

Return times are an important characterization of extreme events. They indicate the average waiting time between events of size larger than a given amplitude. We compare return times of FEBSEP mean pan-Arctic sea ice area anomalies between the control run and the experiments with the rare event algorithm (Figure 2.3(a,b)). For the computation of the return times, we proceed similarly to the modified block maximum estimator presented in Lestang et al. [2018] and in the Supporting Information of Ragone et al. [2018]. Accordingly, an estimate of the return time is given by

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$$r(a) = -\frac{\Delta T}{\ln[1 - \frac{1}{N} \sum_{n=1}^N \mathbb{1}_a(I_n)]} \text{ with } \mathbb{1}_a(I_n) = \begin{cases} 1, & I_n \leq a \\ 0, & I_n > a \end{cases}, \quad (2.4)$$

where I_n is the February-September time-averaged pan-Arctic sea ice area anomaly in trajectory n , a is the return level of a sea ice area anomaly, N the number of trajectories, ΔT is the block length of one year and $\mathbb{1}_a(I_n)$ is the indicator function. As described in Lestang et al. [2018] and in the Supporting Information of Ragone et al. [2018], equation (2.3) can be used to compute the return times from the simulations with the rare event algorithm. Note that for large values of the return time, the formula in (2.4) is approximately equivalent to $r(a) = T_d / \sum_{n=1}^N \mathbb{1}_a(I_n)$, where $T_d = N\Delta T$ is the total length of the time series (see Lestang et al. [2018]).

In Figure 2.3, the red curves show return time estimates obtained from the 3000-year control run. In order to estimate uncertainty ranges, we subdivide the control run into five 600-member ensembles (see section 2.2.3.2) providing five return time estimates. We compute the average over these five estimates (black curve) and use their empirical standard deviation to construct 95% confidence intervals (black shading; see Supplementary Information A1 for more details). In the same way, the blue lines and blue shading show the average return time estimates and confidence intervals obtained from the overlapping output of at least three out of the five 600-member rare event algorithm experiments (note that rare event algorithm experiments with slightly different k values cover slightly different ranges of sea ice area anomalies). Both for the 5-days and for the 30-days re-sampling time experiments, the return curves for the control run and for the rare event algorithm overlap in a range of sea ice area anomaly values. This range corresponds to an overlap between the probability distribution functions of sea ice area anomalies obtained with the control and rare event algorithm ensembles (cf. Figures 2.3(a), 2.2(c), Supplementary Figure A2(a,c) and Figures 2.3(b), 2.2(d), Supplementary Figure A2(b,d)). Consequently, the rare event algorithm consistently computes the probabilities that trajectories generated with the algorithm have with respect to the real model statistics (an analysis of the differences between the control and rare event algorithm estimates of the return levels shows that both estimates are statistically consistent with each other at least for a return time range between a couple of decades and about 750 years (Supplementary Figure A3(a,b)).

The major advantage of computing the return times with the rare event algorithm compared to the control run is the access to much rarer events with the former than with the latter. From the control run, we cannot accurately estimate return times of more than 1000 years. The rare event algorithm experiments are conducted with the same computational cost as the control run (i. e. 3000 years), but allow to compute return times up to 10^5 years with uncertainty ranges comparable with the control run ones for return times of several hundreds of years. Hence the algorithm increases the sampling efficiency of extreme negative February-September mean sea ice area anomalies by two to three orders of magnitude. The plateaux at return times larger than 10^5 years (Figure 2.3(a)) and larger than $5 \cdot 10^4$ years (Figure 2.3(b)) are due to undersampling as discussed in Lestang et al. [2018] and in the Supporting Information of Ragone et al. [2018].

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The result has the following implications. Firstly, the rare event algorithm provides access to ultra-rare sea ice area anomalies that do not occur in the control run. An unrealistic amount of computational cost would be required to observe them with direct sampling. Secondly, the algorithm enriches the general statistics of the extremes. While the control run delivers only a few events with a sea ice area anomaly in the order of three standard deviations away from the climatology, hundreds of them are available in the experiments with the algorithm. Thirdly, the return curve obtained with the 5-days resampling time experiments extends only to marginally larger amplitudes of sea ice area anomaly values than the one obtained with the 30-days resampling time experiments. Thus, the targeted sampling of drivers of sea ice reduction acting on the upper range of synoptic and on submonthly time scales only marginally increases the magnitude of the most extreme negative February-September mean pan-Arctic sea ice area anomalies. We will further address this point in section 2.4.

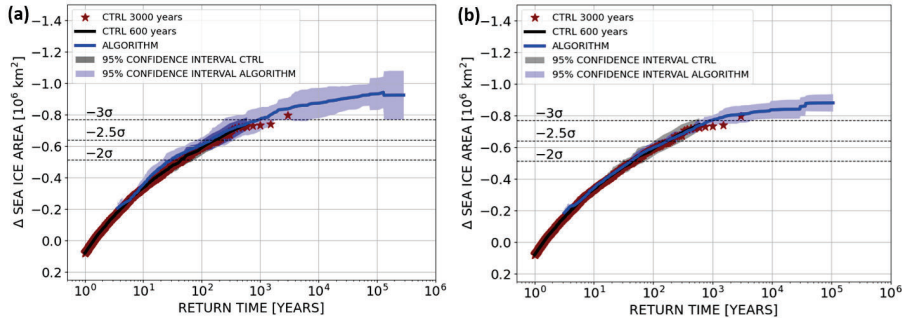


Figure 2.3: Return curves for February-September mean pan-Arctic sea ice area anomalies relative to the control run. (Red stars) The direct estimate of return times from the 3000 year control run, (black line) the average estimate over the five 600-member ensembles of the control run and (blue line) the average estimate over the overlap of at least three out of five 600-member rare event algorithm experiments. Shading denotes the 95% confidence interval obtained from the statistics of the three to five estimates assuming a student's t-distributed estimator (see Supplementary Information A1). (a) Rare event algorithm with 5-days resampling time and (b) with 30-days resampling time. The dashed lines in (a) and (b) indicate anomalies of minus two, minus two and a half and minus three standard deviations with respect to the control run.

2.3.2 Sea ice conditions and state of the atmosphere during summer seasons of extremely low sea ice area

We perform composite analyses to investigate and characterize the average states of the sea ice and of the atmosphere during summer seasons of extreme negative February-September mean pan-Arctic sea ice area anomalies. Composites mathematically correspond to conditional expectation values that we estimate as

$$\mathbb{E}_0[O(\{X_n(t)\}) \mid I_n \leq -m\sigma] = \frac{\mathbb{E}_0[O(\{X_n(t)\}) \cdot \mathbb{1}(-I_n - m\sigma)]}{\mathbb{E}_0[\mathbb{1}(-I_n - m\sigma)]}, \quad (2.5)$$

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where $O(\{X_n(t)\})$ and I_n are the anomalies of a target climate variable (e.g. 500 hPa geopotential height) and of the February-September mean pan-Arctic sea ice area in trajectory n , σ is the control run standard deviation of I , m a positive integer and $\mathbb{1}(-I_n - m\sigma)$ is the indicator function with

$$\mathbb{1}(-I_n - m\sigma) = \begin{cases} 1, & -I_n - m\sigma \geq 0 \\ 0, & -I_n - m\sigma < 0 \end{cases} . \quad (2.6)$$

All anomalies are evaluated relative to the climatology of the control ensembles and $\mathbb{E}_0$ is the expectation operator with respect to the unbiased model statistics (i.e. the statistics of the control run). By using equation (2.3), composites can be computed from the output of the rare event algorithm as described in Ragone and Bouchet [2020] and in the Supporting Information of Ragone et al. [2018] and of Ragone and Bouchet [2021].

One advantage of the rare event algorithm is that it provides more accurate composite estimates for large return times than the control run. For the subsequent analyses, we compute composite estimates for each of the five rare event algorithm ensembles and consider the average over the five estimates respectively. We assess the statistical significance of the composite maps by applying a two-sided t-test to the set of the five estimates (see Supplementary Information A1). We apply the same procedure to five 600-member control ensembles obtained from the 3000-year control run (see section 2.2.3.2). All subsequent results obtained with the rare event algorithm are based on the experiments with a resampling time of $\tau_r = 5$ days. As explained in section 2.2.3.2, this value of resampling time allows to increase the sampling efficiency of a broader range of physical processes compared to a resampling time of $\tau_r = 30$ days.

2.3.2.1 Seasonal mean states of the sea ice and of the atmosphere

We compare the control run and rare event algorithm estimates of average seasonal mean SIC, two metre temperature (T2M) and 500 hPa geopotential height (Z500) anomalies during summer seasons of extreme negative pan-Arctic sea ice area anomalies with return times of more than 200 years (i.e. $I_n \leq -2.5\sigma$) (Figure 2.4). For this threshold, we have access to several hundreds of events with the algorithm and to 13 events with the control run. While the algorithm and control estimates consistently indicate a warm Arctic state during extremely low sea ice seasons, the benefit of the algorithm manifests in the larger statistical accuracy of the estimates compared to the control run. The algorithm composites indicate statistically significant negative mean SIC anomalies in the North Atlantic side of the Arctic, along the Russian coast and in the marginal seas of the Pacific side of the Arctic Ocean (Figure 2.4(d)). Statistically significant positive T2M anomalies occur over the entire Arctic Ocean with largest amplitudes over the Canadian Archipelago, Greenland and Kara Seas (Figure 2.4(e)). The anomalously warm surface conditions are accompanied by positive Z500 anomalies over the Arctic reaching statistical significance from the Canadian Archipelago over Svalbard to the Barents and Kara Seas. Compared to the algorithm, the control run estimates of the mean SIC, T2M and Z500 anomalies are statistically significant in a much smaller amount of grid cells. Apart from the formal statistical significance, the larger amount of extreme events available through the algorithm decreases the likelihood that the composite maps include noisy patterns

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that are not statistically related to the sea ice area anomalies and that are occurring in the control run by the effect of sampling (Figure 2.4(b,c,e,f)).

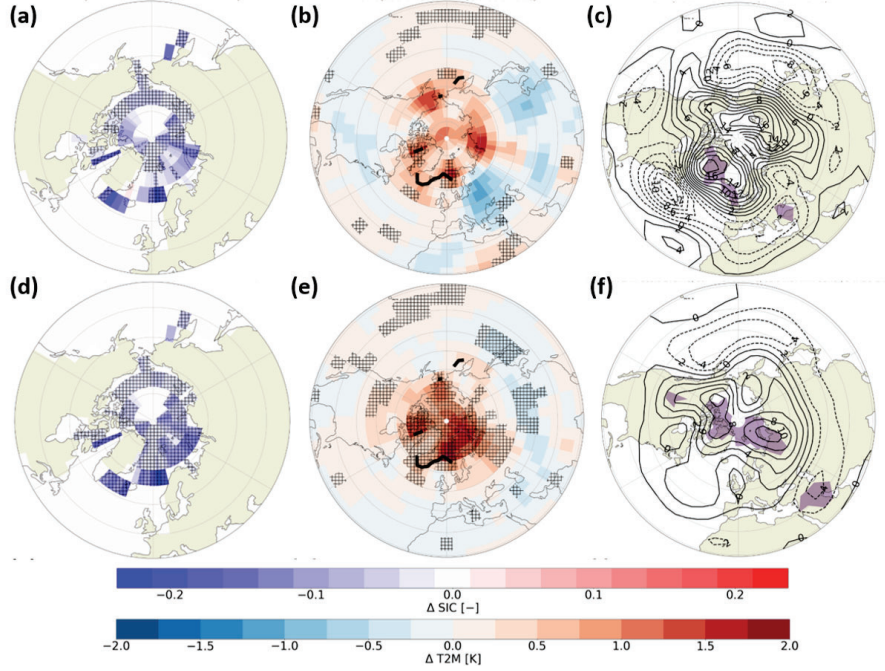


Figure 2.4: Composite mean February-September averaged (a,d) sea ice concentration (SIC [-]), (b,e) two metre temperature (T2M [K]) and (c,f) 500 hPa geopotential height (Z500 [gpm]; contour interval two gpm) anomalies conditional on extreme negative February-September mean pan-Arctic sea ice area anomalies equal or smaller than -2.5 standard deviations of the control ensembles (corresponds to extremes with return times of more than 200 years). Composite maps are presented as an average over (a-c) the five control and (d-f) the five rare event algorithm experiments with a resampling time of $\tau_r = 5$ days. All anomalies are estimated with respect to the climatology of the control ensembles. The hatching in (a,b,d,e) and shading in (c,f) denote statistical significance at the 5% level according to a two-sided t-test (see the Supplementary Information S2A for more details). The black contour line in (b,e) indicates the climatological February-September mean sea ice edge defined as the 15% sea ice concentration line.

2.3.2.2 Seasonal evolution of the states of the sea ice and of the atmosphere

We are interested in the physical processes favouring anomalously warm Arctic states with extremely low pan-Arctic sea ice area during summer. From the physical point of view, understanding the drivers of extremely low pan-Arctic sea ice area is hindered by at least two factors. Firstly, a variety of feedback mechanisms occur in the Arctic climate system [e.g. Screen and Simmonds, 2010; Serreze and Francis, 2006] and can lead to ambiguities of cause and effect relationships between different quantities. This applies, for example,

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to the relationship between the anomalously warm Arctic atmosphere and the negative sea ice concentration anomalies shown in Figure 2.4. The negative sea ice concentration anomalies are potentially driven by the anomalous warm atmosphere. At the same time, however, the positive T2M and Z500 anomalies are potentially a consequence of the anomalous heat flux from the ocean to the atmosphere that results from the reduced sea ice cover. Secondly, extremely low summer pan-Arctic sea ice area may be generated in two different ways. Are we sampling trajectories in which processes on intra-seasonal time scales lead to an extreme reduction of the pan-Arctic sea ice area within a season? Or are we sampling trajectories in which extreme negative February-September mean pan-Arctic sea ice area anomalies are related to preconditioning [cf. Chevallier and Salas-Méla, 2012; Holland et al., 2011; Kauker et al., 2009]?

We firstly identify to what extent extreme negative February-September mean pan-Arctic sea ice area anomalies are related to intra-seasonal sea ice reduction vs. pre-existing anomalies in the sea ice state originating from the previous winter. For this purpose, we analyse the seasonal evolution of mean pan-Arctic sea ice area and sea ice volume anomalies conditional on the occurrence of summer seasons of extremely low pan-Arctic sea ice area (Figure 2.5). On average, extreme negative FEBSEP pan-Arctic sea ice area anomalies are related both to persistent sea ice area anomalies originating from the previous winter and to anomalous sea ice area reduction between late spring and late summer (Figure 2.5(a)). The sea ice area anomalies between February-March and May-June are in the order of one and two-thirds of the interannual standard deviation and have an approximately constant level of about $-0.2 \cdot 10^6 \text{ km}^2$ to $-0.5 \cdot 10^6 \text{ km}^2$. In contrast, the sea ice area anomalies in August-September are in the order of $-1 \cdot 10^6 \text{ km}^2$ to $-1.5 \cdot 10^6 \text{ km}^2$, two to three times as large in magnitude as the interannual standard deviation. As a consequence, the anomalies in the sea ice area reduction between February-March and August-September are about twice as large in magnitude as the pre-existing sea ice area anomalies in late winter. The relative importance of intra-seasonal sea ice area reduction over pre-existing sea ice area anomalies slightly increases with the amplitude of the extremes of the February-September mean pan-Arctic sea ice area anomalies (Figure 2.5(a)).

In contrast to the pan-Arctic sea ice area, pan-Arctic sea ice volume anomalies are directly related to the amount of energy required to produce these anomalies and their seasonal evolution does not directly depend on the open-water-formation-efficiency given by the sea ice thickness field. Pre-existing pan-Arctic sea ice volume anomalies originating from the previous winter are three to four times as large as the anomalies in their reduction from February-March to August-September (Figure 2.5(b)). This result points at a strong contribution of preconditioning of extreme anomalies of the FEBSEP mean pan-Arctic sea ice area through an extremely low winter pan-Arctic sea ice volume, which is both due to negative anomalies in the winter pan-Arctic sea ice area and in the winter pan-Arctic mean sea ice thickness field (cf. Figure 2.5 and Supplementary Figure A4(a,b)). On top of the preconditioning, an anomalous intra-seasonal reduction in the sea ice volume occurs between April-May and July-August. This suggests a contribution of intra-seasonal dynamics to extreme negative FEBSEP sea ice area anomalies in addition to the preconditioning.

2. Sampling extremes from unconditional probability distributions using Plasim-LSG

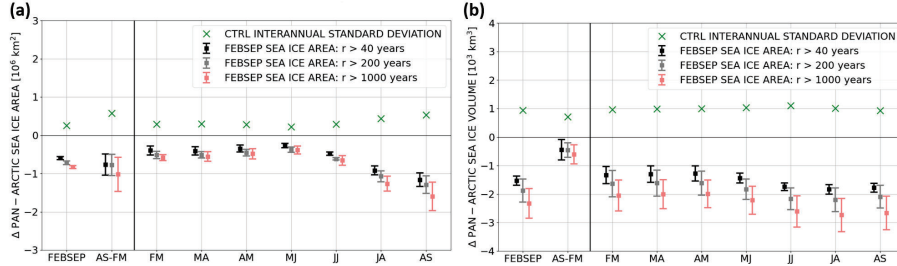


Figure 2.5: Rare event algorithm experiments with a resampling time of $\tau_r = 5$ days: Composite mean (a) pan-Arctic sea ice area anomalies [10^6 km^2] and (b) pan-Arctic sea ice volume anomalies [10^3 km^3] conditional on extreme negative February-September mean pan-Arctic sea ice area anomalies equal or smaller than (black) -2 standard deviations, (gray) -2.5 standard deviations and (red) -3 standard deviations of the control ensembles (roughly corresponds to extremes with return times of more than 40, 200 and 1000 years). The anomalies are computed with respect to the control climatologies of the five control ensembles. The composite estimates are presented as an average over the five rare event algorithm ensembles and the error bars represent 95% confidence intervals (see Supplementary Information S2A). "AS-FM" denotes the difference between August-September (AUGSEP) and February-March (FEBMAR) and the green "x" markers indicate the climatological standard deviation in the control run.

We analyse the seasonal evolution of T2M and Z500 anomalies conditional on extremely low sea ice summer seasons to establish a link between the sea ice lows and the thermodynamic and dynamic states of the atmosphere (Figure 2.6). During extremely low sea ice summers, positive temperature anomalies pre-exist over the Arctic during the beginning of the simulation period in February-March, especially from the Greenland to the Kara Seas and over the Canadian Archipelago (Figure 2.6(a)). Positive T2M anomalies over the Arctic Ocean persist until spring before they largely disappear in June-July (Figure 2.6(a-d)). A reemergence of significant positive two metre temperatures occurs in August-September over the Arctic Ocean, though with a much smaller amplitude than at the beginning of the season (Figure 2.6(a,e)). Possible causes for the anomalously warm atmosphere in late winter and spring include enhanced poleward atmospheric heat and moisture transport [e.g. Alekseev et al., 2019], enhanced poleward oceanic heat transport [e.g. Swaluw et al., 2007; Jungclaus and Koenigk, 2010], an anomalously strong conductive heat flux within an anomalously thin sea ice (see Semtner [1976] for a description of the thermodynamics of sea ice) and enhanced open water area related to negative sea ice area anomalies [Screen and Simmonds, 2010]. Since the positive T2M anomalies in late winter and spring coincide with negative sea ice area and thickness anomalies (cf. Figures 2.5(a), 2.6(a-c) and Supplementary Figure A4), we expect that an increased upward surface sensible heat flux both due to enhanced upward conductive heat flux within an anomalously thin sea ice and due to reduced sea ice area contributes to the positive T2M signal. The decline of the magnitude of the T2M anomalies in summer is consistent with a constraint due to the climatological sea ice melting. Near-surface temperatures are at the freezing point and any additional heat input would accelerate sea ice melt, but not warm the air. The weak positive T2M signal in August-September could both be a consequence of an anomalously large amount of open water and a driver of sea ice

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reduction.

Positive geopotential height anomalies pre-exist over the Arctic at the beginning of the simulation period, even though they are statistically significant only in a few grid points (Figure 2.6(f-g)). From April-May to May-June, they become instead statistically significant over large part of the Arctic (Figure 2.6(g-h)), while the positive T2M anomaly signal at the surface is decreasing (Figure 2.6(b-c)). This suggests that anomalies in the atmospheric circulation in late spring and summer are not a pure consequence of the diabatic heating from the anomalously warm surface, but that on the contrary in this period it is the atmospheric dynamics that plays an active role in contributing to the reduction of sea ice.

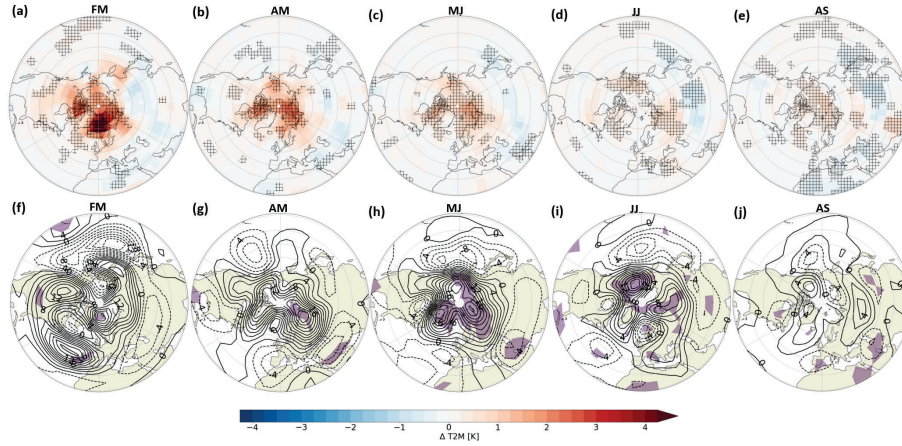


Figure 2.6: Composite mean (a-e) two metre temperature (T2M [K]) and (f-j) 500 hPa geopotential height (Z500 [gpm]; contour interval two gpm) anomalies conditional on extreme negative February-September mean pan-Arctic sea ice area anomalies presented as an average over the five rare event algorithm ensembles. The T2M and Z500 anomalies are averaged over (a,f) February-March (FM), (b,g) April-May (AM), (c,h) May-June (MJ), (d,i) June-July (JJ), (e,j) August-September (AS) and are respectively estimated relative to the climatology of the control ensembles. The sea ice area anomalies are classified as "extreme" if the sea ice area anomaly is smaller than -2.5 standard deviations of the control ensembles. The hatching in (a-e) and the shading in (f-j) denote statistical significance at the 5% level according to a two-sided t-test.

2.3.3 Surface energy budget and feedback mechanisms

We perform a surface energy budget analysis for two purposes. Firstly, we are interested in the amount of anomalous energy accumulation in the snow-sea ice-ocean system that is related to surface-atmosphere energy flux anomalies between February and September. Secondly, we exploit the impact of the thermodynamic atmospheric state (e.g. temperature, water vapour, clouds) on the surface energy fluxes to understand how extreme negative pan-Arctic sea ice area anomalies are physically related to anomalous atmospheric conditions. We define the surface energy budget for an infinitesimally thin interface without heat storage located between the atmosphere and the snow-sea ice-ocean system (cf.

Serreze and Barry [2014]). The different terms of the budget are then given by

$$R_{SW}(1 - \alpha) + R_{LW} + S + L = -\epsilon\sigma T_s^4 + Q + M, \quad (2.7)$$

where R_{SW} and R_{LW} are the downward shortwave and downward longwave radiative fluxes, respectively; α is the surface albedo, S and L are the sensible and latent heat fluxes, ϵ is the surface emissivity, $\sigma = 5.67 \cdot 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$ is the Stefan–Boltzmann constant and T_s is the surface temperature. Q summarizes conductive and turbulent energy fluxes between the surface and the snow-sea ice-ocean system. M is the energy exchange associated with melting and freezing at the surface. Energy fluxes related to bottom sea ice growth, to temperature changes in the snow-sea ice-ocean system and the vertical energy flux from the ocean into the sea ice are implicitly included in Q . If not stated otherwise, we define upward (downward) energy fluxes and associated flux anomalies to be positive (negative).

During summer seasons of extremely low pan-Arctic sea ice area, negative net surface-atmosphere energy flux anomalies occur over the Arctic Ocean and correspond to an anomalous energy accumulation within the snow-sea ice-ocean system (Figure 2.7(a)). The domain-average of these anomalies over all ocean grid boxes north of 70°N is -2.14 Wm^{-2} , which corresponds to a domain- and season- (February–September) integrated net energy accumulation of about $4.5 \cdot 10^{20} \text{ J}$. This amount of energy would be sufficient to melt about $1.48 \cdot 10^3 \text{ km}^3$ of sea ice, which is about three quarters of the February–September mean pan-Arctic sea ice volume anomaly being present during summer seasons of extremely low pan-Arctic sea ice area (Figure 2.5(b)). A direct contribution of the net accumulation of energy to the anomalies in the sea ice volume is, however, difficult for following reasons. One part of the energy is used to increase the temperature of the snow-sea ice-ocean system instead of being used for melting and an important part of the sea ice volume anomaly is already existing in late winter (Figure 2.5(b)). Likewise, the domain-average north of 70°N is limited to representing the vertical surface energy flux anomalies in the high Arctic, while the sea ice extends much further to the south during winter and spring. Nevertheless, the result indicates that the net February–September mean energy exchange between the atmosphere and the Arctic Ocean surface provides a substantial amount of energy potentially available to contribute to enhanced intra-seasonal sea ice reduction.

We are interested in the physical processes that drive the anomalous net energy transfer from the atmosphere to the Arctic Ocean during extremely low sea ice summers. For this purpose, we investigate how the net atmosphere-surface energy flux anomalies are partitioned into their different components over the course of the season (Figure 2.7(b-c)). Both the net atmosphere-surface energy flux anomalies and their different components exhibit a pronounced seasonality. An enhanced net energy transfer from the atmosphere to the snow-sea ice-ocean system occurs between April–May and August–September, which includes the period of anomalous intra-seasonal reduction in the pan-Arctic sea ice area and sea ice volume (cf. Figures 2.7(b) and 2.5). In contrast, slightly positive net atmosphere-surface energy flux anomalies indicate a small anomalous release of energy from the Arctic Ocean to the atmosphere in late winter (Figure 2.7(b)). The latter is consistent with a contribution of preconditioning via the winter sea ice-ocean

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state to extremely low FEBSEP pan-Arctic sea ice area (see section 2.3.2.2).

Regarding the entire season, the net atmosphere-surface energy flux anomalies are dominated by the radiative (net shortwave and net longwave radiation) compared to the non-radiative (sensible and latent heat) fluxes (Figure 2.7(c)). Slightly positive non-radiative flux anomalies explain the small anomalous energy transfer from the Arctic Ocean to the atmosphere in late winter, while negative sensible heat flux anomalies in May-June suggest a direct contribution of anomalously high air temperatures to enhanced snow-sea ice-ocean warming or to enhanced snow-sea ice melt. The negative sensible heat flux anomalies in May-June coincide with the appearance of a statistically significant positive Z500 anomaly pattern and thus with an anomalously warm state of the lower troposphere (cf. Figures 2.7(c) and 2.6). A strong contribution of net shortwave radiative fluxes to the seasonal accumulation of energy in the Arctic Ocean occurs between April-May and August-September. The net longwave radiative flux anomalies are smaller in magnitude than the shortwave ones, but still contribute to a statistically significant anomalous accumulation of energy in the Arctic Ocean between March-April and June-July. An enhanced net longwave radiative forcing on the Arctic sea ice during spring is consistent with Kapsch et al. [2013, 2019]. Kapsch et al. [2013, 2019] establishes a link between observed extremely low September Arctic pan-Arctic sea ice area and an anomalous early melt onset due to the footprint of an anomalous cloudy and moist atmosphere on the net longwave radiative fluxes.

In order to trace back the net radiative flux anomalies to anomalous atmospheric conditions, we subdivide the net shortwave and longwave radiative surface fluxes into their downward and upward components (Figure 2.8(a,b)). Strongly enhanced downward longwave radiation occurs between late winter and late spring, which is partly balanced by enhanced upward longwave radiation in accordance with anomalously high (near-)surface air temperatures during that period (cf. Figures 2.8(a) and 2.6(a-e)). In June-July and July-August, positive downward radiative flux anomalies are much smaller than in spring, but counteracting upward longwave radiative flux anomalies drop to zero because sea ice-snow melting constraints surface temperatures to be close to the freezing point. In August-September, weakly enhanced upward and downward longwave radiative flux anomalies compensate each other. Regarding the shortwave radiative fluxes, reduced downward fluxes are overcompensated by reduced upward fluxes, leading to an anomalous net accumulation of energy in the snow-sea ice-ocean system due to shortwave fluxes between April-May and August-September (Figure 2.8(b)).

The combination of enhanced downward longwave and reduced downward shortwave radiation suggests that extremely low sea ice summers are characterized by enhanced cloudiness. During extremely low sea ice summers, statistically significant positive cloud cover anomalies are present from late winter to late spring (Figure 2.8(c)). The enhanced cloud cover is accompanied by positive integrated water vapour anomalies being statistically significant from late winter to mid-summer (Figure 2.8(c)). Consequently, apart from anomalously high air temperatures, enhanced cloudiness and water vapour in the atmosphere contribute to the positive downward and net longwave radiative surface fluxes during extremely low sea ice summers. Reduced upward shortwave radiative fluxes are naturally emerging due the reduction in the downward shortwave radiative fluxes.

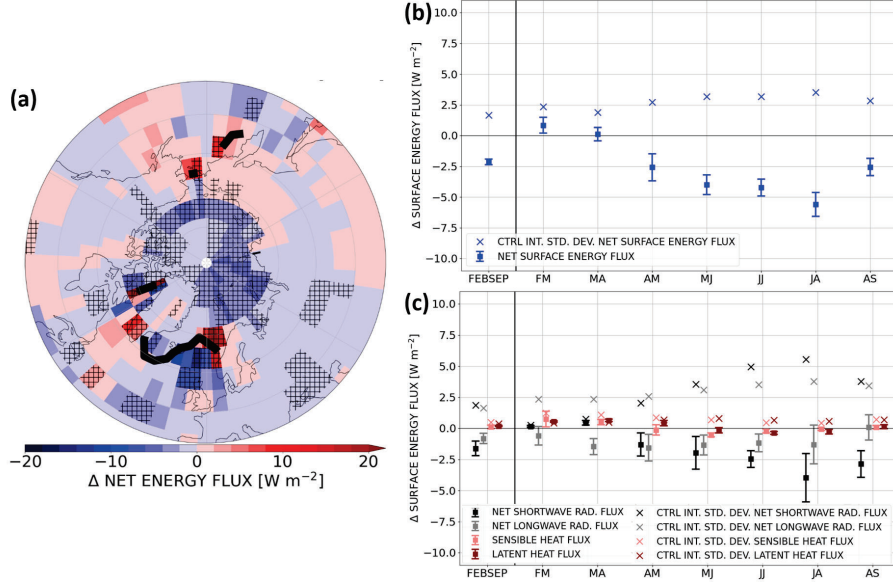


Figure 2.7: Rare event algorithm experiments with a resampling time of $\tau_r = 5$ days: Composite mean surface energy flux [W m^{-2}] anomalies conditional on extreme negative February-September mean pan-Arctic sea ice area anomalies equal or smaller than -2.5 standard deviations of the control ensembles. Mean anomalies are presented as an average over the five rare event algorithm experiments and are evaluated relative to the control run. Hatching in (a) indicates statistical significance at the 5% level and error bars in (b-c) show 95% confidence intervals obtained from the statistics of the five estimates (see Supplementary Information S2A). (a) February-September mean net surface-atmosphere energy flux anomalies (sensible + latent + net longwave + net shortwave). (b-c) February-September and bimonthly mean domain-averaged (b) net surface-atmosphere energy flux anomalies and (c) surface sensible and latent heat flux and net shortwave and net longwave radiative flux anomalies. The averaging is performed over all ocean grid boxes north of 70°N . The "x" markers respectively indicate the climatological standard deviations in the control run. The black contour line in (a) indicates the climatological February-September mean sea ice edge defined as the 15% sea ice concentration line.

However, a strongly reduced surface albedo due to reduced sea ice cover, i.e. the sea ice-albedo feedback, likewise contributes to the accumulation of energy related to the reduced upward shortwave fluxes (Figure 2.8(d)).

2.4 Discussion and conclusions

The present study demonstrates the applicability of a rare event algorithm to improve the sampling efficiency of extremely low pan-Arctic sea ice area during the melting season. The simulations with the rare event algorithm produce several hundreds of times more extremes than the control run for the same computational cost, and allow us to compute return times of extremes two to three orders of magnitude larger than feasible with direct sampling. Owing to the rare event algorithm, we compute statistically significant com-

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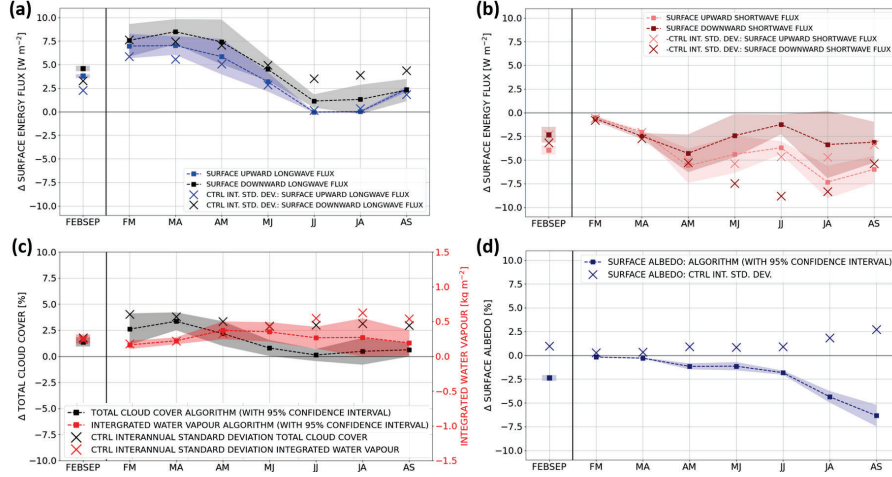


Figure 2.8: Rare event algorithm experiments with a resampling time of $\tau_r = 5$ days: February-September and bimonthly mean domain-averaged anomalies of different variables conditional on extreme negative February-September mean pan-Arctic sea ice area anomalies equal or smaller than -2.5 standard deviations of the control ensembles. Mean anomalies are presented as an average over the five rare event algorithm experiments and are evaluated relative to the control run. Shading indicates 95% confidence intervals obtained from the statistics of the five estimates (see Supplementary Information S2A). The domain is defined as in Figure 2.7. (a-b) Surface upward and downward (a) longwave and (b) shortwave radiative flux anomalies. Direction-independent absolute values of the downward and upward fluxes are considered, i.e., a positive (negative) anomaly indicates a radiative flux that is stronger (weaker) in magnitude than the climatology. (c) (black) Total cloud cover [%] and (red) integrated water vapour [kg m^{-2}] and (d) surface albedo [%] anomalies. (a-d) The "x" markers indicate respectively the climatological standard deviations in the control run.

posites of dynamical quantities conditional on the occurrence of extremely low sea ice summers with return times of more than 200 years. In this way, we identify four processes and conditions that lead to extreme negative February-September mean pan-Arctic sea ice area anomalies in PlaSim-LSG: 1) preconditioning through the winter sea ice-ocean state, 2) enhanced downward longwave radiation due to an anomalously moist and warm Arctic atmosphere in spring, 3) enhanced downward sensible heat fluxes in May-June and 4) the sea ice-albedo feedback becoming active throughout late spring and summer.

The preconditioning manifests in large negative winter pan-Arctic sea ice volume anomalies as a result of both negative sea ice area and sea ice thickness anomalies (Figure 2.5 and Supplementary Figure A4(a,b)). The preconditioning of anomalously low summer pan-Arctic sea ice area through negative winter sea ice thickness anomalies is in agreement with Chevallier and Salas-Méla [2012], Holland et al. [2011] and Kauker et al. [2009], who emphasize the important role of winter-spring sea ice thickness for the probability of sea ice to survive the melt season. Chevallier and Salas-Méla [2012] further argues that the winter-spring sea ice thickness, in particular the area covered by sea ice thicker than a critical thickness, is a better predictor of the summer pan-Arctic sea ice

area than the winter-spring sea ice area itself. Anomalous states in the winter-spring sea ice thickness and sea ice area can be generated by a variety of mechanisms, including the dynamical forcing of the atmospheric circulation on the sea ice [e.g. Ogi et al., 2016; Rigor et al., 2002], mechanisms related to the sea ice memory itself [Blanchard-Wrigglesworth et al., 2011] and an anomalous heat content in the ocean [Polyakov et al., 2012; Comiso, 2012]. While a future study is required to examine the precise cause of the preconditioning in PlaSim-LSG, direct dynamical causes can be excluded due to the fact that a purely thermodynamic sea ice model is used in the present work.

The second process is related to an anomalously moist and warm atmosphere, which manifests in enhanced downward longwave radiation between February-March and July-August accompanied by enhanced downward sensible heat flux in May-June. Enhanced spring downward longwave radiation as one driver of extremely low summer Arctic sea ice area is consistent with Kapsch et al. [2013, 2019], who demonstrate a linkage between observed extremely low September pan-Arctic sea ice area and a persistent anomalously moist and cloudy atmosphere in the preceding spring. Kapsch et al. [2019] and Persson [2012] argue that enhanced downward longwave radiation in spring can lead to enhanced surface warming prior to the melt onset and to an earlier melt onset compared to climatology. Kapsch et al. [2013, 2019] further demonstrate that the observed anomalously moist spring atmosphere prior to extremely low September Arctic sea ice area is related to enhanced meridional water vapour transport. In PlaSim-LSG, the anomalously moist and warm atmosphere may both be a trigger, i.e. via enhanced meridional heat and water vapour transport into the Arctic, and a response of extreme negative sea ice area anomalies, i.e. due to enhanced evaporation and sensible heat loss from the Arctic Ocean to the atmosphere due to positive surface temperature and open water fraction anomalies.

The third process suggests that the atmosphere may act not only as an amplifier but also as a trigger of sea ice retreat. In May-June, enhanced downward sensible heat fluxes over the Arctic Ocean are associated with a reinforcement of positive 500 hPa geopotential height anomalies compared to earlier months, while positive T2M anomalies are decreasing in amplitude (cf. Figures 2.6 and 2.7(c)). Consequently, the positive 500 hPa geopotential height anomalies and thus the anomalously warm lower troposphere during the spring-summer transition cannot be explained alone by a diabatic forcing through an anomalously warm surface. The atmospheric dynamics and energy fluxes in May-June are compatible with the characteristics of midlatitude heatwaves. The possible role of Arctic heatwaves as drivers of extreme sea ice retreat is relatively understudied in the literature, and a detailed analysis of their impacts and dynamical origin will be subject of a future study.

The fourth process is given by the sea ice-albedo feedback, which sets in during April-May as a consequence and amplifier of extremely low sea ice cover. Compared to the different atmosphere-surface flux components discussed in section 2.3.3, the sea ice-albedo feedback explains the largest amount of anomalous Arctic Ocean net energy accumulation during extremely low sea ice summers. Future rare event algorithm simulations with a prescribed surface albedo are a possibility to quantify the relative contribution of the sea ice-albedo feedback to extreme negative pan-Arctic sea ice area anomalies.

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Overall, two reasons let us conclude that, in PlaSim-LSG, the preconditioning through the winter-spring sea ice-ocean state is a more dominant driver of extreme negative February-September mean pan-Arctic sea ice area anomalies than the anomalous atmospheric conditions. Firstly, pan-Arctic sea ice volume anomalies prior to extremely low sea ice summers are about one and a half standard deviations away from the climatology (Figure 2.5(b)), while anomalies of atmospheric quantities and of downward atmosphere-surface energy fluxes are mostly less than one standard deviation away from the climatology (Figures 2.7(c) and 2.8(a-c)). Secondly, the most extreme February-September mean sea ice area anomalies obtained with the 5-days resampling time experiments only have marginally larger amplitudes than the ones obtained with the 30-days resampling time experiments (Figure 2.3). Consequently, the targeted sampling of atmospheric drivers of sea ice reduction that act on the upper range of synoptic and on submonthly time scales do not substantially increase the magnitude of the most extreme sea ice area anomalies compared to the 30-days resampling time experiments, which are primarily designed to efficiently sample oceanic drivers of low sea ice states. We highlight, however, that this study is based on a relatively low resolution climate model with a purely thermodynamic sea ice model. A direct dynamic forcing of the atmospheric circulation on the sea ice, e.g. related to synoptic-scale storms or to the AO and the AD pattern, are therefore not captured by the model.

We point out that, even though the experiments with the rare event algorithm presented in this paper are designed to improve the sampling efficiency of February-September mean pan-Arctic sea ice area anomalies, the method indirectly also oversamples trajectories characterized by negative anomalies of the pan-Arctic sea ice area during the annual sea ice minimum in September (Figure 2.2(a,b); note that the correlation coefficient between FEBSEP and September (SEP) pan-Arctic sea ice area in the control run is 0.69). This suggests a potential applicability of the rare event algorithm to study extremes of the annual Arctic sea ice minimum. This could also be obtained by changing the observable used to weight the trajectories from the pan-Arctic sea ice area to its time derivative. Finally, we highlight that in the experiments presented in this paper the initial conditions of the ensemble have been taken from the control run in order to have an unbiased sampling of the invariant measure of the dynamics. In this way, the return times and statistics computed with the algorithm are related to unconditional probability distributions. A different type of experiment would consist in starting each ensemble member from the same initial condition, as done for ensemble weather and seasonal climate predictions. In this case, the algorithm would give access to the statistics of extreme events conditional on the chosen initial condition. This approach could be of great interest in the context of seasonal predictions in order to estimate the risk of observing a record low of Arctic sea ice in summer given the conditions at the beginning of the melting season. This strategy and the extent to which the accuracy of statistical estimators based on the importance sampling formula in these type of experiments improves the results compared to direct sampling constitute an exciting line of research that will be explored in future works.

Chapter 3

Rare event sampling in seasonal climate prediction setup using PlaSim-LSG

This chapter is based on the following paper, published in *Earth System Dynamics*:

Sauer, J., Massonnet, F., Zappa, G., and Ragone, F.: Ensemble design for seasonal climate predictions: studying extreme Arctic sea ice lows with a rare event algorithm, *Earth System Dynamics*, 16, 683-702, <https://doi.org/10.5194/esd-16-683-2025>, 2025.

Abstract

Initialized ensemble simulations can help identify the physical drivers and assess the probabilities of weather and climate extremes based on a given initial state. However, the significant computational burden of complex climate models makes it challenging to quantitatively investigate extreme events with probabilities below a few percent. A possible solution to overcome this problem is to use rare event algorithms, i.e., computational techniques originally developed in statistical physics that increase the sampling efficiency of rare events in numerical simulations. Here, we apply a rare event algorithm

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to ensemble simulations with the intermediate complexity coupled climate model PlaSim-LSG to study extremes of pan-Arctic sea ice area reduction under pre-industrial greenhouse gas conditions. We construct four pairs of control and rare event algorithm ensemble simulations each starting from four different initial winter sea ice states. The rare event simulations produce sea ice lows with probabilities of two orders of magnitude smaller than feasible with the control ensembles, and drastically increase the number of extremes compared to direct sampling. We find that for a given probability level, the amplitude of negative late summer sea ice area anomalies strongly depends on the baseline winter sea ice thickness, but hardly on the baseline winter sea ice area. Finally, we investigate the physical processes in two trajectories leading to sea ice lows with conditional probabilities of less than 0.001%. In both cases, negative late summer pan-Arctic sea ice area anomalies are preceded by negative spring sea ice thickness anomalies. These are related to enhanced surface downward longwave radiative and sensible heat fluxes in an anomalously moist, cloudy and warm atmosphere. During summer, extreme sea ice area reduction is favoured by enhanced open-water-formation efficiency, anomalously strong downward solar radiation and the sea ice-albedo feedback. This work highlights that the most extreme summer sea ice conditions result from the combined effects of preconditioning and weather variability, emphasizing the need for thoughtful ensemble design when turning to real applications.

3.1 Introduction

Anthropogenic emissions of greenhouse gases have contributed to the loss of Arctic sea ice during the last 45 years [Notz and Marotzke, 2012; Stroeve and Notz, 2018; Gregory et al., 2002; Ding et al., 2017]. Despite the steadily increasing rate of greenhouse gas concentrations [Meinshausen et al., 2017], the decline of the pan-Arctic sea ice area is non-linear, and internal climate variability and feedback mechanisms have been shown to modulate the downward trend of the sea ice [Ding et al., 2017; Baxter et al., 2019; Ono et al., 2019; Francis and Wu, 2020; Tietsche et al., 2011; England et al., 2019]. Accelerated decline of the late summer sea ice area occurred from the mid-2000s to 2012, resulting in record reductions of sea ice area compared to the trend line in 2007 and 2012.

Various studies attributed the 2007 and 2012 drastic sea ice loss events both to climate change via preconditioning through the ongoing winter sea ice thinning and to internal climate variability via particular weather and climate events during the melting season [Lindsay et al., 2009; Kauker et al., 2009; Zhang et al., 2008, 2013; Parkinson and Comiso, 2013; Kirchmeier-Young et al., 2017]. While progress has been made in quantifying the relative contributions of anthropogenically forced vs. internal climate variability to the observed downward trend of the sea ice cover in the Arctic [e.g. Ding et al., 2017; England et al., 2019], their relative contributions to extreme sea ice loss events such as observed in 2007 and 2012 is uncertain [Kirchmeier-Young et al., 2017; Ono et al., 2019]. By applying an extreme event attribution analysis to ensemble simulations with the Second Generation Canadian Earth System Model (CanESM2), Kirchmeier-Young

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et al. [2017] concluded that a sea ice low with an amplitude as observed in 2012 (i.e. a 2012-like sea ice area anomaly relative to the observed 1981-2010 mean) would have been extremely unlikely to occur without global warming. A substantial contribution of internal climate variability to the 2007 and 2012 events is turn evidenced by the fact that, despite ongoing global warming, summer sea ice conditions are still above the 2012 minimum [Baxter et al., 2019; Francis and Wu, 2020].

Different drivers of anomalously low summer Arctic sea ice area were discussed in the literature. These include enhanced North Atlantic and Pacific oceanic heat transport [Årthun et al., 2012; Woodgate et al., 2010], the positive and negative phases of the winter and summer Arctic Oscillation (AO) (e.g. Rigor et al. [2002]; Ogi et al. [2016]), reduced cloudiness during summer [Schweiger et al., 2008], and increased surface downward longwave radiation related to enhanced poleward atmospheric moisture transport during spring [Kapsch et al., 2013, 2019]. In 2007, sea ice reduction was favoured by enhanced inflow of warm Pacific water through Bering Strait [Woodgate et al., 2010] and by anomalously persistent southerly winds in the Pacific sector associated with the Arctic Dipole (AD) Anomaly pattern [Wang et al., 2009; Lindsay et al., 2009; Overland et al., 2012; Kauker et al., 2009]. In 2012, a summer storm contributed to enhanced sea ice reduction by leading to increased bottom melt via anomalously strong vertical mixing in the oceanic boundary layer [Guemas et al., 2013; Zhang et al., 2013].

Even though the physical drivers of individual extremes of Arctic sea ice reduction have been suggested, their quantitative statistical analysis is hampered by the small number of extreme events that can be sampled from observations and numerical simulations. Likewise, it is the small number of events in the lower tail of the distribution of sea ice area values that makes it challenging to quantify the probability of a 2012-like sea ice low event for a given background climate and for a given initial condition. The record of satellite-based sea ice observations includes only a few annual sea ice minima with orders of magnitude comparable to the ones in September 2007 and 2012 [Fetterer et al., 2017]. Moreover, the large computational cost of complex climate models makes it unrealistic to run ensembles with a few thousands of trajectories and to quantitatively study extreme events with probabilities of less than 1%. The use of multiple models instead of one single model would even further increase the computational cost. One workaround is to estimate these very small probabilities with extreme value theory models [Coles, 2001]. However, even when applicable, these methods provide only a statistical extrapolation of the probabilities and do not provide information on the dynamics. A better understanding of the precursors of extremes of summer Arctic sea ice reduction and a more precise estimate of their probabilities are in turn crucial to improve seasonal predictions of these events and to assess their risk of occurrence under different climate change scenarios.

In this work, we study extremely negative summer pan-Arctic sea ice area anomalies using initialized ensemble simulations with the intermediate complexity coupled climate model PlaSim-LSG under pre-industrial greenhouse gas conditions. We investigate the statistical properties of extreme summer sea ice lows as a function of different initial winter states and examine the physical drivers favoring extremes of sea ice area reduction within a single melting season. In order to improve the sampling of extreme sea ice loss events, we use a rare event algorithm. Rare event algorithms are computational techniques devel-

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oped in statistical physics to improve the sampling efficiency of rare events in numerical simulations [e.g. Ragone et al., 2018; Ragone and Bouchet, 2020, 2021; Sauer et al., 2024]. Compared to conventional numerical simulations with the same computational cost, rare event algorithms enable to increase the number of simulated extreme events by several orders of magnitude while preserving the dynamical consistency of the model. In this way, these techniques allow to reduce the uncertainty of probability and return time estimates and of conditional statistics on extreme events (e.g. composites) compared to conventional simulation strategies, and to generate ultra-rare events that are very unlikely to be observed using direct sampling. Rare event algorithms have been introduced in the 1950s [Kahn and Harris, 1951] and have been used since for a wide range of applications (for an overview and the mathematical analysis see e.g. Del Moral [2004]; Giardina et al. [2011]; Grafke and Vanden-Eijnden [2019]). Recently, some of these techniques have been applied in climate science and in fluid dynamics to study heat waves [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021], midlatitude precipitation [Wouters et al., 2023], tropical storms [Plotkin et al., 2019; Webber et al., 2019], weakening and collapse of the Atlantic Meridional Overturning Circulation (AMOC) [Cini et al., 2024], extreme Arctic sea ice lows related to unconditional probability distributions [Sauer et al., 2024] and turbulence [Bouchet et al., 2018; Grafke et al., 2015; Lestang et al., 2020].

Here we use a genealogical selection algorithm [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021; Sauer et al., 2024] adapted from Del Moral and Garnier [2005]; Giardina et al. [2011], that is efficient to study persistent, long lasting events. A first application of this algorithm to study extreme Arctic sea ice lows in the intermediate complexity coupled climate model PlaSim under pre-industrial greenhouse gas conditions is given in Sauer et al. [2024]. In that study, ensemble simulations with the rare event algorithm were initialized with independent initial conditions sampled from a stationary 3000-year control run such that the statistics of extreme events is related to unconditional probability distributions. In such an approach, the rare event algorithm seeks to oversample trajectories leading to low sea ice states in an absolute sense, i.e., independent from the extent to which the sea ice lows are related to multi-annual fluctuations in the sea ice-ocean system (referred to as "preconditioning" in Sauer et al. [2024]) or driven by the dynamics occurring on intra-seasonal time scales. Here, instead, we use a seasonal climate prediction set-up where an ensemble simulation is initialized from a single initial condition to which a small perturbation is added. The goal of these experiments is to disentangle the roles of the initial condition vs. seasonal scale fluctuations in favouring the occurrence of extremely negative summer sea ice area anomalies. A similar investigation on the influence of initial conditions on an extreme event, albeit using action minimization instead of a genealogical selection algorithm and applied to extreme tropical cyclones, is performed in Plotkin et al. [2019]. Here we perform different ensemble simulations starting from different initial conditions sampled from the same control run as in Sauer et al. [2024]. Since each individual ensemble simulation is initialized from a same, slightly perturbed initial condition, statistical and physical properties of low sea ice states inferred from that ensemble need to be interpreted in terms of conditional probabilities.

Owing to the rare event algorithm, we generate extremely low sea ice summers with conditional probabilities of less than 0.001%. Likewise, we investigate the impact of

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different initial conditions on the probabilities and amplitudes of extreme sea ice lows. Finally, we elaborate physical drivers in two trajectories leading to late summer sea ice lows with probabilities of less than 0.001%. The paper is structured as follows. In section 3.2, we present the set-up of the model, the methodology of the rare event algorithm and the design of control and rare event algorithm ensemble simulations. In section 3.3, we show that the rare event algorithm improves the sampling efficiency of extreme sea ice lows conditional on starting from a certain initial condition compared to standard control ensemble simulations. We analyze the impact of the initial condition on the probabilities and amplitudes of the extremes. In section 3.3, we discuss physical processes and conditions in individual trajectories prior to extreme sea ice lows with probabilities with less than 0.001%. In section 3.4, we present our conclusions.

3.2 Materials and methods

3.2.1 Model and data

All simulations are performed with a coupled set-up of the intermediate complexity climate model Planet Simulator (PlaSim) version 17 [Fraedrich et al., 2005]. This set-up includes a dynamic Large-Scale Geostrophic (LSG) ocean [Maier-Reimer et al., 1993; Drijfhout et al., 1996], a mixed-layer ocean and a thermodynamic sea ice model (PlaSim coupled to LSG is referred to as "PlaSim-LSG" in the following).

The atmosphere is run with a horizontal spectral resolution of T21 (triangular truncation at wavenumber 21 $\sim 5.625^\circ \times 5.625^\circ$ on a Gaussian grid), ten levels up to 40 hPa in the vertical and a computational time step of 45 minutes. The LSG is configured on a $2.5^\circ \times 5^\circ$ staggered E-type grid [Arakawa and Lamb, 1977] in the horizontal, with 22 levels and a maximum ocean depth of 6000 m in the vertical and a computational time step of five days. The sea ice model is based on the zero-layer model of Semtner [1976]. It computes the sea ice thickness and sea surface temperature evolution from the energy balances at the top and bottom of a sea ice-snow layer. The sea ice-snow layer is assumed to have a linear temperature gradient and to have no capacity to store heat. No sea ice drift is taken into account. The sea ice concentration is binary, i.e., a grid cell is fully sea ice covered or open water. The computational time step in the sea ice and mixed-layer ocean models is one day.

PlaSim-LSG is run with a fixed pre-industrial effective CO₂ volume mixing ratio of 280 ppmv. We choose a constant greenhouse gas forcing since we are interested in the statistics and dynamics of Arctic sea ice lows related to internal climate variability under a stationary climate. Solar radiation includes the seasonal cycle but not the diurnal cycle. Each model month is 30 days long.

We use data from a stationary 3000-year control run [Sauer et al., 2024] and from a set of control and rare event algorithm ensemble simulations (see section 3.2.2 for more details). We consider the statistics of the pan-Arctic sea ice area

$$A(t) = \sum_{\phi \geq \phi_{min}} \sum_{\lambda} SIC_{\phi,\lambda}(t) \cdot G_{\phi,\lambda}, \quad (3.1)$$

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where $SIC_{\phi,\lambda}(t)$ is the sea ice concentration at time t in a grid cell centered at latitude ϕ and longitude λ , $G_{\phi,\lambda} = \int_{\phi-\frac{\Delta\phi}{2}}^{\phi+\frac{\Delta\phi}{2}} \int_{\lambda-\frac{\Delta\lambda}{2}}^{\lambda+\frac{\Delta\lambda}{2}} R^2 \cos(\phi') d\lambda' d\phi'$ is the grid cell area, R is the earth radius, $\Delta\phi$ and $\Delta\lambda$ are the angular distances between two grid points in the meridional and zonal direction. The summation in (3.1) includes all ocean grid boxes north of 40°N (i.e. $\phi_{min} \cdot \frac{180^\circ}{\pi} = 40^\circ$) with a binary land-sea mask (i.e. a grid cell is either completely ocean or land). The annual average, amplitude of the seasonal cycle and the timing of the annual minimum and maximum of the pan-Arctic sea ice area produced by the model are representative of the observed Arctic sea ice climatology between 1979 and 2015 (cf. Figure 1(a,c) of Sauer et al. [2024] and Figure S1 in the Supplementary Information of Sauer et al. [2024]). Likewise, PlaSim captures a spring predictability barrier-like structure in the persistence of pan-Arctic sea ice area anomalies similar to the one found in comprehensive climate models (cf. Supplementary Figure B1 and Blanchard-Wrigglesworth et al. [2011]; Day et al. [2014]). Compared to the 1979-2015 climatology available from the Pan-Arctic Ice Ocean Modeling and Assimilation System (PIOMAS), PlaSim represents the pan-Arctic sea ice volume reasonably well during spring and slightly underestimates the sea ice volume during summer (cf. Supplementary Figure B2(a) and page 207 of Chevallier et al. [2019]). Differences in the representation of sea ice in PlaSim-LSG compared to observations and reanalysis data include a delayed melting period, a positive sea ice concentration (SIC) bias from the Greenland to the Kara Sea, a negative SIC bias western of Greenland, positive sea ice thickness biases around the North Pole and from the Greenland to Kara Seas (cf. Figure 1(a,c) of Sauer et al. [2024], Figure S1 in the Supplementary Information of Sauer et al. [2024], page 207 of Chevallier et al. [2019] and Supplementary Figure B2(b)). While overall the differences between the pan-Arctic sea ice area in PlaSim-LSG and in observational data are small compared to the range of sea ice area values available from the Coupled Model Intercomparison Project Phase 6 (CMIP6) models [Notz and Community, 2020], the regional sea ice thickness and sea ice concentration biases of PlaSim compared to the derived 1979-2015 climatologies may impact the interpretation of the results. We will discuss this point in section 3.4.

We study extreme anomalies of February-September and August-September mean pan-Arctic sea ice area. We classify a sea ice area anomaly $I'(t)$ as extremely negative if $I'(t) \leq n\sigma_{ctrl}$, where σ_{ctrl} is the standard deviation of sea ice area in the control run or in a control ensemble (see section 3.2.2) and n is a real-valued number. In the following, we will vary n continuously to study an extensive range of extreme event amplitudes.

3.2.2 Rare event algorithm: Methodology and set-up

One key difficulty in the study of climate extremes is the lack of robust statistics as the large computational burden of complex climate models makes it unfeasible to run them long enough to sample a large amount of trajectories corresponding to the tail of the distribution of a target observable.

The rare event algorithm presented in recent studies [Giardina et al., 2011; Ragone et al., 2018; Ragone and Bouchet, 2020, 2021; Sauer et al., 2024] is a genealogical selection algorithm applied on top of an ensemble simulation. It is designed to improve the sampling efficiency of trajectories populating the tail of the distribution of the time-

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average of a target observable $A(t)$. At constant intervals of a resampling time τ_r , we assign to each trajectory a weight. The weight is a function of the time-average of the observable during the past interval of duration τ_r for that trajectory. Before simulating the next time window of length τ_r , trajectories with small weights are removed from the ensemble and are substituted by slightly perturbed copies of trajectories with large weights. The algorithm includes a parameter k which controls the relative amplitude of the weights for given values of the target observable, where the case $k = 0$ would correspond to a regular ensemble simulation. If τ_r is not larger than the decorrelation time of the observable, then the selection will favour the survival of trajectories leading to extreme anomalies of the time-average of a target observable such as the pan-Arctic sea ice area (positive for k positive and vice versa). We refer to Ragone et al. [2018]; Ragone and Bouchet [2020, 2021]; Sauer et al. [2024] for more details about the method and present here the main outcome.

We denote $X(t)$ the vector of all model variables at time t and T_a the total simulation time. We consider an ensemble of N trajectories $\{X_n(t)\}$ ($n = 1, 2, \dots, N$). Let $\mathbb{P}_0(\{X_n(t)\}_{0 \leq t \leq T_a})$ be the probability density of observing a given trajectory $X_n(t)$ from time 0 to time T_a in a direct numerical simulation with the model, and $\mathbb{P}_k(\{X_n(t)\}_{0 \leq t \leq T_a})$ be the probability density of the same trajectory in an ensemble simulation with the rare event algorithm with a given value of the parameter k . For a large ensemble size N the relation between the two is given by the importance sampling formula

$$\mathbb{P}_k(\{X_n(t)\}_{0 \leq t \leq T_a}) \underset{N \rightarrow \infty}{\sim} \frac{e^{k \int_0^{T_a} A(\{X_n(t)\}) dt}}{\mathbb{E}_0[e^{k \int_0^{T_a} A(\{X_n(t)\}) dt}] \mathbb{P}_0(\{X_n(t)\}_{0 \leq t \leq T_a})}, \quad (3.2)$$

where $\mathbb{E}_0$ is the expectation value with respect to $\mathbb{P}_0$, $A\{X_n(t)\}$ the target observable and k a biasing parameter controlling the strength of the selection. Thanks to Equation (3.2), the expectation value according to $\mathbb{P}_0$ (the real statistics of the system) of a generic quantity $O(\{X_n(t)\}_{0 \leq t \leq T_a})$ can be estimated from data generated with the algorithm (which are instead distributed according to $\mathbb{P}_k$) as

$$\mathbb{E}_0[O(\{X_n(t)\}_{0 \leq t \leq T_a})] \underset{N \rightarrow \infty}{\sim} \frac{1}{N} \sum_{n=1}^N Z_k e^{-k \int_0^{T_a} A(\{X_n(t)\}) dt} \cdot O(\{X_n(t)\}_{0 \leq t \leq T_a}). \quad (3.3)$$

where Z_k is a constant factor computed by the algorithm (see Ragone et al. [2018]; Ragone and Bouchet [2020]). Equation (3.3) shows that statistical quantities like composites, probabilities or return times with respect to the real model statistics can be estimated with data generated by the algorithm by weighting the contribution of each trajectory to sample averages by the inverse of the exponential factor which appears in the importance sampling formula. In Ragone et al. [2018], Ragone and Bouchet [2020, 2021] and Sauer et al. [2024], the trajectories appearing in (3.2) and (3.3) were generated from ensembles initialized with different initial conditions randomly selected from a control run to uniformly sample the attractor of the dynamics. In such an application, Equation (3.2) would refer to unconditional probabilities. In this work, however, the ensembles are ini-

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tialized from single initial conditions and the probabilities and expectation values in (3.2) and (3.3) have to be interpreted as conditional on the selected initial state.

We use as target observable $A\{X_n(t)\}$ the pan-Arctic sea ice area and perform $M = 4$ ensemble simulations with the rare event algorithm initialized from four different initial conditions. For each of these four initial conditions, we produce $K = 10$ realizations (i.e. a total number of 40 ensemble simulation) in order to quantify the sampling uncertainty in the estimation of probabilities of exceeding a given sea ice area threshold (see section 3.3.1 and Supplementary Information S3D). In order to have a baseline of the statistics, each of the four experiments is accompanied by $K = 10$ realizations of control ensemble simulation (i.e. a simulation without applying the algorithm) with the same ensemble size, simulation length and initial condition as the one with the rare event algorithm. Each ensemble contains $N = 600$ trajectories and is run for a total simulation time $T_a = 240$ days from 01 February to 30 September. The $K = 10$ realizations of rare event and control ensemble simulations are labeled arbitrarily as "REALIZATION1", "REALIZATION2", ..., "REALIZATION10", i.e., the random perturbation set at the initial condition for e.g. "REALIZATION1" of the rare event simulation is independent from the perturbation set at "REALIZATION1" for the control ensemble. Hereafter, the baseline of the statistics and all climatologies are derived from a $N = 6000$ "master control ensemble" (referred to as "control ensemble" hereafter) where the trajectories of all the ten realizations of the control ensembles are merged together.

The biasing parameter in the simulations with the rare event algorithm is $k = -0.075 \cdot 10^{-6} \text{ km}^{-2} \text{ day}^{-1}$. The precise value of k is chosen empirically. However, a reasonable order of magnitude of the parameter can be derived from the standard deviation and decorrelation time of the sea ice area anomalies in the control ensembles using a scaling argument presented in Ragone and Bouchet [2020] and in the Supporting Information of Ragone and Bouchet [2021]. According to this scaling argument, the selected k -value corresponds to a shift of the mean of the distribution of the February-September mean sea ice area to values between approximately $0.15 \cdot 10^6 \text{ km}^2$ and $0.35 \cdot 10^6 \text{ km}^2$ below the means of the control ensembles. This corresponds to a range of estimated probabilities between about 10% and 1% (see section 3.3.1).

The resampling time in the simulations with the rare event algorithm is $\tau_r = 5$ days. It is chosen to be not larger than the persistence time scale of the large-scale atmospheric circulation [Baldwin et al., 2003] and to be only slightly larger than the typical persistence of synoptic-scale atmospheric fluctuations [Hoven, 1957]. The rare event simulations are therefore suitable to improve the sampling efficiency of extremely low sea ice states both driven by oceanic processes and due to anomalies in the atmospheric circulation that are in the order of or larger than the upper range of the synoptic time scale.

Within an individual ensemble, each trajectory starts from the same initial condition as done for ensemble weather and seasonal climate predictions. In order to allow the trajectories to diverge from each other, we slightly perturb the surface pressure field of each trajectory as described in the Supporting Information of Ragone et al. [2018]. The four different initial conditions for the four ensembles are sampled from the 3000-year control run according to different anomaly values of the January-February mean pan-Arctic sea ice area, i.e. the observable itself, and of the January-February mean

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cumulative area with sea ice thickness equal or larger than 1.93 m (SIT1.93, Figure 3.1 and Table 3.1). The choice of SIT1.93 is motivated by the studies of Chevallier and Salas-Mélia [2012] and Lindsay et al. [2008]. According to those studies, the late winter-early spring cumulative area with sea ice thickness larger than a critical threshold has a larger impact on the late summer sea ice area than the winter-spring sea ice volume and area itself. Here we apply a composite analysis to the PlaSim-LSG control run to identify a sea ice-related variable whose anomaly value during the timing of the ensemble initialization has a potentially large connection with the probability of an extreme late summer sea ice low (Figure 3.1(a); note that the critical thickness values of 0.2 m, 0.5 m, 0.66 m, 0.9 m, 1.5 m, 1.93 m, 2.5 m, 4 m, 4.2 m, 6 m are selected from Chevallier and Salas-Mélia [2012] and Lindsay et al. [2008]). Compared to the various variables shown in Figure 3.1(a), extremely negative February-September and August-September mean sea ice area anomalies are most strongly related to the January-February sea ice volume and cumulative area with sea ice thickness equal or larger than a critical thickness between 1.8 m and 2.1 m respectively. We choose SIT1.93 following the critical threshold used in Lindsay et al. [2008]. We emphasize, however, that the labeling ("SIT1.93–", "SIT1.93=", "SIT1.93+") of the selected initial conditions would be the same as in this study if the labeling were chosen according to the anomaly values of the cumulative area with sea ice thickness equal or larger than the remaining thresholds between 1.80 m and 2.10 m. In PlaSim-LSG, the correlations between SIT1.93 and the cumulative area with sea ice thickness equal or larger than the remaining thresholds between 1.8 m and 2.1 m are between 0.96 and 0.99, and the precise choice of a threshold between 1.8 m and 2.1 m does not affect the interpretation of the results.

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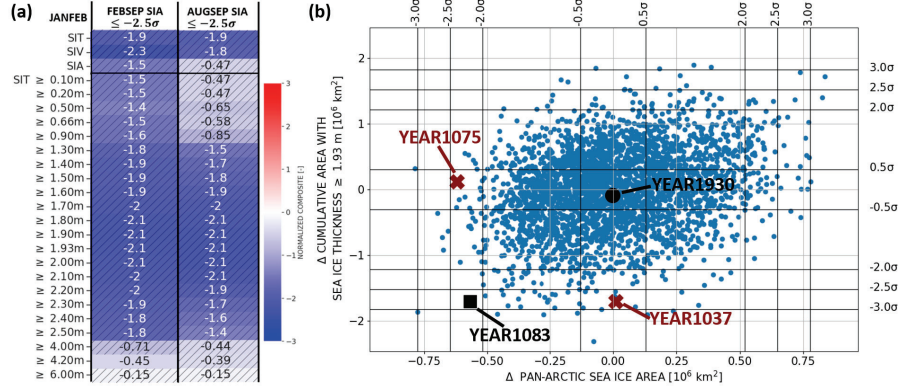


Figure 3.1: PlaSim-LSG 3000-year control run (Sauer et al. [2024]): (a) Normalized mean anomalies of January-February mean quantities conditional on extreme negative (left) February-September (FEBSEP) and (right) August-September (AUGSEP) mean pan-Arctic sea ice area anomalies equal or smaller than -2.5σ . "SIV", "SIA" and "SIT" are the pan-Arctic sea ice volume, sea ice area and mean sea ice thickness. "SIT $\leq$ threshold" are anomalies in the cumulative area with sea ice thickness equal or larger than a critical threshold. Hatching denotes statistical significance at the 5% level assessed from a two-sided t-test applied to five composite estimates after subdividing the 3000-year control run into five 600-member ensembles (see Supplementary Information S3D for more details). (b) Scatter plot of January-February mean anomalies of SIT1.93 vs. pan-Arctic sea ice area including the years from the selected initial conditions.

Table 3.1: 6000-member control and 600-member rare event algorithm ensemble simulations running between 01 February and 30 September. Labeling of the experiments according to the different initial conditions with (middle column) the full label and (right column) short labels used in the text.

Control run year	Full label	Short label
1083	SIA-LOW SIT1.93-LOW	SIA– SIT1.93–
1037	SIA-NEUTRAL SIT1.93-LOW	SIA= SIT1.93–
1075	SIA-LOW SIT1.93-NEUTRAL	SIA– SIT1.93=
1930	SIA-NEUTRAL SIT1.93-NEUTRAL	SIA= SIT1.93=

3.3 Results

3.3.1 Importance sampling of extreme sea ice lows and estimation of their probabilities

We exploit initialized ensemble simulations to investigate the statistical properties of extreme negative February-September and August-September mean pan-Arctic sea ice area anomalies as a function of four different initial winter sea ice states (see section 3.2.2). The goal of using the rare event algorithm is to obtain a better statistics of extremely low sea ice area values than available from standard control ensemble simulations. Compared

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to the latter, the algorithm likewise allows to better infer the order of magnitude of a lower bound of sea ice area values that can be generated internally via atmosphere-ocean dynamics.

We show the time evolution of pan-Arctic sea ice area anomalies relative to the control ensemble mean and the distributions of summer sea ice area for the ensemble simulations starting from a neutral initial winter sea ice state (Figure 3.2(a,c,e); control run model year 1930 and labeled as "SIA= SIT1.93="; see section 3.2.2 for more details) and from an initial winter state characterized by neutral sea ice area and extremely low cumulative area with sea ice thickness equal or larger than 1.93 m (SIT1.93; Figure 3.2(b,d,f); control run model year 1037 and labeled as "SIA= SIT1.93="; note that Figure 3.2 compares for both initial conditions one realization of the rare event simulation with $N = 600$ trajectories with the statistics of $N = 6000$ control ensemble trajectories). Among all four experiments, the "SIA= SIT1.93=" and "SIA= SIT1.93=" rare event simulations delivers the trajectory with the most extremely negative August-September mean sea ice area anomaly relative to the corresponding control ensemble means (i.e. relative to the climatological mean values defined for the two sea ice initial conditions; these anomalies are in both cases $-1.87 \cdot 10^6 \text{ km}^2$), and the "SIA= SIT1.93=" experiment produces the trajectory leading to the lowest August-September mean sea ice area value in an absolute sense among all available simulations.

Both in the "SIA= SIT1.93=" and "SIA= SIT1.93=" experiments, the differences between the sea ice area in the rare event algorithm and the control ensemble mean are small compared to the control intra-ensemble standard deviation until June (Figure 3.2(a,b)). From the end of June onwards, trajectories generated with the rare event algorithm show a systematic shift towards lower sea ice area values compared to the control ensembles, reaching an ensemble mean shift of about $-1.2 \cdot 10^6 \text{ km}^2$ and $-1.5 \cdot 10^6 \text{ km}^2$ in the "SIA= SIT1.93=" and "SIA= SIT1.93=" experiments respectively.

The biasing towards negative sea ice area anomalies with the rare event algorithm compared to the control ensemble reflects the importance sampling of extreme negative sea ice area anomaly values on average over the entire simulation period between February and September (Figure 3.2(c-d)) [cf. Sauer et al. [2024]; Ragone and Bouchet [2021]]. The distributions of February-September mean sea ice area obtained with the rare event algorithm fluctuate around a mean value in the lower tail of the control distribution, and their minimum sea ice area values are smaller than the minima obtained with the corresponding control ensembles (minimum February-September mean sea ice area values of $9.69 \cdot 10^6 \text{ km}^2$ and $9.25 \cdot 10^6 \text{ km}^2$ in the "SIA= SIT1.93=" and "SIA= SIT1.93=" rare event simulations vs. $9.74 \cdot 10^6 \text{ km}^2$ and $9.32 \cdot 10^6$ in the corresponding control ensemble simulations). As the February-September mean sea ice area is strongly related to the August-September one (the minimum-maximum range of the correlation between both quantities across the members in all four control ensembles is $[0.89 \ 0.92]$), the algorithm likewise improves the sampling efficiency of extremely low August-September mean sea ice area exceeding the lower range of sea ice area values obtained with the control ensembles (Figure 3.2(e-f)); minimum August-September mean sea ice area values of $2.82 \cdot 10^6 \text{ km}^2$ and $1.91 \cdot 10^6 \text{ km}^2$ in the "SIA= SIT1.93=" and "SIA= SIT1.93=" rare event simulations vs. $3.16 \cdot 10^6 \text{ km}^2$ and $2.18 \cdot 10^6$ in the control ensemble simulations; we discuss the

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fraction of surviving trajectories and the number of different initial-time ancestors leading to extreme events in the Supplementary Information S3E and Supplementary Figures B7 and B8). The distributions of sea ice area values obtained with the rare event algorithm show a bimodality in both experiments. We will address this behavior in section 3.4.

It is noticeable that the sea ice area obtained with the control and rare event ensemble simulations depends on the chosen initial condition (i.e. its location relative to the distribution of the 3000-year control run varies among the different experiments; Figure 3.2(c-f)). In order to quantify the impact of the initial condition on extreme summer sea ice lows, we compare the probability of extreme negative February-September and August-September mean sea ice area anomalies between the four experiments (Figure 3.3). We compute these probabilities as

$$P(a) = \frac{1}{N} \sum_{n=1}^N \mathbb{1}_a(I_n) \text{ with } \mathbb{1}_a(I_n) = \begin{cases} 1, & I_n \leq a \\ 0, & I_n > a \end{cases}, \quad (3.4)$$

where I_n is the February-September or August-September time-averaged pan-Arctic sea ice area in trajectory n , a is the amplitude of the sea ice area anomaly, N the number of trajectories and $\mathbb{1}_a(I_n)$ is the indicator function. As Equation (3.4) represents the probability as an expectation value of the indicator function, probabilities from the simulations with the rare event algorithm can be computed by applying the estimator in Equation (3.3) to this quantity (see Lestang et al. [2018], Ragone et al. [2018]; Ragone and Bouchet [2020] and Sauer et al. [2024]).

In Figure 3.3, the star markers show the probabilities estimated with the $N = 6000$ trajectory control ensembles. The solid lines and the shadings show the average estimates and 95% confidence intervals obtained from multiple realizations of the rare event algorithm ensemble simulations respectively (see Supplementary Information S3D for a description of the computation of the confidence intervals). The control and rare event algorithm estimates are consistent with each other where they overlap. Compared to the control ensembles, the major advantage of the algorithm is the access to much rarer events with the former than the latter, reaching probability values of 10^{-5} (0.001%) for a computational cost of order 10^3 - 10^4 years. Moreover, compared to direct sampling, the rare event algorithm allows for a statistically more robust estimate of the probabilities of trajectories corresponding to the lower tail of the control distribution (i.e. corresponding to probability estimates below 10^{-3} in this application).

For a fixed probability level, the amplitudes of February-September and August-September mean sea ice area span a range of about three and two standard deviations among the different initial conditions. This confirms a strong impact of the initial condition on the amplitudes and probabilities of extreme negative summer sea ice area anomalies evaluated relative to the 3000-year control run baseline climatology (Figure 3.3). Regarding the February-September seasonal average, both a low state in the winter SIT1.93 and in the winter sea ice area contribute to the preconditioning of an extreme (Figure 3.3(a)). Consequently, the most extremely negative seasonally averaged sea ice area anomalies occur following years with both a low winter state in the sea ice area and in SIT1.93 (Figure 3.3(a)). The contribution of low winter sea ice area and low SIT1.93 to these

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anomalies, however, is not fully additive (Figure 3.3(a)). For a fixed probability level, the sum of the February-September mean sea ice area anomalies relative to the control run mean over the "SIA= SIT1.93=" and "SIA- SIT1.93=" experiments exceeds in magnitude the sea ice area anomalies obtained with the "SIA- SIT1.93=" experiment. We hypothesize that the preconditioning of low states of the seasonally mean sea ice area through low winter sea ice area and SIT1.93 is efficient only for a restricted geographic region where the climatological mean sea ice thickness is small enough to be able to form open water within one season. In parts of that region, the contribution of low winter sea ice area and SIT1.93 to an anomalously large area of open water during summer is likely to overlap spatially (i.e. open water conditions prevail in certain grid boxes independent from whether both winter sea ice area and SIT1.93 are in a low state or only one of them). Moreover, the overlapping confidence intervals between the "SIA= SIT1.93=" and "SIA- SIT1.93=" experiments suggests that low winter states in the sea ice area and SIT1.93 are equally important in favouring an extremely negative February-September mean sea ice area anomaly.

Regarding the August-September mean, the contribution of a low winter sea ice area to an extreme is small compared to the contribution of a low winter state in SIT1.93 (Figure 3.3(b)). Thus, similar amplitudes of extremely low August-September mean sea ice area occur for the "SIA= SIT1.93=" and "SIA- SIT1.93=" experiments. Likewise, the most extremely negative August-September mean sea ice area occurs in the experiment starting from an initial condition with a low SIT1.93 and a neutral winter sea ice area. A low winter sea ice area is therefore not required to produce the most extremely negative August-September sea ice area anomalies.

Despite the important role of preconditioning in favouring extremely low sea ice states, preconditioning represents only a necessary and not a sufficient condition for extremes with the largest amplitudes available in this study (Figure 3.3 and Table 3.2). Extreme sea ice lows with sea ice area values corresponding to the 1% percentile of the model distribution or less occur as a consequence both of winter sea ice-ocean preconditioning and anomalous intra-seasonal processes (e.g. weather patterns; see section 3.3.2) that enhance sea ice reduction within one single melting season. The relative contribution of preconditioning to extreme sea ice lows vs. anomalous dynamics on an intra-seasonal time scale is larger for February-September than August-September mean sea ice area (Figure 3.3 and Table 3.2). Thus, the February-September time-averaged control ensemble mean sea ice area anomaly for the "SIA- SIT1.93=" initial condition explains about 65% of the magnitude of the 1% percentile of February-September mean sea ice area anomalies available from all the ten "SIA- SIT1.93=" rare event algorithm ensemble simulations. In contrast, the August-September time-averaged control ensemble mean sea ice area anomaly for the experiments starting from a "SIT1.93=" initial condition are in magnitude in the order of 40%-50% of the 1% percentile of August-September mean sea ice area anomalies available from ten ensemble simulations with the rare event algorithm respectively (Figure 3.3 and Table 3.2).

The results obtained in Figure 3.3 are consistent with the memory properties of the sea ice in the Arctic. Typically, late summer sea ice area anomalies are poorly connected to the late winter sea ice area [Blanchard-Wrigglesworth et al., 2011; Chevallier and Salas-Méla,

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2012; Day et al., 2014; Tietsche et al., 2014], explaining the non-existing contribution of winter sea ice area anomalies to extreme late summer sea ice area lows. Compared to the sea ice area, quantities related to the sea ice thickness, as shown in Chevallier and Salas-Mélia [2012], act as a preconditioning for extreme reduction of sea ice area via its impact on the open-water formation efficiency during summer. The dependency of extreme negative seasonally-averaged sea ice area anomalies on the winter sea ice area is explainable by the persistence of negative sea ice area anomalies from late winter to spring [Blanchard-Wrigglesworth et al., 2011].

Table 3.2: February-September (FEBSEP) and August-September (AUGSEP) mean sea ice area anomalies relative to the mean μ of the 3000-year control run expressed in the unit of multiple control run standard deviations (" $n\sigma$ " with $n \in \mathbb{R}$). "Control run" refers to a 3000-year long integration of a single trajectory (presented in Sauer et al. [2024]), whereas "control ensembles" refer to multiple trajectories run from 01 February to 30 September and initialized from one single initial condition. The anomalies in the column " $SIA_{0.01}-\mu$ " correspond to the 1% percentile sea ice area value (i.e. preconditioning + anomalous weather) presented as the average over ten estimates available from the output of ten rare event algorithm experiments. The anomalies in the $\mu_{ENS}-\mu$ column correspond to the control ensemble mean, i.e., the impact of preconditioning on the mean of the $N = 6000$ trajectory control ensemble. For the computation of the percentiles with the algorithm, we weight the contribution of each trajectory to the percentile by the product of Z_k and the exponential factor shown in Equation (3.3). The values in brackets show 95% confidence intervals around the percentile estimates derived from ten realizations (assuming t-distributions).

	FEBSEP		AUGSEP	
Initial condition	$(SIA_{0.01} - \mu)$ [$n\sigma$]	$(\mu_{ENS} - \mu)$ [$n\sigma$]	$(SIA_{0.01} - \mu)$ [$n\sigma$]	$(\mu_{ENS} - \mu)$ [$n\sigma$]
SIA– SIT1.93–	–3.80 [–3.73, –3.86]	–2.49	–3.32 [–3.19, –3.45]	–1.36
SIA= SIT1.93–	–2.76 [–2.69, –2.83]	–1.39	–3.91 [–3.80, –4.00]	–1.89
SIA– SIT1.93=	–2.81 [–2.61, –3.00]	–1.71	–1.82 [–1.51, –2.10]	–0.19
SIA= SIT1.93=	–0.98 [–0.91, –1.05]	+0.22	–2.14 [–1.96, –2.33]	–0.19

3.3.2 Physical processes and conditions prior to sea ice lows with probabilities of less than 0.001%

In this section we study the physical processes and conditions favouring extremely low late summer sea ice area. In contrast to the work in Sauer et al. [2024], the development of low sea ice states relative to the initial condition-specific control ensemble mean are entirely attributable to intra-seasonal drivers as all trajectories within an ensemble start from the same initial condition. Using the "SIA= SIT1.93=" and "SIA= SIT1.93–" experiments, we discuss the trajectory leading to the lowest August-September mean pan-Arctic sea ice area value available within each of the two experiments respectively (Figures 3.4-3.7). The lowest August-September mean sea ice area values in the "SIA= SIT1.93=" and

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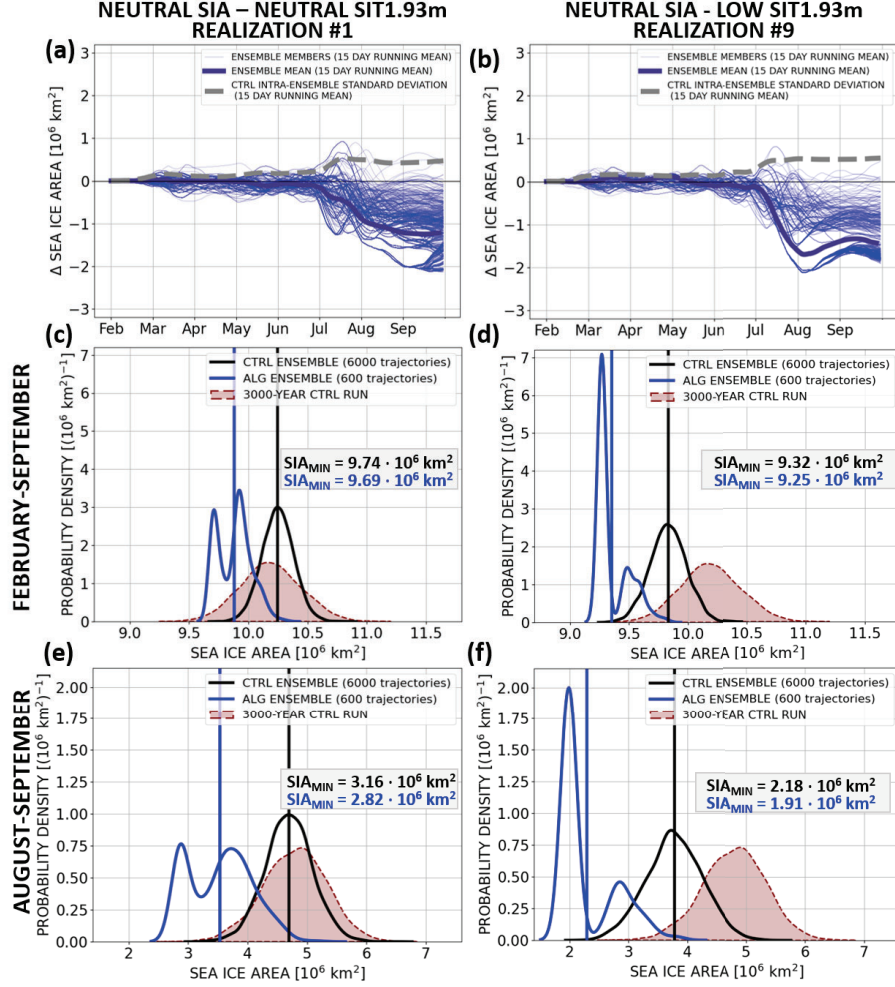


Figure 3.2: Ensemble simulations initialized on 01 February (a,c,e) 1930 and (b,d,f) 1037 of the control run. (a-b) Rare event simulations: $N = 600$ trajectories (thin blue lines) and ensemble mean (thick blue line) of daily pan-Arctic sea ice area anomalies relative to the daily climatology of the corresponding control ensembles. The gray dashed lines show the intra-ensemble standard deviations in the control ensembles. All lines are presented as 15-day running means. (c-f) Probability distribution functions of (c-d) February-September and (e-f) August-September mean pan-Arctic sea ice area for (blue) the rare event simulation, (black) the control ensembles ($N = 6000$ trajectories) and (red) the 3000-year control run. The vertical lines show the mean of the distributions. The black and blue values indicate the smallest February-September and August-September mean sea ice area value in the control and rare event ensemble simulations respectively.

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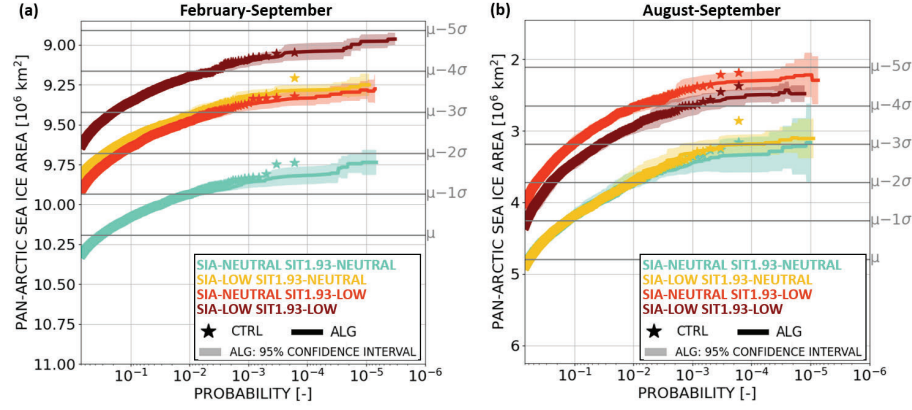


Figure 3.3: Probabilities (x -axes) of (a) February-September and (b) August-September mean sea ice area equal or smaller than a given threshold (y -axes) as a function of four different initial conditions for (stars) the $N = 6000$ trajectory control ensembles (i.e. ten realizations are merged into one single ensemble) and (solid lines) the average over four to ten algorithm estimates. The shading are 95% confidence intervals derived from the t -distribution of the four to ten estimates (see Supplementary Information S3D for a description of the computation of the confidence intervals). Note that the y -axes are displayed in reverse order. In the legend, “SIA” and “SIT1.93” indicate the state of the January-February mean anomaly of the pan-Arctic sea ice area and the cumulative area with sea ice thickness equal or larger than 1.93 m respectively. The grey labels on the right of each panel show how many standard deviations a sea ice area value is below the mean of the 3000-year control run.

“SIA= SIT1.93–” ensembles are $2.82 \cdot 10^6 \text{ km}^2$ and $1.91 \cdot 10^6 \text{ km}^2$ and thus about 40% and 49% smaller than the control ensemble mean values of $4.69 \cdot 10^6 \text{ km}^2$ and $3.78 \cdot 10^6 \text{ km}^2$. These sea ice area anomalies are therefore larger in magnitude than the deviation of the observed 2012 mean August-September mean sea ice area from a trend line fitted to the period 1979–2006 (about -32%; $3.09 \cdot 10^6 \text{ km}^2$ compared to $4.53 \cdot 10^6 \text{ km}^2$; see Figure B3 in the Supplementary Information). The computation of the probabilities to generate a sea ice area equal or smaller than a given threshold indicates that the sea ice lows in the trajectories of the two ensemble simulations are below 0.001% (Figure 3.3).

3.3.2.1 Seasonal evolution of the state of the sea ice

The most dominant negative sea ice area anomalies in both trajectories start to develop in June-July and reach their peak amplitudes in August-September (Figure 3.4(a,d)). Negative August-September mean sea ice area anomalies are characterized by enhanced open water area in the Barents and Kara Seas, the eastern central Arctic Ocean and northern of the Canadian Archipelago (Figure 3.4(b,e)). From late winter to late spring, sea ice area anomalies are close to zero in the “SIA= SIT1.93=” experiment. In the “SIA= SIT1.93–” experiment, sea ice area anomalies are slightly positive in early spring and are close to zero during late spring. The fact that winter-spring sea ice area anomalies are small in magnitude compared to the late summer ones supports the conclusion from Figure 3.3 that winter-spring sea ice area anomalies do not play an important role for the

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formation of late summer sea ice lows.

It is noticeable that late summer negative sea ice area anomalies are preceded by negative pan-Arctic sea ice volume anomalies starting to develop in spring (Figure 3.4(a,d)). These are related to the development of negative sea ice thickness anomalies before an anomalous reduction of the pan-Arctic sea ice area. In the "SIA= SIT1.93=" experiment, these negative sea ice thickness anomalies develop predominantly on the Eurasian side of the Arctic and northern of the Canadian Archipelago (Figure 3.4(c)). In the "SIA= SIT1.93-" experiment, negative sea ice thickness anomalies are present from the Kara and Barents Seas towards the Canadian Archipelago and in the Beaufort Sea. In both experiments, the anomalously strong sea ice thinning acts as a preconditioning for enhanced open water formation in late summer as described in Chevallier and Salas-Mélia [2012]. The presence of negative spring sea ice volume anomalies relative to the control ensemble mean suggests that the spring sea ice volume provides an additional source of predictability of extremely negative late summer sea ice area anomalies relative to the climatology of the full control run on top of the predictability emerging from the late winter initial condition. This result is consistent with the findings of Bonan et al. [2019] and Bushuk et al. [2020] according to which late summer sea ice area is substantially stronger connected to late spring to early summer sea ice volume than to mid spring sea ice volume. In this way, sea ice volume contributes to a spring barrier of the predictability of late summer sea ice area in addition to a part of the predictability barrier that may be purely related to a substantial increase in the persistence of sea ice area anomalies from May to July [Tietsche et al., 2014; Day et al., 2014; Bonan et al., 2019; Bushuk et al., 2020].

3.3.2.2 Seasonal evolution of the state of the atmosphere

We are interested in the processes favouring the development of negative sea ice thickness and ensuing negative sea ice area anomalies. Firstly, we analyze the seasonal evolution of two metre temperature (T2M) and 500 hPa geopotential height (Z500) anomalies to establish a link between sea ice lows and the thermodynamic and dynamic states of the atmosphere (Figure 3.5). The evolution of the atmospheric state differs between the "SIA= SIT1.93=" and "SIA= SIT1.93-" trajectories. In the "SIA= SIT1.93=" trajectory, the Arctic region is in an anomalously warm state from late winter to late spring. Positive T2M anomalies occur over the central Arctic Ocean in February-March and show a wavenumber 3-like positive T2M pattern in spring associated with a baroclinic signal in the 500 hPa geopotential height anomaly field (Figure 3.5(b,c,g,h)). In May-June, anomalously warm conditions prevail over the eastern Arctic and north of the Canadian Archipelago, and thus spatially coincide with the region of negative sea ice thickness anomalies (cf. Figures 3.5(c) and Figure 3.4(c)). In June-July, the magnitude of T2M anomalies declines as two metre temperatures are constrained by the climatological sea ice melting to be close to the freezing point (Figure 3.5(d)). The reemergence of anomalously warm conditions in August-September (Figure 3.5(e)) may both be a driver of sea ice reduction and a consequence of reduced sea ice conditions. In contrast to the "SIA= SIT1.93=" experiment, February-March two metre temperature anomalies in the "SIA= SIT1.93-" trajectory are close to zero over the Arctic Ocean (Figure 3.5(k)).

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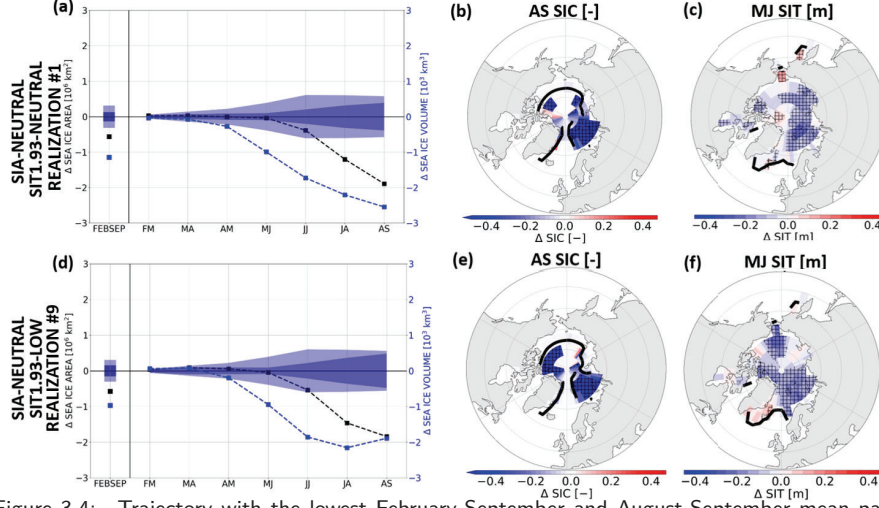


Figure 3.4: Trajectory with the lowest February-September and August-September mean pan-Arctic sea ice area obtained with the rare event simulation starting from a winter initial condition characterized by (a-c) neutral sea ice area and neutral SIT1.93 (control run year 1930) and (d-f) neutral sea ice area and low SIT1.93 (control run year 1037). (a,d) Pan-Arctic sea ice (black) area [10^6 km^2] and (blue) volume [10^3 km^3] anomalies. Shading shows the intra-ensemble standard deviation of the corresponding control ensemble. (b,e) August-September mean sea ice concentration and (c,f) May-June mean sea ice thickness anomalies. Hatching indicates anomalies larger in magnitude than the intra-ensemble standard deviation of the control ensemble. (a-f) All anomalies are computed with respect to the climatology of the corresponding control ensemble.

This approximately neutral temperature state is followed by a strong warming with a barotropic positive geopotential height anomaly response over the Norwegian Sea and the Arctic Ocean during spring (Figure 3.5(k,l,m,p,q,r)). Positive 500 hPa geopotential height anomalies persist until early summer, while T2M are constrained to be close to the freezing point in June-July in large parts of the Arctic Ocean before reemerging in August-September as for the "SIA= SIT1.93=" trajectory (cf. Figures 3.5(n,o,s,t) and 3.5(d,e)).

3.3.2.3 Surface energy budget analysis

We perform a surface energy budget analysis to understand how the anomalous reduction of sea ice is physically related to anomalous atmospheric conditions (Figures 3.6-3.7). We define the surface energy budget for an infinitesimally thin interface without heat storage located between the atmosphere and the snow-sea ice-ocean system (cf. Serreze and Barry [2014]). The different terms of the budget are then given by

$$R_{SW}(1 - \alpha) + R_{LW} + S + L = -\epsilon \sigma T_s^4 + Q + M, \quad (3.5)$$

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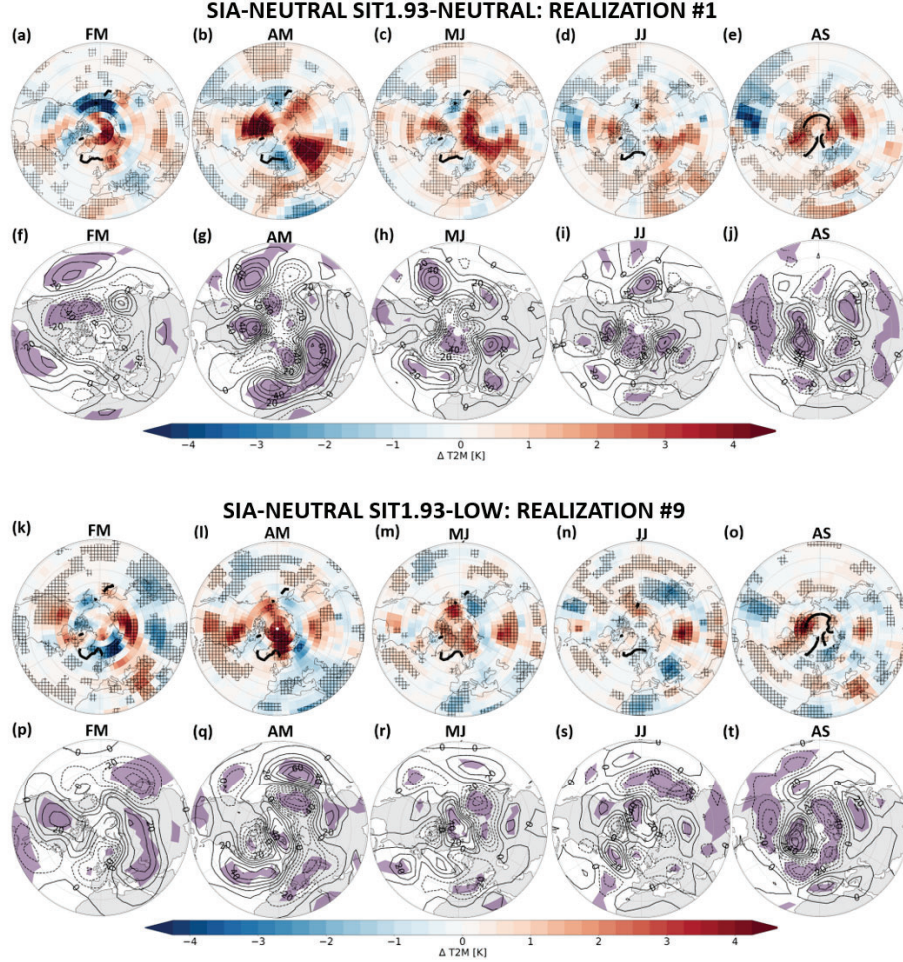


Figure 3.5: Trajectory with the lowest February-September and August-September mean pan-Arctic sea ice area in the rare event simulation starting from a winter initial condition characterized by (a-j) neutral sea ice area and neutral SIT1.93 (control run year 1930) and (k-t) neutral sea ice area and low SIT1.93 (control run year 1037). (a-e) and (k-o) February-March (FM), April-May (AM), May-June (MJ), June-July (JJ) and August-September (AS) mean T2M anomalies [K] and (f,j) and (p-t) FM, AM, MJ, JJ, AS mean Z500 anomalies [gpm]. Contour interval for Z500 is 10 gpm. Hatching indicates anomalies larger in magnitude than the intra-ensemble standard deviation of the control ensemble. All anomalies are computed with respect to the climatology of the corresponding control ensembles. The black contour line in (a-e) and (k-o) shows the climatological sea ice edge defined as the 15% sea ice concentration contour line.

where R_{SW} and R_{LW} are the downward shortwave and downward longwave radiative fluxes, respectively; α is the surface albedo, S and L are the sensible and latent heat

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fluxes, ϵ is the surface emissivity, $\sigma = 5.67 \cdot 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$ is the Stefan–Boltzmann constant and T_s is the surface temperature. Q summarizes conductive and turbulent energy fluxes between the surface and the snow-sea ice-ocean system. M is the energy flux associated with melting and freezing at the surface. Energy fluxes related to bottom sea ice growth, to temperature changes in the snow-sea ice-ocean system and the vertical energy flux from the ocean into the sea ice are implicitly included in Q . In Figure 3.6, we complement the analysis of the atmosphere-surface energy fluxes by the analysis of the vertical oceanic heat flux. If not stated otherwise, we define upward (downward) energy fluxes and associated flux anomalies to be positive (negative).

Both in the "SIA= SIT1.93=" and "SIA= SIT1.93—" trajectories, strongly negative net surface-atmosphere energy flux anomalies occur over the Arctic Ocean from April-May to August-September, indicating an anomalous energy accumulation within the snow-sea ice-ocean system (Figure 3.6(a,b)). Anomalies in the vertical oceanic heat flux are much smaller than the atmospheric ones, but are still systematically positive in summer in both trajectories (Figure 3.6(a,b)).

The contribution of different flux components to the negative net atmosphere-surface energy flux anomalies varies among the season and both trajectories show two distinct phases. While these two phases show similarities between the two trajectories, their precise characteristics differ from each other. In the "SIA= SIT1.93=" trajectory, enhanced net energy accumulation in the snow-sea ice-ocean system during spring is predominantly explained by negative net longwave radiative flux anomalies and enhanced downward sensible heat fluxes (Figure 3.6(c,e)). During summer, the anomalies in the atmosphere-surface energy transfer are dominated by the shortwave fluxes. Compared to the "SIA= SIT1.93=" trajectory, enhanced longwave radiative forcing on the sea ice in the "SIA= SIT1.93—" trajectory has a larger magnitude, but is restricted to April-May (Figure 3.6(d)). In May-June, instead, a transition takes place towards enhanced downward sensible heat fluxes and enhanced shortwave radiative forcing on the sea ice (Figure 3.6(d,f)). The shortwave radiative forcing on the sea ice during mid to late summer is twice as large for the "SIA= SIT1.93=" trajectory as for the "SIA= SIT1.93—" trajectory.

We further subdivide the net shortwave and longwave radiative surface flux anomalies into their downward and upward components to trace back the net radiative surface flux anomalies to anomalous atmospheric conditions (Figure 3.7). In the "SIA= SIT1.93=" trajectory, reduced downward solar radiation and enhanced downward longwave radiation occurs in April-May and May-June (Figure 3.7(a,c)). The signal in the longwave radiative fluxes are associated with enhanced atmospheric water vapour and cloudiness (Figure 3.7(e)). In the "SIA= SIT1.93—" trajectory, instead, enhanced downward radiative flux anomalies associated with clouds and water vapour primarily occur in April-May (Figure 3.7(b,d,f)). In summer, a reduction in clouds occurs and the shortwave radiative fluxes in combination with the sea ice-albedo feedback become the dominant driver of sea ice reduction in both experiments. The latter is, however, much more dominant in the "SIA= SIT1.93—" than in the SIA= SIT1.93= trajectory.

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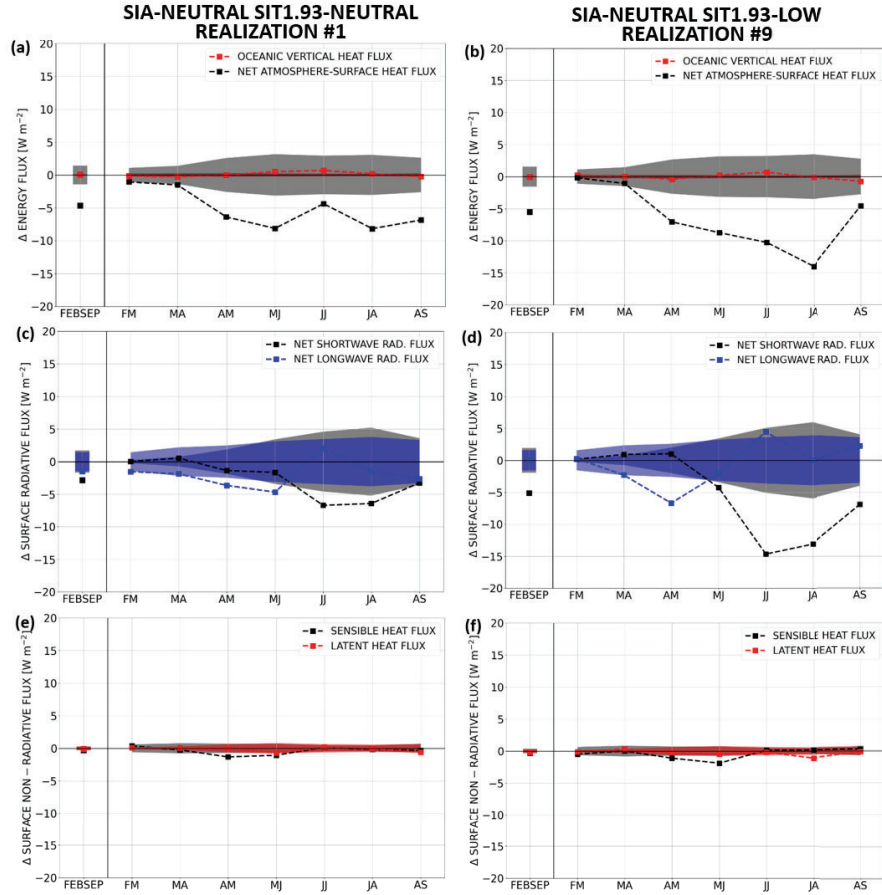


Figure 3.6: Trajectory with the lowest February-September and August-September mean pan-Arctic sea ice area in the rare event simulation starting from a winter initial condition characterized by (a,c,e) neutral sea ice area and neutral SIT1.93 (control run year 1930) and (b,d,f) neutral sea ice area and low SIT1.93 (control run year 1037). Mean energy flux anomalies [W m⁻²] on average over all ocean grid boxes northern of 70°N. (a-b) (black) Net atmosphere-surface energy flux (sensible + latent + net longwave + net shortwave) and (red) vertical ocean heat flux. (c-d) Net surface (blue) longwave radiative and (black) shortwave radiative flux. (e-f) Surface (red) latent and (black) sensible heat flux anomalies. The sign convention is chosen such that positive anomalies correspond to enhanced upward fluxes. (a-f) Shading indicates the intra-ensemble standard deviation of the corresponding control ensembles. All anomalies are computed with respect to the climatology of the corresponding control ensembles.

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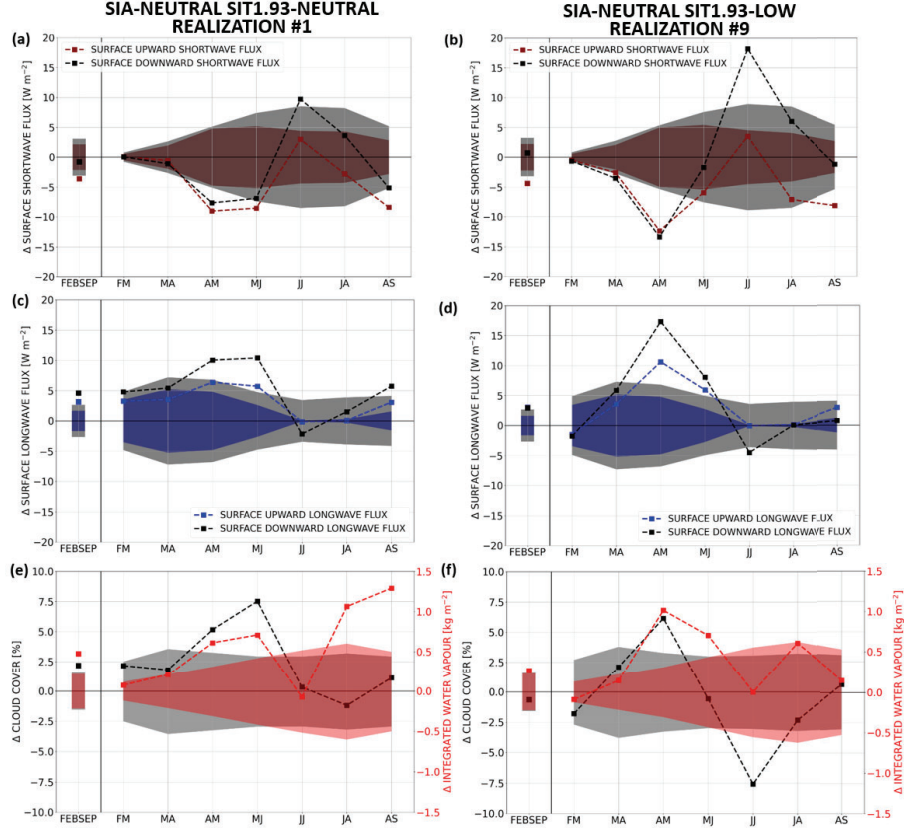


Figure 3.7: Trajectory with the lowest February-September and August-September mean pan-Arctic sea ice area in the rare event ensemble simulation starting from a winter initial condition characterized by (a,c,e) neutral sea ice area and neutral SIT1.93 (control run year 1930) and (b,d,f) neutral sea ice area and low SIT1.93 (control run year 1037). Mean anomalies of different quantities spatially averaged over all ocean grid boxes northern of $70^{\circ}N$. (a-b) Surface (dark-red) upward and (black) downward shortwave radiative flux anomalies [$W m^{-2}$]. (c-d) Surface (blue) upward and (black) downward longwave radiative flux anomalies [$W m^{-2}$]. (a-d) Direction-independent absolute values of the downward and upward fluxes are considered, i.e., a positive (negative) anomaly indicates a radiative flux that is stronger (weaker) in magnitude than the climatology. (e-f) (Black) Total cloud cover [%] and (red) integrated water vapour [$kg m^{-2}$] anomalies. (a-f) Shading indicates the intra-ensemble standard deviation of the corresponding control ensembles. All anomalies are computed with respect to the climatology of the corresponding control ensembles.

3.4 Discussion and conclusions

We exploit four initialized ensemble simulations to study the statistical properties of extreme negative summer and late summer pan-Arctic sea ice area anomalies as a function of four different initial winter states. Likewise, we investigate physical processes in two trajectories leading to extreme late summer sea ice lows with larger amplitudes than the one observed in 2012. In order to circumvent the poor sampling of rare events in numerical simulations, we apply a rare event algorithm to improve the sampling efficiency of trajectories leading to extremely low pan-Arctic sea ice area on average over the melting season and during the annual sea ice minimum. The simulations with the rare event algorithm produce several hundreds of times more extremes than conventional control ensemble simulations for the same computational cost, and allow to estimate extreme sea ice low probabilities that are two orders of magnitude smaller compared to direct sampling (Figure 3.3).

The approach used in this study is complementary to the rare event algorithm study of Sauer et al. [2024]. In the latter, ensemble simulations are initialized with independent initial conditions sampled from an entire 3000-year control run and the statistics computed with the rare event algorithm corresponds to unconditional probability distributions. Such an approach allows to improve the sampling efficiency of low sea ice states both related to multi-annual variability in the sea ice-ocean system (referred to as "preconditioning" in Sauer et al. [2024]) and driven by the dynamics occurring on intra-seasonal time scales. The single-initial condition approach used in this study, instead, corresponds to a seasonal climate prediction set-up giving access to the probability to observe an extreme late summer sea ice low as a function of a given initial state. This approach also enables a targeted study of intra-seasonal drivers of anomalously strong sea ice reduction during the melting season. Within each ensemble simulation, a contribution of multi-annual sea ice-ocean preconditioning to the generation of low sea ice states compared to the control ensemble mean is by definition excluded as each trajectory starts from the same sea ice-ocean state.

The statistics obtained from the four different experiments indicates a strong impact of the late winter sea ice initial condition on the probability and amplitudes of extremely negative summer pan-Arctic sea ice area anomalies computed relative to a 3000-year control run baseline climatology. For a fixed probability level, amplitudes of extremely negative February-September and August-September mean sea ice area anomalies span a range of about three and two control run standard deviations over the four experiments (Figure 3.3 and Table 3.2). While winter preconditioning is a necessary condition to generate a sea ice low with an amplitude larger than a certain threshold, the most extreme sea ice lows available in this study require both preconditioning and anomalous intra-seasonal dynamics (e.g. anomalies in the atmospheric circulation) favouring enhanced reduction of sea ice area during the melting season (Figure 3.3 and Table 3.2). The relative importance of preconditioning compared to intra-seasonal dynamics in driving extremely low sea ice area is larger for the February-September than August-September mean sea ice area (Table 3.2). Thus, about 65% of the magnitude of the anomaly corresponding to the 1% percentile value of February-September mean sea ice area in the "SIA– SIT1.93– experiment" is explainable by the impact of the preconditioning on the control ensemble

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mean sea ice area (Table 3.2). For August-September sea ice area, instead, about 40-50% of the magnitude of the anomaly value corresponding to the 1% percentile value are explainable by the impact of the preconditioning on the control ensemble mean in the experiments initialized with the "SIA− SIT1.93−" and "SIA= SIT1.93−" initial conditions (Table 3.2).

The analysis of the four initialized experiments suggests that an extremely negative February-September mean pan-Arctic sea ice area anomaly is preconditioned by low January-February mean states of both the pan-Arctic sea ice area and the cumulative area with sea ice thickness larger than a given threshold (the precise value used in this study is 1.93 m). In contrast, a source of predictability of an extreme late summer sea ice low is given by the winter sea ice thickness information, but not from the winter sea ice area. Both results are in line with the memory properties of the sea ice in the Arctic [Blanchard-Wrigglesworth et al., 2011; Chevallier and Salas-Mélia, 2012; Bonan et al., 2019; Bushuk et al., 2020; Tietsche et al., 2014]. Using a preindustrial simulation with the Centre National de Recherches Météorologiques Coupled Global Climate Model version 3.3 (CNRM-CM3.3), Chevallier and Salas-Mélia [2012] finds that the cumulative area with sea ice thickness larger than a threshold between 0.9 and 1.5 m provides a potential source of predictability of the September pan-Arctic sea ice area six months in advance. The authors argue that winter-spring sea ice thickness influences summer sea ice area by modulating the open-water-formation efficiency during the melting season. The dependency of extremely negative February-September mean sea ice area anomalies both on the winter SIT1.93 and winter pan-Arctic sea ice area itself can be explained by the fact that late winter sea ice area anomalies have a non-zero persistence until spring [Blanchard-Wrigglesworth et al., 2011; Chevallier and Salas-Mélia, 2012]. All in all, we emphasize that the precise critical sea ice thickness threshold used to define the cumulative area covered by sea ice thickness larger than a given value and the precise time lag may vary between different models.

Owing to the rare event algorithm, we analyze the physical properties in two individual trajectories leading to extremely negative August-September mean sea ice area anomalies with conditional probabilities of less than 0.001%. While the precise thermodynamic and dynamical evolution of the atmosphere differs between both trajectories, common mechanisms can be detected between both trajectories. In both cases, an anomalously strong reduction of the pan-Arctic sea ice area in mid to late summer is anticipated by the development of negative sea ice thickness anomalies during spring. Even though this result is based on two individual trajectories instead of being inferred from a robust statistics of extreme sea ice low events, it suggests that late spring to early summer sea ice volume potentially provides an additional source of predictability of extremely negative late summer sea ice area anomalies relative to the full control run in addition to the predictability associated with the late winter initial condition. This finding is consistent with the studies of Bonan et al. [2019] and Bushuk et al. [2020]. Bonan et al. [2019] and Bushuk et al. [2020] argue that sea ice volume captures a spring barrier in the predictability of late summer sea ice area resulting from the fact that late summer sea ice area is substantially stronger connected to late spring to early summer sea ice volume than to the sea ice volume during mid spring. Apart from a small contribution of

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enhanced vertical ocean heat flux anomalies to the anomalous reduction of sea ice in the two trajectories discussed in this study, the largest amount of net energy accumulation in the sea ice-ocean system is related to enhanced downward net atmosphere-surface energy fluxes. Within the season, we observe two phases with two different physical properties. During spring, enhanced cloudiness and atmospheric water vapour results in negative (i.e. downward) net surface longwave radiative flux anomalies, providing enhanced energy to warm or melt sea ice. This is consistent with the finding of Kapsch et al. [2013, 2019] showing that observed extreme September sea ice lows have been preceded by enhanced downward longwave radiative fluxes in an anomalously moist and cloudy atmosphere. During summer, anomalous reduction of sea ice area is favoured by enhanced downward solar radiative flux, the sea ice-albedo feedback and enhanced open water formation efficiency in an anomalously thin sea ice environment.

We hypothesize that the bimodality in the distribution of late summer sea ice area values obtained with the rare event simulation (Figure 3.2) is favoured by the particular characteristics of the atmosphere-sea ice-ocean system in the Arctic, including preconditioning of anomalously low sea ice area via enhanced spring sea ice thinning and amplifying feedback mechanisms. A bimodality in a rare event simulation, however, does not necessarily imply a physical bimodality in the real model distribution. It could also be purely related to sampling [Ragone and Bouchet, 2021]. For example, the peak of the probability density function at an August-September mean sea ice area value of $2.9 \cdot 10^6 \text{ km}^2$ in the "SIA= SIA=" experiment is related to hundreds of replicated trajectories originating from two ancestors (cf. Figure 3.2(a,e) and Supplementary Figure B4). The bimodality may therefore simply emerge from the fact that trajectories leading to sea ice area values corresponding to the local minimum of the probability density function are undersampled in this particular simulation. Out of the ten realizations of the "SIA= SIA=" experiment, a pronounced bimodality as in Figure 3.2(e) occurs in a total number of three realizations (cf. Figure 3.2(a,c,e) and Supplementary Figure B5). The August-September mean sea ice area values at which the two peaks and the local minimum of the probability distribution functions occur, however, vary from one realization to the next (cf. Figure 3.2(e) and Supplementary Figure B5). Therefore, we do not expect that the real model probability density function has a bimodality explained by two peaks at specific sea ice area values. Nevertheless, we point out that trajectories belonging to the peak at August-September mean sea ice area values of $2.9 \cdot 10^6 \text{ km}^2$ show different physical characteristics than the ones leading to sea ice area values centered around a peak at $3.75 \cdot 10^6 \text{ km}^2$ (cf. Figure 3.2(e), Figure B4 and Figure B6 in the Supplementary Information). Thus, compared to the latter, the former show a more pronounced spring preconditioning via anomalously strong sea ice thinning in a more humid Arctic atmosphere and a more pronounced water vapour feedback during late summer (Figure B6 in the Supplementary Information).

This study shows how rare event algorithms can be applied to initialized ensembles to study the probability of extreme states conditional on given initial conditions. This approach could be extremely useful in the context of seasonal to decadal predictions, both in terms of risk quantification, and to inform ensemble initialization strategies by the identification of important physical drivers for the development of extremes. The approach can be used to better quantify the relative contribution of a given initial con-

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dition to specific extreme sea ice loss events such as observed as in 2007 and 2012 (by comparing an ensemble initialized with the state of e.g. the 01 March 2012 of a historical simulation with an ensemble initialized with the state of e.g. the 01 March 1979 of a historical simulation). Moreover, the experimental design can be adapted to make quantitative statements about the relative contributions of global warming vs. internal climate variability to the probabilities and amplitudes of extreme sea ice loss events, and to quantify the probability of observing a sea ice-free Arctic within a given period of time. This can be achieved by initializing an ensemble with late winter initial conditions sampled from e.g. the period 2016-2025 (i.e. an ensemble of 300 trajectories could be generated by producing 30 perturbed replicates of one initial condition per year respectively) and comparing the statistics with another ensemble initialized with data drawn from e.g. the period 1986-1995 of a historical simulation. In this study, we use the rare event algorithm to provide an estimate of the probability of a 2012-like late summer sea ice area anomaly relative to a linear trend fitted to the period 1979-2006 (see Figure B3 in the Supplementary Information). As described in section 3.3, the observed August-September mean sea ice area anomaly in 2012 deviated by $-1.44 \cdot 10^6 \text{ km}^2$ from that trend line. The probabilities to generate a sea ice area anomaly being equal or larger in magnitude than $-1.44 \cdot 10^6 \text{ km}^2$ compared to the control ensemble mean (i.e. related to processes on an intra-seasonal time scale) estimated with the four PlaSim ensemble simulation experiments ranges between $2.99 \cdot 10^{-5}$ and $7.59 \cdot 10^{-4}$ (Figure 3.3).

Finally, we emphasize that this study is based on a relatively low resolution climate model with a purely thermodynamic sea ice model. A variety of idealisations such as the lack of sea ice dynamics [Wang et al., 2009; Ogi et al., 2016], the coarse atmospheric and oceanic resolutions [Docquier et al., 2019], biases in the mean sea ice thickness state (cf. Figure B2(b) in the Supplementary Information and page 207 of Chevallier et al. [2019]), response of clouds to sea ice changes and the binary sea ice concentrations without representation of polynyas potentially affect the results about the physical drivers and the estimation of the probabilities of low sea ice states. Due to the lack of sea ice dynamics, the impact of anomalous winds associated with anomalous states of the Arctic Oscillation (AO) and the Arctic Dipole (AD) pattern on the export of sea ice from the marginal Arctic seas into the central Arctic Ocean and out of the Arctic via Fram Strait [Wang et al., 2009; Ogi et al., 2016] as well as the dynamical impact of synoptic storms on the sea ice [Zhang et al., 2013] are not captured in this model. We hypothesize that this leads to an underestimation of the amplitude of the most extremely negative sea ice area anomalies compared to more complex models than PlaSim. Consequently, the lack of sea ice dynamics potentially also leads to an underestimation of the probability of observing a 2012-like sea ice area anomaly presented in this study. Moreover, regional biases in the sea ice thickness field in PlaSim-T21-LSG compared to the PIOMAS reanalysis (too thick sea ice on annual average around the North Pole and in the Barents Sea; cf. Figure B2(b) in the Supplementary Information and page 207 of Chevallier et al. [2019]) may affect the results of this study. Thus, the trajectories with the most extremely negative sea ice concentration anomalies available from the ensembles show no substantial sea ice concentration anomalies around the North Pole, while strongly negative sea ice concentration anomalies are present in the Barents and Kara Seas (Figure 3.4). In observations,

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the Barents and Kara Seas are sea ice-free in late summer [Kapsch et al., 2019]. While the overestimation of sea ice in the Barents and Kara Seas in PlaSim compared to observations likely contributes to an overestimation of the amplitudes of extremely negative pan-Arctic sea ice area anomalies compared to the real world, an opposing effect is to be expected from the positive sea ice thickness bias around the North Pole in PlaSim compared to observations.

All in all, based on the analysis of two individual trajectories, the present study illustrates possible thermodynamics states of the atmosphere to generate sea ice lows larger in magnitude than the one observed in 2012. Likewise, it makes an important step forward towards the computation of probabilities of extreme Arctic sea ice lows as a function of different initial and climate states. A similar rare event algorithm study using the EC-Earth model version 3.3.1, including a more complex physics than PlaSim, a dynamic sea ice model and initialized with two sea ice-ocean initial conditions selected from a historical run, is in preparation. A possibility to rely on multiple models instead of one single model will consist in complementing the EC-Earth3 study by an analysis of extreme sea ice lows in existing large ensembles of the models of the Phases 5 and 6 of the Coupled Model Intercomparison Project.

Chapter 4

Disentangling the thermodynamic vs. dynamic drivers of extreme Arctic sea ice reduction using rare event sampling in EC-Earth3

This chapter is based on the following paper, in preparation and to be submitted to *Journal of Climate*:

Sauer, J., Zappa, G., Ragone, F., and Massonnet, F.: Disentangling the thermodynamic vs. dynamic drivers of extreme Arctic sea ice reduction using rare event sampling in EC-Earth3, *Journal of Climate*, in preparation.

Abstract

Several studies attributed the 2007 and 2012 drastic Arctic sea ice loss events both to sea ice-ocean preconditioning and to particular weather and climate events during the melting season. The advancement of our understanding of the drivers and predictability of extremes of sea ice reduction, however,

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is hindered by the small number of events that can be sampled in observations and numerical simulations with computationally expensive climate models. Recent studies tackled the problem of sampling climate extremes by using rare event algorithms, i.e., computational techniques developed in statistical physics to increase the sampling efficiency of rare events in numerical simulations. Here we apply a rare event algorithm to ensemble simulations with the European community Earth-System-Model version 3 (EC-Earth3) to study extremes of intra-seasonal pan-Arctic sea ice area reduction under present-day climate conditions. We construct two pairs of $N = 300$ trajectory control and rare event algorithm ensemble simulations, each starting from two different initial sea ice-ocean states. The rare event simulations produce late summer sea ice area anomalies with probabilities of 2 orders of magnitude smaller than feasible with the control ensembles, and provide events with larger amplitudes compared to the deviation of the observed 2012 late summer sea ice area from the trend line. We find that the contribution of observed 2012–AVG<1995–2005> winter sea ice-ocean changes to the amplitudes of extremely negative late summer sea ice area anomalies relative to a fixed baseline climatology is comparable in magnitude to the amplitudes of strong weather-induced inter-annual fluctuations of late summer sea ice area. Finally, we compute statistically significant composite maps of dynamical quantities conditional on the occurrence of extreme sea ice lows with probabilities of less than approximately 1% per year. We also investigate physical processes in two independent trajectories leading to ultra-rare sea ice lows with estimated conditional probabilities of less than 10^{-4} per year. We study the drivers of extremely low sea ice states on synoptic to seasonal time scales, including a sea ice area and sea ice volume budget analysis to disentangle the roles of dynamic vs. thermodynamic forcing on the sea ice. On statistical average over the extremes, enhanced thermodynamic melting accounts for approximately 75% (70%) of enhanced sea ice area (sea ice volume) loss and predominantly occurs on the Pacific-North American side, while enhanced dynamic sea ice loss appears on the Eurasian side of the Arctic. Moreover, we show that extreme sea ice lows are on statistical average preceded by persistent cyclonic mean sea level pressure anomalies over the central to eastern Arctic Ocean during the spring-summer transition. These low-pressure systems promote sea ice loss thermodynamically due to enhanced convergence of the vertically integrated sensible heat and water vapor transport, cloudiness, surface downward long-wave radiation and dynamically through the impact of anomalous winds on the export of sea ice out of the central Arctic Ocean via Ekman drift. The common physical drivers emerging on statistical average over a multitude of extreme sea ice loss events are also visible in the two ultra-rare sea ice reduction trajectories examined in this study. However, these two ultra-rare trajectories have two particularities that differ from the typical extremes: one of the two trajectories is associated with a particularly strong and particu-

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larly persistent negative mean sea level pressure anomaly over the central Arctic Ocean during early summer, including a synoptic-scale storm of the type of the one observed in 2012, and anomalous sea ice export out of the central Arctic Ocean explains about 50% of anomalous seasonally-integrated sea ice volume loss. The extreme sea ice reduction in the other trajectory is almost entirely explained by thermodynamic processes related to a persistent southerly flow transporting heat and moisture from the North Pacific towards the Arctic Ocean during late spring and early summer, resulting in a substantially increased sea ice-albedo feedback compared to the typical extremes. The state of the atmosphere in this second trajectory is associated with a positive phase of the Arctic Dipole pattern and is reminiscent of the mechanism behind the observed 2007 drastic sea ice loss event.

4.1 Introduction

The Arctic late summer sea ice area dropped by about 40% compared to the beginning of the satellite-based observations in the late 1970s (cf. Fetterer et al. [2017], Figure 1.1 and Supplementary Figure C7(b)). This downward trend occurred against the background of steadily increasing greenhouse gas concentrations and associated anthropogenically-induced global warming [Notz and Marotzke, 2012; Notz and Stroeve, 2016; Gregory et al., 2002; Ding et al., 2017; Meinshausen et al., 2017]. However, the decline of the pan-Arctic sea ice area is non-linear, and internal climate variability and feedback mechanisms have been shown to modulate the downward trend of the sea ice area [Ding et al., 2017; Baxter et al., 2019; Ono et al., 2019; Francis and Wu, 2020; England et al., 2019]. Ding et al. [2017], for example, argues that internal climate variability, which controls a substantial part of observed changes in the summer Arctic atmospheric circulation, may account for about 30%-50% of September sea ice loss since 1979. While accelerated late summer sea ice decline has been noticeable from the mid-2000s to 2012, including record reductions of the sea ice area compared to the trend line in 2007 and 2012, the downward trend of sea ice area slowed substantially after 2012 (cf. Supplementary Figure C7(b) and England et al. [2025]; Francis and Wu [2020]). According to England et al. [2025], no statistically significant decline of September sea ice area occurred during the last two decades.

Various physical causes of extreme sea ice reduction events have been proposed in the literature. A general consensus exists that both sea ice-ocean preconditioning and particular weather and climate events during the melting season contributed to the drastic sea ice loss events in 2007 and 2012 [Lindsay et al., 2009; Kauker et al., 2009; Zhang et al., 2008, 2013; Parkinson and Comiso, 2013; Kirchmeier-Young et al., 2017]. In 2007, extreme sea ice reduction was favored by enhanced inflow of warm Pacific water through the Bering Strait [Woodgate et al., 2010] and by anomalously persistent southerly winds in the Pacific sector associated with the Arctic Dipole pattern [Wang et al., 2009]. In 2012, a summer storm contributed to enhanced sea ice reduction by leading to increased bottom melt via anomalously strong vertical mixing in the oceanic boundary layer [Guevas et al., 2013; Zhang et al., 2013; Parkinson and Comiso, 2013; Simmonds and Rudeva, 2012]. More generally, possible drivers of low summer Arctic sea ice area include North

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Atlantic and Pacific oceanic heat transport [Årthun et al., 2012; Woodgate et al., 2010], the positive and negative phases of the winter and summer Arctic Oscillation (AO) [Rigor et al., 2002; Ogi et al., 2016], and reduced cloudiness during summer [Schweiger et al., 2008]. In contrast, Kapsch et al. [2019], Horvath et al. [2021a] and Liang et al. [2022] attributed negative summer sea ice anomalies to persistent episodes of two types of atmospheric circulation during spring-summer: 1) negative 500 hPa geopotential height anomalies over the central Arctic projecting onto the positive phase of the AO and favoring cyclonic flow from Eurasia into the Pacific side of the Arctic Ocean and 2) a positive phase of the Arctic Dipole (AD) pattern promoting enhanced heat and moisture transport from the North Pacific into the Arctic.

The drivers of individual extremes of sea ice reduction have been suggested and the mechanisms driving the variability in the bulk of the distribution of summer sea ice area are comprehensively documented in the literature [Guémas et al., 2016; Chevallier and Salas-Méla, 2012; Massonnet et al., 2026]. However, a quantitative statistical analysis of extremes of sea ice reduction is hampered by the small number of rare events that can be sampled in observations and computationally expensive climate models. Going beyond individual case studies, a quantitative analysis of the relative importance of different atmospheric and oceanic precursors of extreme sea ice lows is therefore lacking. Likewise, it is the small number of extreme events in the lower tail of the distribution of sea ice area that makes it challenging to quantify the probability of a 2012-like sea ice low for a given background climate and initial condition. In this context, extreme value theory (EVT) models [Coles, 2001] allow to compute the probabilities of extreme events with amplitudes beyond the range of available data. However, even if applicable, these methods only provide a statistical extrapolation of the probabilities and do not provide information on the dynamics driving the extremes. A better understanding of precursors of extremes of summer Arctic sea ice reduction and a more precise estimate of their probabilities are crucial to improve seasonal predictions of these events, to quantify their risk of occurrence under different climate change scenarios and to better assess their impacts.

In this work, we study extremely negative late summer pan-Arctic sea ice area anomalies using initialized ensemble simulations with EC-Earth3 [Döscher et al., 2022] under present-day climate conditions. We study the statistical properties of extreme annual sea ice minima as a function of two different late winter sea ice-ocean initial conditions and investigate the physical drivers of extremes of sea ice area reduction within a single melting season. To circumvent the poor sampling of extremes related to computational cost limitations, we use a rare event algorithm. Rare event algorithms are computational techniques developed in statistical physics that allow to guide an ensemble simulation with a numerical model to oversample rare dynamical trajectories leading to extreme events of interest. While preserving the dynamical consistency of the model, these techniques allow to increase by several orders of magnitude the number of extreme events available in the simulations compared to direct sampling for a given computational cost. In this way, rare event algorithms allow to perform robust statistical and dynamical studies on the extremes, and to generate ultra-rare but high impact events that would hardly be possible to study otherwise.

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Rare event algorithms have been introduced in the 1950s [Kahn and Harris, 1951] and have been used since for a wide range of applications (for an overview and the mathematical analysis see e.g. Del Moral [2004]; Giardina et al. [2011]; Grafke and Vanden-Eijnden [2019]). Recently, some of these techniques have been applied in climate science and in fluid dynamics to study heat waves [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021], midlatitude precipitation [Wouters et al., 2023], tropical storms [Plotkin et al., 2019; Webber et al., 2019], weakening and collapse of the Atlantic Meridional Overturning Circulation (AMOC) [Cini et al., 2024], extreme Arctic sea ice lows related to unconditional and conditional probability distributions [Sauer et al., 2024, 2025], and turbulence [Bouchet et al., 2018; Grafke et al., 2015; Lestang et al., 2020]. Generally, different rare event algorithms are suited to study different problems, as the underlying design mechanisms are tailored to target extremes with specific properties.

Here we use a genealogical selection algorithm [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021; Sauer et al., 2024, 2025], adapted from Del Moral and Garnier [2005] and Giardina et al. [2011], that is efficient to study extremes whose dynamics is characterized by time-persistency. We refer to this method as the Giardina-Kurchan-Lecomte-Taillieur (GKLT) rare event algorithm. The GKLT algorithm has been used to study extremes of Arctic sea ice reduction with an intermediate complexity coupled climate model using two different approaches [Sauer et al., 2024, 2025]. In the former, ensemble simulations were initialized from independent initial conditions sampled from a long control run such that the method improves the sampling of extreme sea ice lows in an absolute sense. In the latter, the rare event simulations are performed in a seasonal climate prediction setup, allowing to improve the sampling of extreme Arctic sea ice lows conditional on starting from a given initial condition. In this work, we apply the seasonal climate prediction setup approach to the Coupled Model Intercomparison Project Phase 6 (CMIP6)-generation climate model EC-Earth3 to study extremes of intra-seasonal pan-Arctic sea ice area reduction in a comprehensive climate model, including a dynamic sea ice model. The goal of these experiments is to disentangle the relative contributions of one decade of observed sea ice-ocean changes vs. (sub)seasonal-scale fluctuations in favouring the occurrence of extremely negative late summer sea ice area anomalies. A similar investigation on the influence of initial conditions on an extreme event, albeit using action minimization instead of a genealogical selection algorithm and applied to extreme tropical cyclones, is performed in [Plotkin et al., 2019]. Here we perform different ensemble simulations starting from two different initial conditions. Since each individual ensemble member is initialized from a same, slightly perturbed initial condition, statistical and physical properties of low sea ice states inferred from that ensemble need to be interpreted in terms of conditional probabilities.

Owing to the rare event algorithm, we have access to negative late summer sea ice area anomalies that are larger in magnitude compared to the deviation of the observed 2012 late summer sea ice area from the 1979-2025 linear trend line. Likewise, we investigate the impact of the observed winter sea ice-ocean changes between the 1995-2005 average and 2012 (referred to as "2012-AVG<1995-2005>" hereafter) on the probabilities and amplitudes of extreme sea ice lows. Finally, we compute statistically significant composite maps of dynamical quantities conditional on the occurrence of extreme sea

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ice lows with probabilities of less than approximately 1% per year, and elaborate physical drivers in two trajectories leading to late summer sea ice lows with probabilities of less than 0.01% per year. In this context, we apply a sea ice volume and sea ice area budget analysis [Holland and Kwok, 2012] to disentangle the relative contributions of thermodynamic vs. dynamic forcing to extreme sea ice volume and sea ice area anomalies during extremes of sea ice reduction.

This chapter is structured as follows. In section 4.2, we describe the setup of the model, the methodology of the rare event algorithm and the design of the control and rare event algorithm simulations. The latter includes a precise explanation of the application of "anomaly initialization" to create two different late winter sea ice-ocean initial conditions. In section 4.3, we demonstrate that the rare event algorithm improves the sampling of model trajectories leading to extremely low late summer sea ice area values compared to conventional control ensemble simulations. We analyze the impact of the initial condition on the probabilities and amplitudes of the extremes, and we discuss the probability of occurrence of a 2012-like sea ice low under present-day climate conditions. In section 4.4, we provide a quantitative statistical analysis of the drivers of extremes of intra-seasonal pan-Arctic sea ice area reduction with probabilities of approximately less than 1% per year. This includes a sea ice volume and sea ice area budget analysis to disentangle the thermodynamic vs. dynamic forcing on the sea ice during the extremes. Likewise, we conduct a surface energy budget analysis to trace back enhanced thermodynamically-induced sea ice loss to anomalous atmospheric conditions. Finally, a comparison between physical properties emerging on statistical average over a multitude of extreme events and the drivers of two independent ultra-rare sea ice loss trajectories with estimated probabilities of less than 0.01% per year is conducted. In section 4.5, we present our conclusions.

4.2 Data and Methods

4.2.1 Model and data

All simulations are conducted with the Coupled Model Intercomparison Project Phase 6 (CMIP6)-generation European community Earth-System-Model version 3 (EC-Earth3) [Döscher et al., 2022] (repository tag 3.3.1 in the EC-Earth development portal for members of the consortium: <http://www.ec-earth.org>). The atmosphere is given by the cycle 36r4 Integrated Forecast System (IFS, European Center for Medium Range Forecast [2010]) and includes the H-TESEL land-surface scheme [Balsamo et al., 2009]. The ocean consists of the Nucleus for European Modelling of the Ocean (NEMO; Madec et al. [2008]) version 3.6, including the Louvain-la-Neuve (LIM3; Vancoppenolle et al. [2012]) sea ice model. Field exchanges between the ocean and the atmosphere are specified by the OASIS3-MCT [Valcke, 2013] coupler version 3.0.

The atmosphere is run with a horizontal resolution of T255 (i.e. triangular truncation at wavenumber 255 in spectral space, corresponding to a spacing of about 80 km), 91 levels up to 0.01 hPa in the vertical and a numerical time step of 45 minutes. Consequently, EC-Earth3 is run with exactly the same numerical time step for the atmosphere as PlaSim-LSG, even though the former has a substantially higher spatial resolution than

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the latter. This is possible since the IFS model uses a time stepping scheme that allows for relatively long time steps even if a relatively fine spatial resolution is used. The sea ice-ocean is configured on the tripolar ORCA1L75 grid, corresponding to an average horizontal resolution of $1^\circ \times 1^\circ$ and 75 vertical levels. The numerical time step of the sea ice-ocean is 45 minutes. The LIM3 model applies a sea ice thickness distribution framework to represent metre-scale variations in the sea ice thickness [Rousset et al., 2015]. This allows to account for the non-linear dependence of sea ice processes, in particular growth and melt, on the sea ice thickness. The present set-up includes five categories with upper sea ice thickness boundaries at 0.454, 1.129, 2.141, 3.671 and 99 metres.

We consider a 250-year post-spin up control run (Figure 4.1) and a set of control and rare event algorithm ensemble simulations (see section 4.2.2.2 for more details). All simulations are performed with stationary year-2000 greenhouse gas conditions (CO_2 volume mixing ratio of 369 ppmv), a fixed seasonal cycle in the solar radiation (representative of the year 2000) and diurnal cycle. We choose a constant greenhouse gas and solar forcing as we are interested in the statistics and dynamics of extreme Arctic sea ice reduction for two prescribed winter sea ice-ocean initial conditions (see section 4.2.2.2 for details about the two initial conditions).

We consider the statistics of the pan-Arctic sea ice area

$$SIA(t) = \sum_{\phi \geq \phi_{min}} \sum_{\lambda} SIC_{\phi,\lambda}(t) \cdot G_{\phi,\lambda}, \quad (4.1)$$

where $SIC_{\phi,\lambda}(t)$ is the sea ice concentration at time t in a grid cell located at latitude ϕ and longitude λ and $G_{\phi,\lambda}$ is the grid cell area available from the model. The summation in (4.1) includes all ocean grid boxes north of 40°N (i.e. $\phi_{min} \cdot \frac{180^\circ}{\pi} = 40^\circ$) with a binary land-sea mask (i.e. a grid cell is either completely ocean or land). On average over the 250-year control run, the simulated pan-Arctic sea ice area and the annual mean sea ice thickness are representative of the observed 1979-2015 Arctic sea ice climatology (cf. Figure 4.1, Supplementary Information of Sauer et al. [2024] and page 207 of Chevallier et al. [2019]). Moreover, the model reasonably captures the main characteristics of large-scale Arctic climate, including the Beaufort Gyre and Transpolar Drift Stream (cf. Supplement Figure C1 and page 184 of Serreze and Barry [2014]). The summertime Arctic Oscillation and the Arctic Dipole pattern are largely captured by the EC-Earth3 model (cf. Supplement Figures C2, C3 and e.g. Wang et al. [2009] and Ogi et al. [2016]). The precise geographical locations of the centers of action of the modes of atmospheric circulation variability, however, differ between EC-Earth3 and ERA5 [Hersbach et al., 2020] (see Supplementary Information S4A and Supplement Figures C2 and C3 for more details). Finally, as evident for example from Liu et al. [2015b], spring-summer melt ponds may substantially impact the surface energy budget in the Arctic Ocean and thus influence the state of the late summer sea ice minimum. EC-Earth3 does not explicitly resolve melt ponds, but parametrizes the effect of melt ponds on the surface albedo α by setting different albedo values depending on the presence of dry snow ($\alpha = 0.85$), melting snow ($\alpha = 0.75$), dry ice ($\alpha = 0.60$) and bare puddled ice ($\alpha = 0.50$).

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We study extreme anomalies of August-September mean pan-Arctic sea ice area. We classify a sea ice area anomaly $SIA'(t)$ as extremely negative if $SIA'(t) \leq n\sigma_{CTRL}$, where σ_{CTRL} is the standard deviation of the sea ice area in a control ensemble (see section 4.2.2.2 for more details) and n is a real-valued number being defined in section 4.3.

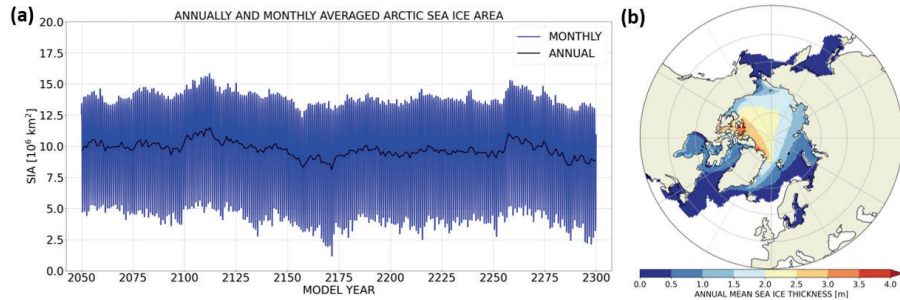


Figure 4.1: EC-Earth3 control run: (a) Pan-Arctic sea ice area and (b) annual mean sea ice thickness computed as an average over the model years 2050-2299.

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4.2.2 Rare event algorithm

4.2.2.1 Methodology

We apply the Giardina-Kurchan-Lecomte-Tailleur (GKLT) rare event algorithm [Ragone et al., 2018; Ragone and Bouchet, 2020, 2021; Sauer et al., 2024, 2025] to ensemble simulations with EC-Earth3 to circumvent the lack of robust statistics on extreme events. The GKLT algorithm is designed to improve the sampling efficiency of trajectories characterized by extreme anomalies of a target observable on time-average over the total simulation time T_a where T_a is longer than the typical decorrelation time of the observable. We describe the main steps of the algorithm in the following. More details about the formulas and treatment of the method can be found in Ragone et al. [2018] and Ragone and Bouchet [2020, 2021].

We denote $X(t)$ the vector of all model variables at time t , we consider an ensemble of N trajectories $\{X_n(t)\}_{0 \leq t \leq T_a}$ ($n = 1, 2, \dots, N$) running from $t = 0$ to $t = T_a$ and we define a target observable $A\{X_n(t)\}_{0 \leq t \leq T_a}$, for example the pan-Arctic sea ice area or the pan-Arctic sea ice volume. At regular intervals of a fixed resampling time τ_r , some trajectories are killed and some others are cloned depending on the values of weights defined on the past evolution of the trajectories. The weights are exponential functions of the time-average of the target observable during the past resampling time τ_r . The resampling works in such a way that each trajectory produces a random number of replicates of itself proportional on average to the value of its weight. A parameter k included in the definition of the weights determines the strength of the resampling, and the sign of k determines whether trajectories with extremely positive or extremely negative time-averaged anomalies are favored by the weights. The choice of $k = 0$ would approximately correspond to a regular ensemble simulation. In that case, however, the occasional formation of replicates of trajectories would occur as we add after each resampling event a random number drawn from a uniform distribution to the weights. In practice, the resampling procedure takes care of keeping the total number of trajectories in the ensemble constant after each resampling event, and the surface pressure field of each trajectory is slightly perturbed just before running the next resampling time in order to allow the replicated trajectories to diverge from each other (see section 4.2.2.2). When the final time T_a is reached, we perform one last resampling and reconstruct an effective ensemble by attaching at each resampling event from the end to the beginning of the simulation the ancestors to the pieces of surviving trajectories. All trajectories that did not survive until the end of the simulation are discarded from the ensemble.

Finally, let $\mathbb{P}_0(\{X_n(t)\}_{0 \leq t \leq T_a})$ be the probability density of observing a given trajectory in a direct numerical simulation with the model, and $\mathbb{P}_k(\{X_n(t)\}_{0 \leq t \leq T_a})$ be the probability density of the same trajectory in an ensemble simulation with the rare event algorithm with a given value of the parameter k . For a large ensemble size N , the relation between the two probability densities is given by the importance sampling formula

$$\mathbb{P}_k(\{X_n(t)\}_{0 \leq t \leq T_a}) \underset{N \rightarrow \infty}{\sim} \frac{e^{k \int_0^{T_a} A(\{X_n(t)\}) dt}}{\mathbb{E}_0[e^{k \int_0^{T_a} A(\{X_n(t)\}) dt}] \mathbb{P}_0(\{X_n(t)\}_{0 \leq t \leq T_a})}, \quad (4.2)$$

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where $\mathbb{E}_0$ is the expectation value with respect to $\mathbb{P}_0$. Thanks to Equation (4.2), the expectation value according to $\mathbb{P}_0$ (the real statistics of the system) of a generic quantity $\phi(\{X_n(t)\}_{0 \leq t \leq T_a})$ can be estimated from data generated with the algorithm (which are instead distributed according to $\mathbb{P}_k$) as

$$\mathbb{E}_0[\phi(\{X_n(t)\}_{0 \leq t \leq T_a})] \underset{N \rightarrow \infty}{\sim} \frac{1}{N} \sum_{n=1}^N Z_k e^{-k \int_0^{T_a} A(\{X_n(t)\}) dt} \cdot \phi(\{X_n(t)\}_{0 \leq t \leq T_a}). \quad (4.3)$$

where Z_k is a constant factor computed by the algorithm (see Ragone et al. [2018]; Ragone and Bouchet [2020]). Equation (4.3) shows that statistical quantities like composites, probabilities or return times with respect to the real model statistics can be estimated with data generated by the algorithm by weighting the contribution of each trajectory to sample averages by the inverse of the exponential factor which appears in the importance sampling formula. In Ragone et al. [2018], Ragone and Bouchet [2020, 2021] and Sauer et al. [2024], the trajectories appearing in (4.2) and (4.3) were generated from ensembles initialized with different initial conditions randomly selected from a control run to uniformly sample the attractor of the dynamics. In such an application, Equation (4.2) and Equation (4.3) would refer to unconditional probabilities. As in Sauer et al. [2025], however, the ensembles in this work are initialized from single initial conditions and the probabilities and expectation values in (4.2) and (4.3) have to be interpreted as conditional on the selected initial state.

4.2.2.2 Set-up of the experiments and "anomaly initialization"

We perform two sets of control and rare event algorithm ensemble simulations initialized from two different initial sea ice-ocean states (Table 4.1). Each ensemble contains $N = 300$ trajectories and runs for a total simulation time of $T_a = 215$ days from 01 March to 01 October. The two experimental sets are labeled "SI-NEUTRAL" and "SI-LOW" respectively. Regarding the ensemble size, we halved the number of trajectories compared to the rare event simulations with PlaSim-LSG (Chapter 2 and Chapter 3) to account for the substantially larger computational cost of EC-Earth3 compared to PlaSim-LSG. Preliminary test simulations with PlaSim-LSG (not shown) suggested that an ensemble size in the order of 200 to 300 trajectories may be a lower limit for which rare event sampling of extreme Arctic sea ice lows does not suffer from degeneracy. The optimal choice of the ensemble size, however, is highly empirical and may depend on the model and on the observable.

In SI-NEUTRAL, the initial condition is selected according to the neutrality of February-March mean anomalies in the pan-Arctic sea ice area and in the cumulative area with sea ice thickness equal or larger than 1.80 metres (SIT1.80; model year "2237"). In line with Chevallier and Salas-Mélia [2012], Lindsay et al. [2008] and Sauer et al. [2025], an analysis of the EC-Earth3 control run showed that the late winter cumulative area with a sea ice thickness equal or larger than a given threshold, in particular SIT1.80, is more relevant in determining the risk of occurrence of an extremely low late summer sea ice area than the pan-Arctic sea ice volume and sea ice area itself (Supplement Figure C4(a)).

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For the SI-LOW experiment, instead, we use "anomaly initialization" [Tian et al., 2021] to add to the initial condition of the SI-NEUTRAL experiment on a grid point level the observed differences of selected snow-sea ice-ocean variables between 2012 and the 1995-2005 climatology (" $2012 - \text{AVG} < 1995-2005 >$ "). Comparing the statistics of extremely negative late summer sea ice area anomalies between the SI-NEUTRAL and SI-LOW experiments serves to assess the relative contributions of sea ice-ocean preconditioning ("slow drivers" in the order of one decade of sea ice-ocean changes) vs. (sub)seasonal weather variability ("fast drivers") to the risk and amplitudes of these extremes. In addition, the SI-NEUTRAL and SI-LOW experiments allow to study the drivers of extremes of intra-seasonal sea ice area reduction for two independent initial states in the sea ice-ocean system.

The initialized variables in SI-LOW include northern hemispheric sea ice concentration, sea ice and snow volume in five thickness categories at a grid-cell level and three-dimensional ocean temperature and salinity (see Supplement Figures C4, C5 and C6 for details regarding the initialized fields). Following the procedure of Tian et al. [2021] and Polkova et al. [2019], horizontal velocities are not updated with respect to the SI-NEUTRAL initial condition. When anomalies are added to the SI-NEUTRAL initial condition, the sea ice concentration (SIC), sea ice volume (SIV) and snow volume (SNV) may in some cases violate the physically valid range (i.e. " $[0-1]$ " for SIC and " ≥ 0 " for SIC, SIV, SNV). To account for this, all three quantities are set to zero if either the sea ice area fraction or the sea ice volume are equal or smaller than zero. Sea ice area fraction larger than 1.0 is reset to 0.997 and negative snow volume values are reset to zero.

The $2012 - \text{AVG} < 1995-2005 >$ differences are derived from a historical integration with NEMO version 4.2.2 (NEMO4.2.2). This integration with NEMO4.2.2 underestimates the magnitude of the long-term trend of the pan-Arctic sea ice volume compared to the Pan-Arctic Ice Ocean Modeling and Assimilation System (PIOMAS; Supplement Figure C5(a)). To account for this, we rescale the imposed sea ice volume (i.e. thickness) anomalies on a grid-point level to match the average between the NEMO4.2.2 and PIOMAS trends. The imposed sea ice volume anomalies are negative within the entire central Arctic Ocean, showing maximum amplitudes northeastern of Svalbard (Supplement Figure C5(b)). The total imposed sea ice volume anomaly is $-3.93 \cdot 10^3 \text{ km}^3$ and thus corresponds to 3.6 standard deviations of the historical sea ice volume variability around a linear trend line (the standard deviation of sea ice volume residuals around a linear trend fitted to the period 1979-2021 is $1.09 \cdot 10^3 \text{ km}^3$ both in NEMO4.2.2 and PIOMAS; Supplement Figure C5(a)). Regarding the sea ice concentration and near-surface ocean temperature fields, enhanced open water and positive ocean temperature anomalies occur in the Nordic Seas, while positive sea ice concentration and negative near-surface ocean temperature anomalies are imposed from the Labrador Sea to Iceland and in the Bering Sea (Supplement Figure C5(c,d)).

In terms of representativeness with respect to the observed climate, the sea ice volume in the initial condition of the SI-NEUTRAL experiment approximately corresponds to the 1979-2015 mean sea ice thickness state available from PIOMAS (Supplement Figure C6(a,b)). Moreover, the SI-NEUTRAL control ensemble reasonably captures the

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observed variability of late summer sea ice area. Thus, the standard deviations of August-September mean sea ice area and of the differences between August-September and late winter sea ice area in SI-NEUTRAL control ensemble are $0.4 \cdot 10^6 \text{ km}^2$ respectively (Supplement Figure C7(a)). For these two metrics, the standard deviations of the observed residuals relative to a linear trend fitted to the period 1979-2025 in European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Ocean and Sea Ice Satellite Application Facility (OSI SAF) are $0.38 \cdot 10^6 \text{ km}^2$ and $0.42 \cdot 10^6 \text{ km}^2$ (Supplement Figure C7(b,c)). Consequently, the SI-NEUTRAL experiment is suitable to provide extreme sea ice low probability estimates that are approximately applicable to the average climate conditions between 1979 and 2025. Compared to the SI-NEUTRAL experiment, one decade of sea ice-ocean changes may alter the variability of late summer sea ice area in the SI-LOW experiment [cf. Goosse et al., 2009]. This aspect will be addressed in section 4.3.

In SI-NEUTRAL, we perform $M = 2$ ensemble simulations with the rare event algorithm (Table 4.1). One rare event simulation is performed using the pan-Arctic sea ice area $SIA\{X_n(t)\}$ as an observable (referred to as "ALG(SIA)") and one is performed using the pan-Arctic sea ice volume $SIV\{X_n(t)\}$ as an observable (referred to as "ALG(SIV)"). The SI-LOW experiment contains $M = 1$ ensemble simulation with the rare event algorithm using $SIV\{X_n(t)\}$ as the observable. Both the SI-NEUTRAL and SI-LOW experiments contain respectively one control ensemble simulation (i.e. an ensemble simulation without the rare event algorithm) to obtain two baselines of the statistics for the two independent initial conditions. The biasing parameters are $k = -0.02 \cdot 10^{-3} \text{ km}^{-3} \text{ d}^{-1}$ for the two ALG(SIV) experiments and $k = -0.04 \cdot 10^{-6} \text{ km}^{-2} \text{ d}^{-1}$ for the ALG(SIA) experiment. The precise choice of k is empirical. However, a reasonable order of magnitude of the parameter can be derived from the standard deviation and decorrelation time of the anomalies of the observable in the control ensembles using a scaling argument presented in Ragone and Bouchet [2020] and in the Supplement of Ragone and Bouchet [2021] (i.e. the standard deviations and decorrelation times of the sea ice volume and sea ice area for the ALG(SIV) and ALG(SIA) experiments respectively). According to this scaling argument, the selected k value in the ALG(SIV) (ALG(SIA)) experiment corresponds to a shift of the mean of the distribution of the March-September averaged sea ice volume (sea ice area) to values of approximately $1.5 \cdot 10^3 \text{ km}^3$ ($0.35 \cdot 10^6 \text{ km}^2$) below the control ensemble mean. This corresponds to estimated probabilities of between 1% and 0.1% in the ALG(SIV) experiment and of about 1% in the ALG(SIA) experiment (Supplement Figure C11). The resampling time in all simulations with the rare event algorithm is $t_r = 5 \text{ d}$. It is chosen to be not larger than the persistence timescale of the large-scale atmospheric circulation [Baldwin et al., 2003] and to be only slightly larger than the typical persistence of synoptic-scale atmospheric fluctuations Hoven [1957]. The rare event simulations are therefore suitable to improve the sampling efficiency of extremely low sea ice area states both driven by oceanic processes and due to anomalies in the atmospheric circulation that are in the order of or larger than the upper range of the synoptic timescale.

Within an ensemble, each trajectory starts from the same initial condition, as done for ensemble weather and seasonal climate predictions. In order to allow the trajectories

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to diverge from each other, we slightly perturb the surface pressure field of the "IFS initial condition" files. Precisely, we multiply the amplitudes of the spherical harmonics of order (i,j) of the natural logarithm of the surface pressure by $\gamma = 1 + \epsilon R_{ij}$, where $\epsilon = 10^{-4}$ and R_{ij} are uniform random numbers extracted between -1 and 1 . We set $R_{0j} = 0$ to avoid a modification of the zonal mean of the surface pressure field. From a technical point of view, the implementation of these perturbations is different compared to PlaSim-LSG. In PlaSim-LSG, perturbations are added within the source code, while in EC-Earth3 the perturbations are added to the IFS initial condition files. From the physical point of view, however, the perturbations used for the work with PlaSim-LSG and EC-Earth3 are identical. In this context, the perturbations added at the beginning of the simulation and after each resampling event are identical.

Table 4.1: The $N = 300$ trajectory control and rare event algorithm ensemble simulations running between 01 March and 01 October (SI-NEUTRAL and SI-LOW) and the $N = 1$ trajectory 250-year control run (FREE) between the model dates 01 January 2050 and 31 December 2299.

Initial condition	Simulation	Observable	Biasing parameter k
SI-NEUTRAL	ALG(SIA)	sea ice area	$-0.04 \cdot 10^{-6} \text{ km}^{-2}$
	ALG(SIV)	sea ice volume	$-0.02 \cdot 10^{-3} \text{ km}^{-3}$
	control ensemble	—	0
SI-LOW	ALG(SIV)	sea ice volume	$-0.02 \cdot 10^{-3} \text{ km}^{-3}$
	control ensemble	—	0
FREE	250-year control run	—	—

4.2.2.3 Computation of confidence intervals and statistical significance

In Sauer et al. [2024] and Sauer et al. [2025], ensemble simulations with the rare event algorithm are repeated M times, and the empirical variance of statistical estimators is derived from the statistics of the M estimates. The substantially larger computational cost of EC-Earth3 compared to the intermediate complexity climate model Planet Simulator (PlaSim) makes that approach challenging for this work. Here, instead, we assess the confidence intervals and statistical significance using one single realization of an experiment. In the case of rare event sampling, a key issue is the fact that the killing-cloning procedure leads to a substantial statistical dependence between different trajectories. However, several papers have proposed estimators of the variance of a statistical estimator that can be computed from one single rare event sampling experiment [Olsson and Douc, 2019; Chan and Lai, 2013; Lee and Whiteley, 2018; Abbot et al., 2021; Lancelin et al., 2025]. As discussed in Abbot et al. [2021] and in Lancelin et al. [2025], the variance in one single rare event simulation can be computed via two different approaches: there is one "optimistic" approach that systematically underestimates the variance and there is one "pessimistic" one that tends to overestimate the variance when the sample size becomes reasonably large. While the optimistic estimator treats each individual trajectory as a single independent data point and therefore typically overestimates the true sample size, the pessimistic one aggregates all descendants of a given ancestor into a single effective trajectory and therefore typically underestimates the true sample size.

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In this work, we apply the "pessimistic" variance estimator to obtain a conservative estimate of the statistical uncertainty. This estimator requires to track the genealogy of the rare event simulation. We denote $Q_t(\phi)$ the statistical estimate computed with the algorithm as defined in Equation (4.3). We then compute the variance of $Q_t(\phi)$ as

$$\text{VAR}[Q_t(\phi)] = \sum_{n=1}^N \left[\sum_{m: B_t^n = n} \frac{Z_k e^{-k \int_0^{T_a} A(\{X_m(t)\}) dt}}{N} \left\{ \phi(\{X_m(t)\}_{0 \leq t \leq T_a}) - Q_t(\phi) \right\} \right]^2, \quad (4.4)$$

where B_t^n is the index of the ancestor of $X_n(t)$ at time 0 (referred to as "eve variables" in Lee and Whiteley [2018]). The quantity equals to zero when all trajectories have the same ancestor at time 0.

Starting from equation 4.4, we use a two-sided t-test to estimate the statistical significance of conditional averages (i.e. composites) and we use the t-distribution to construct 95% confidence intervals. We denote K the number of independent extreme events (e.g. an August-September mean sea ice area anomaly equal or smaller than -2.5 control ensemble standard deviations) being associated with distinct ancestors (i.e. extreme trajectories that share no common history except from the initial condition at time 0). We then compute the t-value as $z = \sqrt{K} \frac{Q_t(\phi)}{\sqrt{\text{VAR}[Q_t(\phi)]}}$. We qualify an estimate as statistical significant at the 5% level if the absolute value of z is larger than 2.776 for $K = 5$ and 2.262 for $K = 10$. We likewise construct 95% confidence intervals from the student's t-distribution. Regarding the computation of probability-amplitude curves, the number of independent events strongly depends on the extreme event amplitudes. In that case, we use for all amplitudes a generic factor of $z = 2$ to construct the confidence intervals.

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4.3 Results

4.3.1 Importance sampling and initial condition-dependence of extremes of sea ice reduction

We use initialized ensemble simulations to examine the statistical properties of extremely negative August-September mean pan-Arctic sea ice area anomalies as a function of two different initial winter sea ice-ocean states. The purpose of using the rare event algorithm is to obtain a better statistics of extremes of sea ice area reduction compared to direct sampling. Compared to direct sampling, the algorithm also provides a better estimate of a lower bound of sea ice area values that can be generated internally via atmosphere-sea ice-ocean dynamics.

Figure 4.2 shows the seasonal evolution of daily pan-Arctic sea ice area anomalies relative to the SI-NEUTRAL control ensemble mean and the distributions of August-September mean pan-Arctic sea ice area values. Throughout the melting season, trajectories generated with the "SI-NEUTRAL: ALG(SIA)" simulation (i.e. the algorithm observable is the sea ice area; see section 4.2.2.2) show a systematic shift towards lower sea ice area values compared to the control ensemble (Figure 4.2(a)). This corresponds to the importance sampling of trajectories leading to extremely negative pan-Arctic sea ice area anomalies on average over the entire simulation period. Compared to the full simulation period, the shift reaches its largest amplitude in August and September, and the distribution of August-September mean sea ice area values obtained with the rare event algorithm includes values below the minimum of the control ensemble (Figure 4.2(b)).

In contrast to ALG(SIA), the two ALG(SIV) rare event simulations (i.e. the algorithm observable is the sea ice volume) are designed to perform importance sampling of trajectories leading to extremely negative sea ice volume anomalies on average over the entire simulation period (Figure 4.2(c-f)). Nevertheless, the result in Figure 4.2(c-f) demonstrates that this set-up also allows to increase the sampling of extremely low states of late summer sea ice area compared to the two control ensembles. We hypothesize that a rare event simulation with the sea ice volume as an observable is efficient in sampling low states of late summer sea ice area as it directly improves the sampling of trajectories developing an anomalously strong sea ice thinning during spring. Unlike in the "SI-NEUTRAL: ALG(SIA)" experiment, sea ice area anomalies in the "SI-NEUTRAL: ALG(SIV)" simulation do not become systematically negative before the end of June (Figure 4.2(a,c)), whereas sea ice volume anomalies in that experiment become systematically negative during May (cf. Figure 4.2(a,c) and Supplementary Figure C8). This is in line with the studies of Sauer et al. [2025] and Chevallier and Salas-Mélia [2012] according to which anomalously low spring-summer sea ice thickness states can act as a preconditioning for anomalously low states of late summer sea ice area. Finally, similar to Chapter 3 and Chapter 2, we discuss the adequacy of the rare event simulations, i.e. the extent to which they provide sufficiently enough independent extreme events to gather robust statistics on these events, in the Supplementary Information (S4B and Supplementary Figures C21, C22 and C23).

The result in Figure 4.2 suggests a substantial impact of the winter initial condition on the seasonal evolution and late summer state of the sea ice area. For example,

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the trajectories obtained with the SI-LOW control ensemble (independent from the rare event simulation) develop negative sea ice area anomalies relative to the SI-NEUTRAL control ensemble mean (Figure 4.2(e)). The magnitude of those sea ice area anomalies increases from the beginning to the end of the melting season. This effect corresponds to the impact of the imposed "2012-AVG<1995-2005>" sea ice-ocean changes on the mean of the distribution of late summer sea ice area, partly due to an increased open water formation efficiency related to reduced sea ice thickness (cf. Chevallier and Salas-Mélia [2012]) and partly due to positive ocean temperature anomalies in the Nordic Seas, compared to the initial condition of the SI-NEUTRAL experiment (Supplementary Figures C5 and C9). In order to quantify the impact of the late winter initial condition on the risk of occurrence of an extreme late summer sea ice low within the year of the initial condition, we compare the probabilities of obtaining an extremely low late summer sea ice area value within the given year between the SI-NEUTRAL and the SI-LOW experiments (Figure 4.3). These probabilities can be computed as

$$P(a) = \frac{1}{N} \sum_{n=1}^N \mathbb{1}_a(AS-SIA_n) \text{ with } \mathbb{1}_a(AS-SIA_n) = \begin{cases} 1, & AS-SIA_n \leq a \\ 0, & AS-SIA_n > a \end{cases}, \quad (4.5)$$

where $AS-SIA_n$ is August-September time-averaged pan-Arctic sea ice area in trajectory n , a is the amplitude of the sea ice area anomaly, N the number of trajectories and $\mathbb{1}_a$ is the indicator function. As Equation (4.5) represents the probability as an expectation value of the indicator function, probabilities from the simulations with the rare event algorithm can be computed by applying the estimator in Equation (4.3) to this quantity (see Lestang et al. [2018], Ragone et al. [2018]; Ragone and Bouchet [2020], Sauer et al. [2024] and Sauer et al. [2025]).

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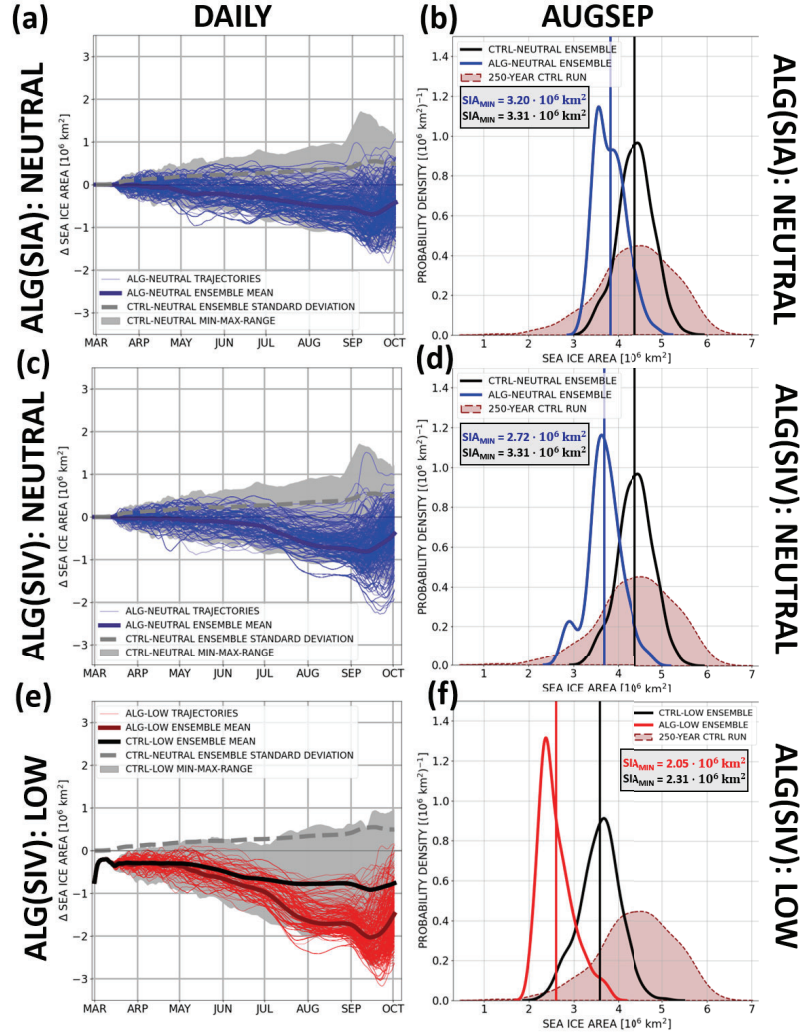


Figure 4.2: Pairs of $N = 300$ trajectory control and rare event algorithm ensemble simulations initialized from (a-d) the SI-NEUTRAL and (e-f) the SI-LOW sea ice-ocean initial condition. The algorithm observable is the pan-Arctic (a,b) sea ice area and (c-f) sea ice volume. (a,c,e) Trajectories (thin lines) and ensemble means (colored thick lines) of 15-day running mean sea ice area anomalies [10^6 km^2] obtained with the algorithm and computed relative to the SI-NEUTRAL control ensemble mean. (e) The dark line shows the sea ice area anomalies in the SI-LOW control ensemble mean relative to the SI-NEUTRAL control ensemble mean. (a,c,e) The gray dashed lines and shadings are (a,c) the SI-NEUTRAL and (e) the SI-LOW control ensemble standard deviations and minimum-maximum ranges. (b,d,f) Probability density functions for August-September sea ice area for (black) the control ensembles, (red line) the algorithm and (red shading) the 250-year control run. The vertical lines show the distribution means.

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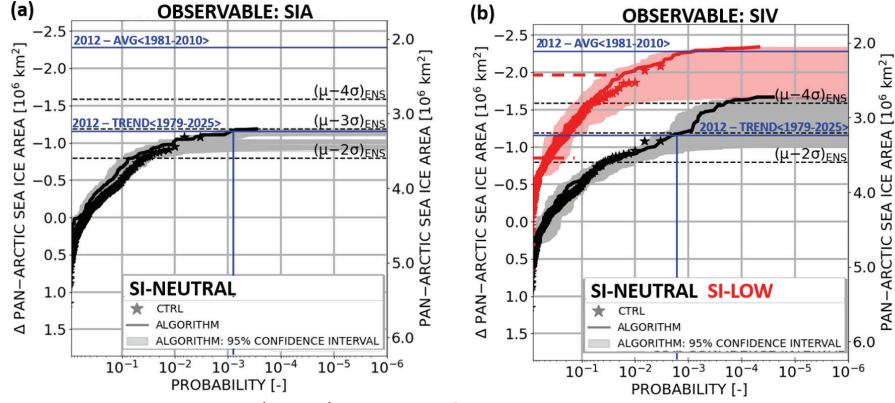


Figure 4.3: Probabilities (x -axes) of August-September mean sea ice area equal or smaller than a given threshold (y -axes) as a function of two different sea ice-ocean initial conditions for the $N = 300$ trajectory (stars) control and (solid lines) rare event algorithm ensembles. The observable used for the simulations with the algorithm is the pan-Arctic (a) sea ice area and (b) sea ice volume. Note that black stars in (a) and (b) show the same curve and are displayed twice for the purpose of visualization. While the right y -axes shows absolute sea ice area values, the left y -axes expresses these as anomalies relative to the SI-NEUTRAL control ensemble mean. Both are displayed in reverse order. The shading in direction of the x -axes shows $\pm 2\sigma$ intervals around the probability estimates using Equation (4.4) in section 4.2.2.3. The gray dashed lines indicate how many standard deviations a sea ice area value is below the mean of the SI-NEUTRAL control ensemble. The blue lines indicate the 2012 observed August-September mean sea ice area anomaly relative to the 1979-2025 linear trend line and 1981-2010 average. The horizontal dashed red lines in (b) indicate the mean of the SI-LOW control ensemble and the location of the blue "2012 - TREND<1979-2025>" line with respect to the SI-LOW control ensemble mean.

In Figure 4.3, the star markers depict the probabilities estimated with the $N = 300$ trajectory control ensembles (one control ensemble for the "SI-NEUTRAL" and one control ensemble for the "SI-LOW" experiment). The solid lines and the horizontal shading show the estimates obtained from the rare event algorithm and the corresponding 95% confidence intervals (in the direction of the probabilities). The control ensembles and the rare event algorithm provide consistent estimates where they overlap. The major advantage of using the algorithm compared to the control is the access to much rarer events with the former than the latter, reaching probability values of order 10^{-4} for a computational cost of 10^2 years.

For a fixed amplitude level (e.g. $-1.16 \cdot 10^6 \text{ km}^2$; blue line in Figure 4.3), the probability of exceeding that amplitude varies by about two orders of magnitude between the SI-NEUTRAL and SI-LOW experiments (Figure 4.3; from 10^{-3} to 10^{-1}). This confirms a strong impact of imposed "2012-AVG<1995-2005>" sea ice-ocean changes on the probabilities and amplitudes of extremely low late summer sea ice area values. The impact of these sea ice-ocean changes on the mean of the distribution of late summer sea ice area is $-0.81 \cdot 10^6 \text{ km}^2$, whereas the 1% percentile values estimated with the ALG(SIA) and ALG(SIV) SI-NEUTRAL rare event simulations are $0.92 \cdot 10^6 \text{ km}^2$ and $0.98 \cdot 10^6 \text{ km}^2$

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Table 4.2: August-September mean sea ice area anomalies relative to the SI-NEUTRAL control ensemble mean ($\mu_{\text{ENS-NEU}}$) [10^6 km^2] and ensemble standard deviations (σ_{ENS}) of August-September mean sea ice area [10^6 km^2]. The anomalies in the column " $\text{SIA}_{0.01} - \mu_{\text{ENS-NEU}}$ " correspond to the 1% percentile sea ice area value computed from the output of the rare event algorithm (i.e. preconditioning + anomalous weather in SI-LOW and anomalous weather in SI-NEUTRAL). The anomalies in the $\mu_{\text{ENS}} - \mu_{\text{ENS-NEU}}$ column correspond to the control ensemble means, i.e., the impact of preconditioning on the means of the $N = 300$ trajectory control ensembles (by definition zero for SI-NEUTRAL). For the computation of the percentiles with the algorithm, we weight the contribution of each trajectory to the percentile by the product of Z_k and the exponential factor shown in Equation (4.3). The values in the square brackets show the 95% confidence intervals for the estimates of the standard deviation.

Initial condition	Simulation	$\mu_{\text{ENS}} - \mu_{\text{ENS-NEU}}$ [10^6 km^2]	$\text{SIA}_{0.01} - \mu_{\text{ENS-NEU}}$ [10^6 km^2]	σ_{ENS} [10^6 km^2]
SI-NEUTRAL	ALG(SIA)	-	-0.98	-
	ALG(SIV)	-	-0.92	-
	control ensemble	0.00	-	0.40 [0.37,0.43]
SI-LOW	ALG(SIV)	-	-2.07	-
	control ensemble	-0.81	-	0.45 [0.41,0.49]

below the SI-NEUTRAL control ensemble means. Consequently, the contribution of imposed "2012-AVG<1995-2005>" sea ice-ocean changes to the amplitudes of extreme sea ice area lows is comparable to the contribution of weather-induced variability in causing extreme sea ice reduction.

Finally, the rare event simulations provide extreme sea ice area anomalies with larger amplitudes compared to the observed 2012 sea ice area anomaly relative to the 1979-2025 linear trend (cf. Figure 4.3 and Supplementary Figure C7). While the observed sea ice area anomaly relative to the 1979-2025 trend line is $-1.16 \cdot 10^6 \text{ km}^2$, the most extremely negative August-September mean sea ice area anomalies relative to the local control ensemble mean in the "SI-NEUTRAL: ALG(SIA)", the "SI-NEUTRAL: ALG(SIV)" and the "SI-LOW: ALG(SIV)" experiments are $-1.19 \cdot 10^6 \text{ km}^2$, $-1.67 \cdot 10^6 \text{ km}^2$ and $-1.53 \cdot 10^6 \text{ km}^2$. Both the "ALG(SIA)" and the "ALG(SIV)" "SI-NEUTRAL" experiments, i.e. ensembles that are initialized from a late winter sea ice state that is compatible with the 1979-2015 mean sea ice thickness, suggest that the probability of exceeding a sea ice area anomaly larger in magnitude compared to the 2012 anomaly relative to the 1979-2025 linear trend is in the order of 10^{-3} . However, this value may vary substantially with the chosen initial condition. Thus, the probability estimated with the "SI-LOW" experiment is in the order 10^{-2} (Supplement Figure C12). This is consistent with e.g. Goosse et al. [2009] who demonstrated that the variance of summer sea ice area increases with decreasing sea ice area for a certain range of sea ice area values.

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4.3.2 Sea ice conditions and state of the atmosphere during extremes of sea ice reduction

Based on the rare event algorithm experiments using the pan-Arctic sea ice volume as an observable, we study the physical processes and conditions leading to extreme reductions of the pan-Arctic sea ice area within one single melting season. As in Sauer et al. [2025], these experiments are designed to investigate intra-seasonal drivers of low sea ice states as all trajectories within one ensemble start from the same sea ice-ocean initial condition. While sea ice-ocean preconditioning may impact the variance of late summer sea ice area and therefore the amplitudes of the extremes (cf. section 4.3.1 and Goosse et al. [2009]), the triggers of enhanced sea ice reduction are by construction related to fluctuations occurring on time scales of at most one melting season. In this study, we both address single trajectories leading the most extremely negative August-September sea ice area anomalies available from the two experiments, and we apply composite analyses to investigate the mean physical properties on average over all trajectories characterized by August-September mean sea ice area values more than 2.5 standard deviations below the control ensemble means (referred to as "AS- Δ SIA ALG MIN" and "AS- Δ SIA $\leq -2.5\sigma$ "). As described in Sauer et al. [2024] and Ragone and Bouchet [2020], the composites can be computed from the output of the rare event algorithm as

$$\mathbb{E}_0[O(\{X_n(t)\}) \mid (AS-\Delta SIA)_n \leq -2.5\sigma] = \frac{\mathbb{E}_0[O(\{X_n(t)\}) \cdot \mathbb{1}((AS-\Delta SIA)_n)]}{\mathbb{E}_0[\mathbb{1}((AS-\Delta SIA)_n)]}, \quad (4.6)$$

where $O(\{X_n(t)\})$ and $(AS-\Delta SIA)_n$ are the anomalies of a target climate variable (e.g. mean sea level pressure) and of the August-September mean pan-Arctic sea ice area in trajectory n , σ the control ensemble standard deviations of the two experiments and $\mathbb{1}(AS-\Delta SIA)$ is the indicator function with

$$\mathbb{1}(AS-\Delta SIA) = \begin{cases} 1, & AS-\Delta SIA \leq -2.5\sigma \\ 0, & AS-\Delta SIA > -2.5\sigma \end{cases}. \quad (4.7)$$

All anomalies are computed relative to the experiment-specific control ensemble means, and $\mathbb{E}_0$ is the expectation operator with respect to the unbiased model statistics (i.e. the statistics of the control ensembles). By using Equation 4.2 and 4.3, composites can be computed from the output of the rare event algorithm as described in Ragone and Bouchet [2020] and in the Supporting Information of Ragone et al. [2018] and of Ragone and Bouchet [2021].

4.3.2.1 Seasonal evolution of the state of the sea ice

In August-September, the trajectory with the most extreme sea ice area reduction among the two experiments is associated with enhanced sea ice cover eastern of Greenland and strongly reduced sea ice cover within the entire Pacific-Eurasian side of the Arctic (Figure 4.4(a,b)). While the pan-Arctic sea ice area anomaly exceeds in magnitude the observed

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2012 event by $0.5 \cdot 10^6 \text{ km}^2$ (i.e. the August-September mean sea ice area anomaly relative to the 1979-2025 linear trend as defined in section 4.3.1), the spatial distribution of sea ice cover anomalies in the simulated extreme is compatible with the one observed in 2012 (Figure 4.4(a)). Consequently, the model used in this study reasonably captures the lowest tail of the distribution of late summer sea ice area anomalies. Both " $\text{AS-}\Delta\text{SIA} \leq -2.5\sigma$ " composites reveal that the dipole with enhanced and reduced sea ice cover around Greenland and on the Pacific-Eurasian side of the Arctic reflects a common behaviour in these two experiments (Figure 4.4(c,d)). Statistically significant negative sea ice cover anomalies occur both on the Pacific side of the Beaufort Gyre and in regions located upstream of the transpolar drift. Eastern of Greenland, i.e., downstream of the transpolar drift, statistically significant positive sea ice cover anomalies are noticeable.

Regarding the seasonal evolution of composite mean sea ice volume and sea ice area anomalies, enhanced melting systematically starts around the beginning of May, and negative sea ice volume anomalies become statistically significant in May-June. This is temporally coinciding with the predictability barrier of late summer sea ice cover presented in Bonan et al. [2019]; Bushuk et al. [2020] according to which forecasts of late summer sea ice area initialized in July show substantially larger predictive skill compared to forecasts initialized in May. Qualitatively similar to Sauer et al. [2025], negative sea ice volume anomalies anticipate the formation of negative sea ice area anomalies. At the end of June, for example, composite mean sea ice area and sea ice volume values are about 1.25 and 2.25 control ensemble standard deviations below the control ensemble means. The result in Figure 4.5 suggests that extremely negative late summer sea ice area anomalies are systematically preceded by a persistent forcing during the spring-summer transition causing and maintaining negative sea ice area and sea ice volume anomalies beyond the predictability barrier.

4.3.2.2 Statistical link between extreme sea ice reduction and the atmospheric circulation

Changes in the atmospheric circulation may influence sea ice thermodynamically by affecting cloud cover, water vapour, the thermal state of the Arctic atmosphere [e.g. Kapsch et al., 2019; Liang et al., 2022; Baxter et al., 2019] and dynamically through the impact of anomalous winds on the transport of sea ice [e.g. Cavallo et al., 2025; Wang et al., 2009]. In order to establish a linkage between enhanced sea ice loss during the spring-summer transition and the atmospheric circulation, we analyze May-June and June-July mean sea level pressure, two metre temperature and sea ice motion anomalies conditional on the occurrence of extremely low annual sea ice minima ($\Delta\text{AS-SIA} \leq -2.5\sigma$; Figure 4.6).

Both the "SI-NEUTRAL" and the "SI-LOW" experiments show statistically significant negative mean sea level pressure anomalies over the central to eastern Arctic Ocean and slightly positive mean sea level pressure anomalies in parts of the North Atlantic-European and East Asian-North Pacific sectors. The signal in the mean sea level pressure field is accompanied by a substantial modulation of the thermal state of the near-surface atmosphere. In both experiments, statistically significant positive two metre temperature anomalies extend from the Canadian Archipelago to the Pacific side of the Arctic Ocean, spatially coinciding with enhanced open water conditions during extremely low annual

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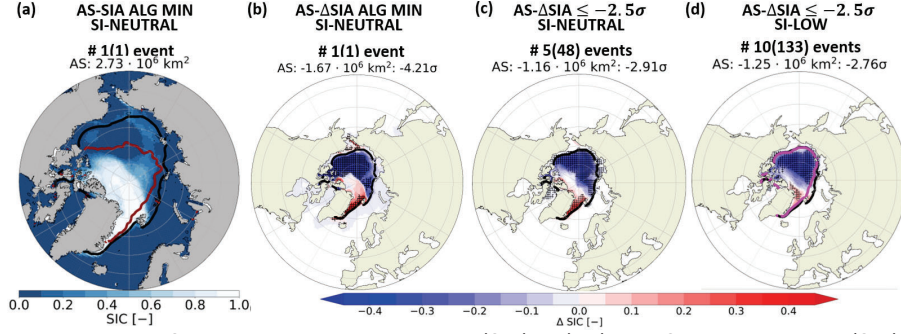


Figure 4.4: AUGSEP mean sea ice concentration (SIC) in (a-c) the "SI-NEUTRAL: ALG(SIV)" and (d) the "SI-LOW: ALG(SIV)" experiment. (a-b) Trajectory with the most extreme sea ice reduction available from the ensemble for (a) absolute SIC values and (b) SIC anomalies relative to the SI-NEUTRAL control ensemble mean. The dark red line in (a) shows the observed 2012 September 15% sea ice concentration line [EUMETSAT Ocean and Sea Ice Satellite Application Facility, 2017]. (c-d) Composite mean SIC anomalies conditional on the occurrence of an AUGSEP mean sea ice area of at least 2.5 control ensemble standard deviations below the control ensemble means for (c) the SI-NEUTRAL and (d) SI-LOW experiment. Hatching indicates SIC anomalies (b) that are larger in magnitude than the control ensemble standard deviation and (c-d) that are statistically significant at a 5% level (section 4.2.2.3). The black and magenta lines indicate the AUGSEP mean 15% SIC line in the SI-NEUTRAL and SI-LOW control ensembles respectively.

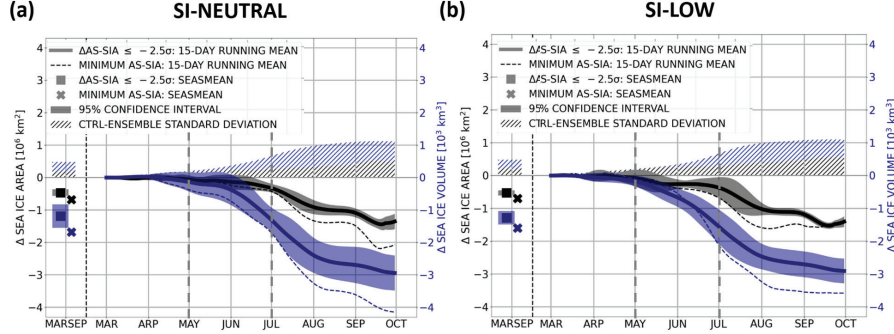


Figure 4.5: March-September (MARSEP) and 15-day running mean (blue) sea ice volume and (black) sea ice area anomalies relative to the control ensemble means for (a) the "SI-NEUTRAL: ALG(SIV)" and (b) the "SI-LOW: ALG(SIV)" experiments. Thick lines and square markers are composite mean anomalies conditional on the occurrence of an August-September sea ice area of at least 2.5 control ensemble standard deviations below the control ensemble means. The shading shows 95% confidence intervals around the composite estimates (section 4.2.2.3) and the hatching shows the control ensemble standard deviations. The thin lines are the trajectories with the most extreme sea ice reduction available from the two experiments respectively.

sea ice minima. Outside of the Arctic, positive two metre temperature anomalies tend to occur upstream of anticyclonic conditions over the East Asian-North Pacific sector, in particular in the "SI-NEUTRAL" experiment. This reveals that extremes of sea ice reduc-

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tion are not only systematically associated with cyclonic conditions over the central and eastern Arctic Ocean, but with large-scale atmospheric circulation anomalies extending far south of the polar region.

In terms of sea ice dynamics, the cyclonic conditions over the high-Arctic are associated with a substantial impact on the sea ice motion. Thus, cyclonic sea ice motion anomalies occur over the central Arctic Ocean in May-June and June-July in both experiments. The sea ice motion vectors are tilted to the right compared to the isobars of mean sea level pressure anomalies, consistent with Ekman drift according to which the sea ice moves 8° to the right of the geostrophic wind [Serreze and Barry, 2014, p. 190]. The sea ice motion vector anomalies suggest enhanced sea ice divergence out of the central Arctic Ocean towards the marginal seas. A quantification of the relative contribution of sea ice dynamics vs. thermodynamics will follow in section 4.4.

4.3.3 The relative contributions of thermodynamic vs. dynamic forcing to extreme sea ice reduction

We perform a sea ice area and sea ice volume budget analysis [Holland and Kwok, 2012] to assess the relative contributions of thermodynamic and dynamic processes to extreme sea ice area reduction within one single melting season. The temporal evolution for the sea ice concentration A and for the sea ice volume per grid cell area (i.e., mean sea ice thickness within a grid cell or local sea ice volume; here referred to as "sea ice volume") V are given by

$$\begin{aligned} \frac{\partial A}{\partial t} + \mathbf{u} \cdot \nabla A + A \nabla \cdot \mathbf{u} &= f_A + r_A \\ \frac{\partial V}{\partial t} + \mathbf{u} \cdot \nabla V + V \nabla \cdot \mathbf{u} &= f_V + r_V, \end{aligned} \tag{4.8}$$

where t and $\mathbf{u}$ are time and the horizontal sea ice velocity vector, f_V and f_A are the sea ice volume and sea ice concentration change due to freezing and melting (thermodynamic), r_A is the sea ice concentration change due to mass-conserving mechanical sea ice redistribution (ridging and rafting) and r_V is the sea ice volume change related to a change of the sea ice porosity during ridging. The sum of the advection (second term from the left) and the divergence (third term from left) is denoted "sea ice transport" and corresponds to the dynamic impact of the atmospheric and oceanic circulations on the sea ice. In this study, we neglect the subgrid-scale terms r_A and r_V as we are interested in the large-scale (e.g. spatial scales in the order of the Arctic Ocean) impact of atmospheric circulation anomalies on the sea ice.

For the following analyses, the tendencies of (4.8) are integrated over a particular time period to yield net changes, and anomalies relative to the means of the two control ensembles (SI-NEUTRAL and SI-LOW) are discussed. Firstly, we consider a seasonally integrated sea ice volume and sea ice area budget (Figure 4.7 and "MARSEP" in Figure 4.8). For this purpose, we integrate the tendencies from 01 March to each of the 61 days

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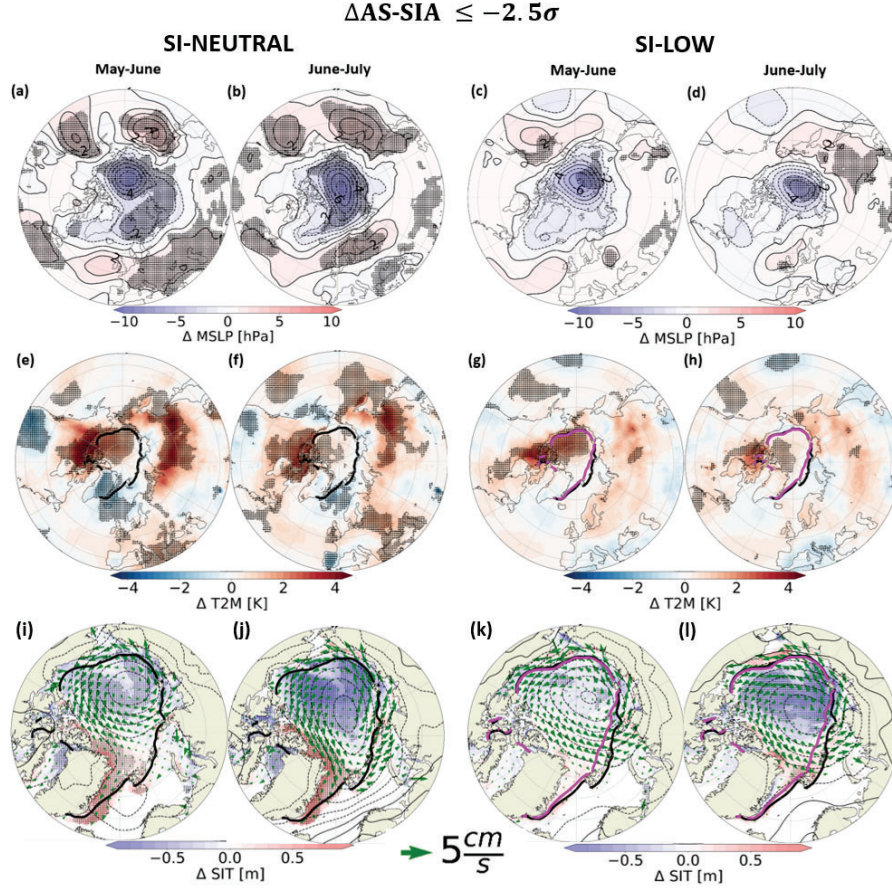


Figure 4.6: May-June and June-July composite mean (a-d) mean sea level pressure [hPa], (e-h) two metre temperature [K] and (i-l) horizontal sea ice motion vector [$cm s^{-1}$] and sea ice thickness [m] anomalies conditional on the occurrence of an August-September sea ice area of at least 2.5 control ensemble standard deviations below the control ensemble means. The hatching indicates statistical significance at the 5% level (see section 4.2.2.3). The results are based on (a,b,e,f,i,j) the "SI-NEUTRAL: ALG(SIV)" and (c,d,g,h,k,l) the "SI-LOW: ALG(SIV)" experiments. The black and magenta contour lines indicate the August-September mean 15% sea ice concentration line in the SI-NEUTRAL and SI-LOW control ensembles respectively.

in August and September and plot the average over these 61 integrations. This allows us to understand to what extent extremely negative August-September mean sea ice area and sea ice volume anomalies are driven by thermodynamic and dynamic processes accumulated over the entire simulation period. Secondly, we discuss bimonthly integration periods to investigate the seasonal evolution of the different terms of Equation (4.8), linking the budget terms to the anomalous spring-summer atmospheric circulation presented

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in section in 4.3.2 (Figure 4.8). In terms of sign convention, negative (positive) anomalies in Figures 4.7 and 4.8 correspond to enhanced (reduced) sea ice reduction compared to the climatological mean seasonal cycle.

4.3.3.1 Seasonally integrated sea ice volume and sea ice area budget

On statistical average (i.e. composite) and integrated over the entire melting season, extremes of sea ice reduction are characterized by strongly enhanced loss of sea ice volume and sea ice area on the Pacific and Eurasian side of the Arctic and slightly reduced sea ice loss eastern of Greenland (cf. Figure 4.7(a,d,g,j) and Figure 4.4(c,d)). Spatially, the contribution of thermodynamic vs. dynamic forcing shows a dipole-like structure: statistically significant enhanced thermodynamic sea ice melting occurs from the Canadian Archipelago over the Pacific side of the Arctic to Siberia (Figure 4.7(b,e,h,k)). Enhanced thermodynamic melting therefore spatially coincides with positive two metre temperature anomalies during late spring (cf. Figure 4.7(b,e,h,k) and Figure 4.6). Dynamics-related sea ice anomalies are smaller in magnitude than the thermodynamic ones, but statistically significant enhanced sea ice loss is noticeable on the Eurasian side of the Arctic and thus spatially coincides with the center of anomalously low spring-summer mean sea ice level pressure (cf. Figure 4.7(c,f,i,l) and Figure 4.6(a-d)).

We spatially integrate the budget components over the domains defined by the 15% August-September mean sea ice concentration contour lines derived from the experiment-specific control ensemble means to quantify the relative contribution of anomalous sea ice transport out of those domains to enhanced sea ice loss (Figure 4.8 and Supplement Figure C13; the domains are indicated in Figure 4.7 by the magenta line for the SI-LOW and white line for the SI-NEUTRAL experiment; those contour lines are referred to as climatological mean sea ice edge in the following). The rationale behind this computation is that the climatological late summer sea ice edge provides a natural border between a "cold" inner Arctic Ocean and a "warm" ocean outside of the domain. Sea ice being transported out of the domain has a larger chance to melt during summer compared to sea ice that remains in the central Arctic Ocean. This computation neglects, however, the effect of sea ice being transported along temperature gradients without leaving the domain. In that case, transport might enhance thermodynamic melt without being accounted as transport-driven sea ice loss. On statistical average and integrated from March to the end of summer, enhanced sea ice volume (area) transport out of the domain explains in the order of 25% to 35% of (20% to 30%) of anomalous sea ice volume (area) loss (Figure 4.8 and Supplementary Figure C13). This range considers uncertainties related both to sampling and to the threshold used to define the extremes. Substantial fluctuations of the relative contributions of the transport to enhanced sea ice loss may occur. Thus, enhanced transport explains about 50% (40%) of enhanced sea ice volume (area) loss in the most extreme sea ice loss trajectory of the SI-NEUTRAL experiment, while the most extreme sea ice loss trajectory available from the SI-LOW experiment is almost entirely explained by thermodynamics. A detailed analysis about the sensitivity of those ratios with respect to different amplitude ranges of extreme events is presented in the Supplement Figure C13.

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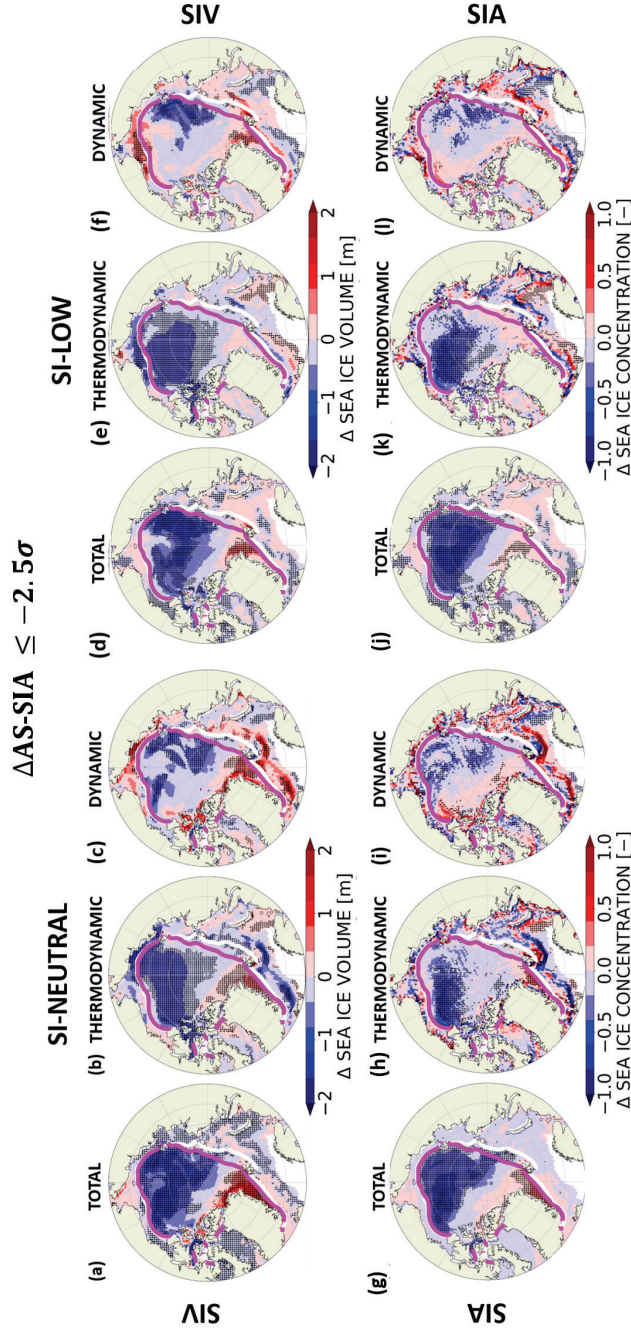


Figure 4.7: Composite mean anomalies of the seasonally-integrated ($\text{AVG} < 01 \text{ March-01 August, } 01 \text{ March-02 August, } \dots, 01 \text{ March-30 September} >$) terms of (a-f) the sea ice volume [m] and (g-l) the sea ice area [-] budget analysis (Equation (4.8)) conditional on trajectories with an AUGSEP sea ice area of at least 2.5 control ensemble standard deviations below the control ensemble means. The results are based on (a-c,g-i) the "SI-NEUTRAL: ALG(SIV)" and (d-f,j-l) the "SI-LOW: ALG(SIV) experiments". The white and magenta lines indicate the AUGSEP mean 15% SIC line in the SI-NEUTRAL and SI-LOW control ensembles respectively. Hatching indicates statistical significance at the 5% level (see section 4.2.2.3). The term "DYNAMIC" is the sea ice transport, i.e., the sum of the second and third terms from the left in Equation (4.8).

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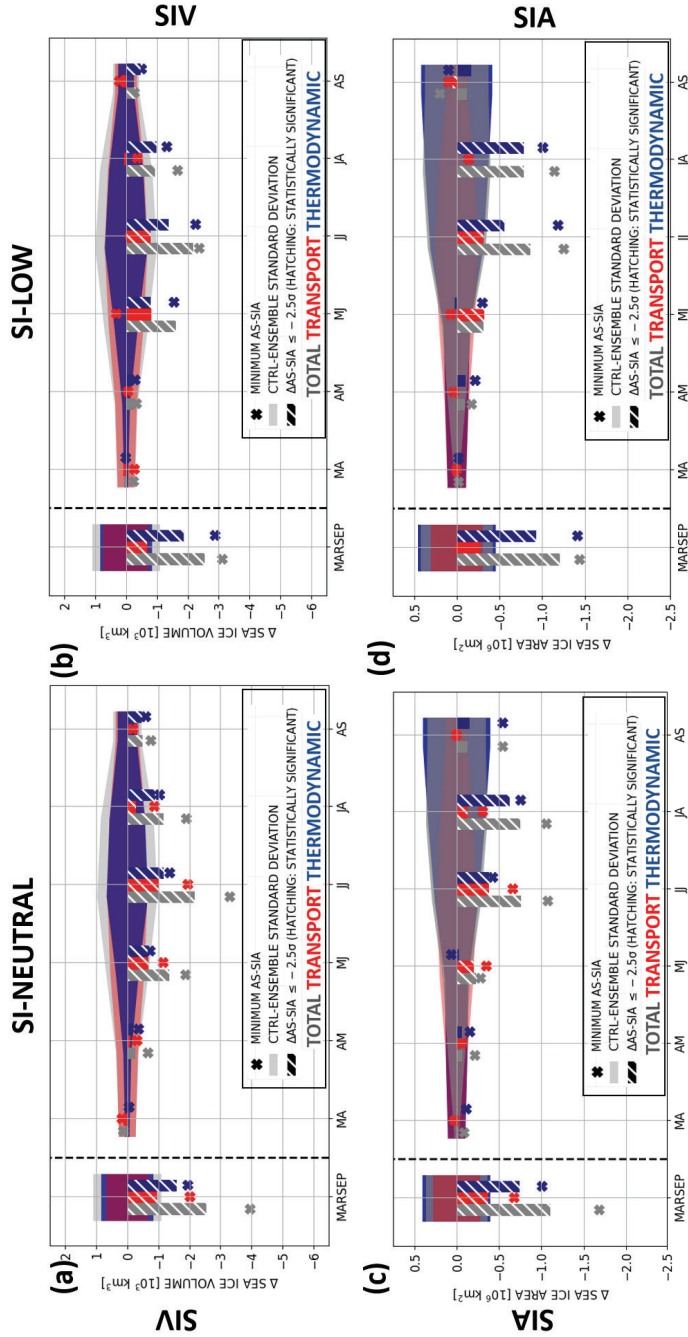


Figure 4.8: Mean anomalies of the terms of the sea ice volume (a-b) and sea ice area (c-d) budget (Equation 4.8) for (a,c) the "SI-NEUTRAL: ALG(SIV)" and (b,d) the "SI-LOW: ALG(SIV)" simulations computed relative to the experiment-specific control ensemble means. The budget terms are spatially integrated over the domains enclosed by the AUGSEP mean 15% sea ice concentration lines of the two control ensembles (white and magenta lines in Figure 4.7). In time, the budget terms are integrated over pairs of two months (e.g. AM: 01 April - 31 May) and over the full melting season (MARSEP as in Figure 4.7). The bars show composites ($\Delta AS-SIA \leq -2.5\sigma$) as defined in Figure 4.7 and the stars the trajectories leading to the most extreme sea ice area reductions available from the two experiments. Hatching within the bars indicates statistical significance at the 5% level and shading the control ensemble standard deviation.

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4.3.3.2 Seasonal evolution of sea ice volume and sea ice area budget

Regarding the seasonal evolution, enhanced sea ice volume and area loss become statistically significant in May-June, consistent with the result in Figure 4.5 (Figure 4.8). In terms of the relative importance of thermodynamic vs. dynamic processes, we identify two phases during the season: both enhanced transport and thermodynamic processes similarly contribute to sea ice volume loss during May-June-July, while thermodynamics dominates enhanced sea ice volume loss during late summer. Regarding sea ice area, transport substantially contributes to enhanced May-June and June-July sea ice loss, while enhanced thermodynamic sea ice reduction starts to become more relevant in terms of magnitude than the transport in June-July. It is noticeable that transport explains about 60% of enhanced June-July sea ice loss in the most extreme late summer sea ice low trajectory available from the "SI-NEUTRAL" experiment, while drastic thermodynamically-induced sea ice reduction occurs in the most extreme late summer sea ice low trajectory available from the "SI-LOW" experiment.

4.3.4 Common drivers of extreme sea ice reduction vs. processes prior to events with probabilities of less than 0.01%

4.3.4.1 Atmospheric moisture, clouds and moisture flux convergence

An anomalously cyclonic atmospheric circulation over the central and Eurasian Arctic Ocean during spring-summer (see section 4.3.2.2) may promote increased transport of heat and moisture into the Arctic [Horvath et al., 2021b; Liang et al., 2022; Kapsch et al., 2019]. To establish a link between enhanced late spring-early summer sea ice loss and an anomalous thermodynamic atmospheric state, we compute composite mean May-June integrated water vapour (IWV) and total cloud cover (TCC) anomalies conditional on the occurrence of extremes of sea ice reduction (Figure 4.9). Both the SI-NEUTRAL and SI-LOW experiments reveal statistically significant positive IWV anomalies over the North American side of the Arctic Ocean, while total cloud cover is systematically enhanced over the North Pacific-Siberian side. The increased May-June atmospheric moisture (i.e. the combined effect of water vapor and cloud cover) spatially coincides with positive May-June two metre temperature anomalies and with the region of enhanced thermodynamic sea ice melt from March to the end of summer (cf. Figures 4.6, 4.7 and 4.9). This suggests that enhanced late spring-early summer atmospheric moisture over the North Pacific-side of the Arctic Ocean systematically contributes to extreme sea ice reduction via increased downward longwave radiative fluxes. This aspect is further addressed in section 4.3.4.2.

We compute the vectors and divergence of the vertically integrated water vapor flux to connect enhanced atmospheric moisture with anomalous atmospheric flow (Figure 4.10). In both the SI-NEUTRAL and the SI-LOW experiments, vertically integrated moisture flux vectors depict a cyclonic structure over the North Pacific-Siberian side of the Arctic in accordance with negative mean sea level pressure anomalies (cf. Figure 4.10 and Figure 4.6). Enhanced moisture flux occurs from Siberia over the Bering Sea to the Canadian Archipelago and converges into the domain of enhanced thermodynamically-induced sea ice melting (cf. Figure 4.10(a,b,d,e) and Figure 4.7(b,e,h,k)).

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To further elucidate the relative importance of moisture flux convergence for the presence of enhanced atmospheric water vapor during extremes of sea ice reduction, we exploit Gauss's law (Figure 4.10(c,f)): in a hypothetical thought experiment without local sinks and sources (evaporation, condensation, (re)sublimation), the spatial integral of the vertically integrated moisture flux convergence over a certain domain corresponds to the amount of water vapor entering the domain from outside per unit of time. Here we define the domain via all grid cells where thermodynamically-induced sea ice volume anomalies are significantly negative in at least one of the two experiments (i.e. the union of the regions of statistically significant negative thermodynamically-induced sea ice volume anomalies over both experiments; cf. Figure 4.7(b,e) and Supplementary Figure C13 for the spatial domain). In order to make the magnitude of the vertically and spatially (i.e. horizontally) integrated moisture flux convergence MF_{DIV} comparable with the one of the water vapor anomalies shown in Figure 4.9, the time series shown in Figure 4.10(c,f) is rescaled by $-\frac{1}{2A_{domain}} \int_{t_0}^{t_1} MF_{DIV} dt$, where t_0 and t_1 define the integration period (e.g. 01 May to 30 June for the data point located at "MJ") and A_{domain} is the area of the horizontal integration domain. Applying the factor 1/2, the values shown in Figure 10(c,f) mathematically correspond to the bimonthly mean integrated water vapor anomalies associated with the anomalous moisture flux convergence in the hypothetical absence of local water vapor sinks and sources. Moisture flux convergence induced positive water vapor anomalies are statistically significant from late spring to July-August in both experiments and peak in May-June and June-July during the phase of cyclonic mean sea level pressure anomalies (Figure 4.10(c,f)). In May-June and June-July, these anomalies are in the order of 2.5 kg m^{-2} and 4 kg m^{-2} in the SI-LOW and SI-NEUTRAL experiments and are therefore larger in magnitude than the water vapor anomalies shown in Figure 4.9(a,c). Moreover, the May-June mean latent heat flux anomalies are -0.83 Wm^{-2} and -0.55 Wm^{-2} in the SI-LOW and SI-NEUTRAL experiments (see section 4.3.4.2), corresponding to surface evaporation-related enhanced water vapor of 0.87 kgm^{-2} and 0.58 kgm^{-2} . Consequently, late spring-early summer moisture flux convergence associated with anomalous cyclonic atmospheric flow constitute the major source of positive water vapor anomalies compared to local sinks and sources. Since air masses are converging from subpolar latitudes into the high Arctic, the cyclonic flow also tends to be associated with enhanced convergence of the vertically integrated horizontal flux of sensible energy (Supplementary Figure C15). Compared to the moisture flux convergence, however, the signal in the convergence of the flux of sensible energy is statistically less robust (Supplementary Figure C15). This can potentially be explained by the fact that positive lower tropospheric temperature anomalies (cf. Figure 4.6(e-h)) can be generated locally via the impact of increased cloudiness and atmospheric water vapor on the downward longwave radiation and through cloud formation-induced latent heat release.

4.3.4.2 Surface energy budget

We trace back anomalous thermodynamic sea ice loss to the different terms of the surface energy budget (Figure 4.11). This allows us to investigate how extremes of sea ice reduction are on statistical average related to anomalous conditions, and to identify the dominant thermodynamic processes making the difference between "typical" extremes

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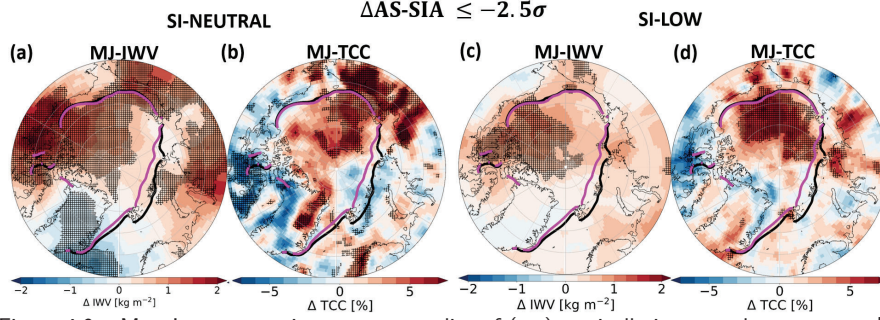


Figure 4.9: May-June composite mean anomalies of (a,c) vertically integrated water vapor [kg m^{-2}] and (b,d) total cloud cover [%] over all trajectories with an AUGSEP sea ice area of at least 2.5 control ensemble standard deviations below the control ensemble means. The hatching indicates statistical significance at the 5% level. The results are based on (a,b) the "SI-NEUTRAL: ALG(SIV)" and (c,d) the "SI-LOW: ALG(SIV)" experiments. The black and magenta lines are the AUGSEP mean 15% SIC line in the SI-NEUTRAL and SI-LOW control ensembles respectively.

(i.e. an extreme that emerges in the composite) and the most extreme sea ice lows available from the experiments. The energy flux anomalies are spatially averaged over a domain defined by all grid cells where thermodynamically-induced sea ice anomalies are significantly negative in at least of one the two experiments (cf. Figure 4.7(b,c) and the Supplementary Figure C14; this is the same domain as in section 4.3.4.1). Following the notation of Sauer et al. [2024, 2025], we define the surface energy budget for an infinitesimally thin interface without heat storage located between the atmosphere and the snow-sea ice-ocean system (cf. Serreze and Barry [2014]). The governing equation then can be written as

$$R_{SW}(1 - \alpha) + R_{LW} + S + L = -\epsilon\sigma T_s^4 + Q + M, \quad (4.9)$$

where R_{SW} and R_{LW} are the downward shortwave and downward longwave radiative fluxes, respectively; α is the surface albedo, S and L are the sensible and latent heat fluxes, ϵ is the surface emissivity, $\sigma = 5.67 \cdot 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$ is the Stefan-Boltzmann constant and T_s is the surface temperature. Q summarizes conductive and turbulent energy fluxes between the surface and the snow-sea ice-ocean system. M is the energy flux associated with melting and freezing at the surface. Energy fluxes related to bottom sea ice growth, to temperature changes in the snow-sea ice-ocean system and the vertical energy flux from the ocean into the sea ice are implicitly included in Q .

The SI-NEUTRAL and SI-LOW experiments show a very common behavior in the seasonal evolution of the composite mean atmosphere-surface energy flux anomalies (Figure 4.11). Enhanced net energy accumulation within the sea-ocean system due to increased atmosphere-surface energy fluxes occurs from the beginning of May to the end of summer, temporally coinciding with significant total and thermodynamic negative sea ice volume anomalies (cf. Figure 4.10(a,b) and Figure 4.8(a,b)). Moreover, both experiments reveal

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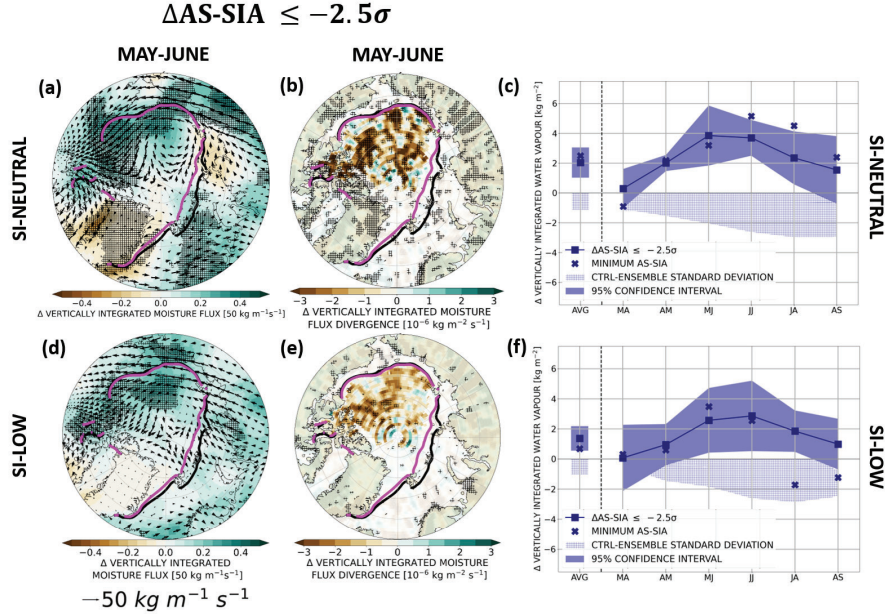


Figure 4.10: (a-c) "SI-NEUTRAL: ALG(SIV)" and (d-f) "SI-LOW: ALG(SIV)" experiments: (a,b,d,e) May-June composite mean anomalies ($\Delta AS-SIA \leq -2.5\sigma$) of (a,d) the vertically integrated water vapor flux [$50 \text{ kg m}^{-1} \text{ s}^{-1}$] (IWV flux, vectors and magnitude) and (b,e) the horizontal divergence of the IWV flux [$10^{-6} \text{ kg m}^{-2} \text{ s}^{-1}$] computed relative to the control ensemble means. Hatching denotes statistical significance at the 5% level. (b,e) Colors in grid cells outside of a domain defined by the union of statistically significant negative thermodynamically-induced sea ice volume anomalies over the two experiments (cf. Figure 4.7(b,e,h,k) and Supplementary Figure C14) are made quasi-transparent. (c,f) Seasonal evolution of the IWV flux divergence presented as a spatial average over the domain with non-transparent colors in (b,e) (see Figure C14 for the domain) [kg m^{-2}]. As explained in the main text, the values in (c,f) are rescaled to be comparable with the bimonthly mean IWV anomalies shown in Figure 4.9(a,c). Squares are composites as in (a,b,d,e) and stars show the single trajectories leading to the most extreme sea ice area reductions available from the two experiments. Shading indicates 95% confidence intervals and hatching the control ensemble standard deviations.

two temporal phases noticeable in the statistical average over the extremes: significantly positive (i.e. downward) net longwave radiative flux anomalies occur during May-June in association with enhanced atmospheric water vapor and cloudiness, while the surface energy budget is dominated by strongly positive net shortwave radiative flux anomalies from June to August (Figure 4.11(c,d)). The latent and sensible heat flux anomalies are small in magnitude compared to the radiative flux anomalies, though slightly enhanced upward latent heat fluxes (consistent with increased evaporation due to reduced sea ice cover) in May-June and slightly increased downward sensible and latent heat fluxes in July-August are visible (Figure 4.11(e,f)).

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In contrast to the average behavior, substantial differences in the energy flux anomalies are noticeable between the most extreme sea ice low trajectories available from the two experiments (Figure 4.11(a-f)). The total net and the radiative flux anomalies in the "MINIMUM AS- Δ SIA ALG MIN" trajectory of the SI-NEUTRAL experiment closely fluctuate around the composite estimate, consistent with the fact that this sea ice low is substantially driven by anomalous transport (cf. Figure 4.11 and Figure 4.8). In contrast, the "MINIMUM AS- Δ SIA ALG MIN" trajectory in the SI-LOW experiment exhibits a drastically enhanced net atmosphere-surface energy accumulation compared to the composite mean from the mid of May to July (Figure 4.11(b)). This is both due to an almost two months long episode of enhanced net longwave radiative flux anomalies between May and July and due to a drastically increased sea ice-albedo feedback compared to the average behavior.

4.3.4.3 A 2012-like storm vs. a thermodynamically-driven extreme and the role of modes of atmospheric variability

As shown in sections 4.3.3, the relative importance of sea ice transport vs. thermodynamic processes may vary substantially between individual extremes. While the most extreme late summer sea ice low available from the SI-LOW experiment is almost entirely driven by thermodynamic processes, sea ice transport explains about 50% of anomalous sea ice volume loss during the most extreme trajectory available from the SI-NEUTRAL experiment. In the latter, a particularly strong transport-related sea ice loss occurs in June-July (Figure 4.8). In order to trace this transport back to anomalous atmospheric conditions, we investigate the spatial fields of June-July mean sea level pressure, sea ice motion and sea ice volume transport, divergence and advection (Figure 4.12(a-e)). Strongly cyclonic conditions lead to a complete disappearance of the Beaufort Gyre, enhanced sea ice motion out of the central Arctic Ocean towards the American and Eurasian coasts via Ekman drift and towards Fram Strait (Figure 4.12(a,b)). While extremes of sea ice reduction are systematically associated with cyclonic mean sea level pressure anomalies as shown in the composite analysis in section 4.3.2, the amplitude of the negative mean sea level pressure anomalies in the AS- Δ SIA ALG MIN trajectory is substantially larger compared to the signal in the composite, substantially impacting the sea ice transport (Figure 4.12(c-e)). Particularly strong transport-related sea ice volume loss occurs in the vicinity of the center of the cyclonic anomaly, whereas positive sea ice transport anomalies along the marginal Arctic seas illustrate the displacement of sea ice mass from the central Arctic Ocean towards the continents. This is both explained by enhanced sea ice velocity divergence and by sea ice advection, whereby the former dominates over the latter in terms of magnitude (Figure 12(c-e)).

Various studies argue that a strong August synoptic-scale storm contributed to the 2012 record sea ice low by mechanical breaking, divergence, advection and by enhancing vertical mixing in the oceanic mixed-layer [Lukovich et al., 2021; Simmonds and Rudeva, 2012; Zhang et al., 2013; Parkinson and Comiso, 2013]. To trace back the cyclonic anomalies shown in Figure 4.12(a,b) to synoptic activity, we compute the time series of the spatial minimum of daily mean sea level pressure within a region enclosed by the climatological 15% contour line of August-September mean sea ice concentration (i.e.

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the domain indicated in Figures 4.12(c-e) and Figure 4.4(a-c)). The time series reveals a tendency towards cyclonic conditions over the Arctic Ocean during most of the time in June-July. In addition, a pronounced drop of the domain-minimum mean sea level pressure towards 972 hPa is noticeable around 04 July. This is associated with a cyclone that starts to form over the Eurasian coast approximately on 30 June and that decays within the central Arctic Ocean approximately on 12 July (cf. Figure 4.12(f) and Supplementary Figure C16). The duration and core pressure of this storm is similar to the one observed in 2012, implying the capability of EC-Earth3 to simulate Arctic cyclones that resemble the ones of the real world. According to Simmonds and Rudeva [2012], the August 2012 storm lived from 02 August to 14 August and reached a core pressure of 966 hPa.

We further quantify the direct impact of the late June-early July storm in the SI-NEUTRAL AS- Δ SIA ALG MIN trajectory on enhanced sea ice volume loss (Table 4.3). For this purpose, we spatially integrate the total, thermodynamic and dynamic sea volume anomalies over the domain enclosed by the climatological August-September mean 15% sea ice concentration contour line of the SI-NEUTRAL experiment and subsequently integrate the resulting scalar quantity over the periods 01 MARCH - 29 JUNE (prior to the storm), 30 JUNE - 12 JULY (during the storm) and 01 MARCH - August-September (total). The 13-day episode of the storm directly explains about 25%, 29% and 21% of the seasonally-integrated (01 MARCH - AUGSEP) total, dynamic and thermodynamic sea ice volume loss anomalies. This corresponds to a substantial temporal rate of sea ice loss during the storm considering that the episode of the storm covers only about 7% of the total integration period. Moreover, these estimates likely underestimate the full impact (i.e. direct and indirect) of the storm on the total sea ice anomalies as EC-Earth3 does not capture sea ice-ocean wave interactions, and the contribution of storm-induced feedback mechanisms, in particular the sea ice-albedo feedback after the storm and the increased open-water-formation efficiency due to reduced sea ice thickness, on enhanced sea ice volume and sea ice area loss are difficult to quantify without a dedicated sensitivity experiment. Despite the substantial contribution of the storm on the total negative sea ice volume anomalies, we emphasize that about 45%, 49% and 40% of the seasonally-integrated (01 MARCH - AUGSEP) total, dynamic and thermodynamic negative sea ice volume loss anomalies are explained by the period 01 MARCH - 29 JUNE prior to the storm. This implies that one synoptic event alone is not sufficient to explain the extreme late summer sea ice low in the SI-NEUTRAL AS- Δ SIA ALG MIN trajectory, but that multiple factors, providing a forcing on the sea ice with a duration beyond the synoptic time-scale, is required to explain the ultra-rare sea ice loss in this trajectory. This is also in line with the studies of Simmonds and Rudeva [2012]; Guemas et al. [2013]; Zhang et al. [2013] according to which the 2012 record sea ice low was amplified by the observed August 2012 storm, but according to which also other ingredients such as preconditioning and anomalously high atmospheric near-surface temperatures substantially favored the occurrence of the record sea ice low. Finally, while the AS- Δ SIA ALG MIN trajectory of the SI-NEUTRAL experiment demonstrates how synoptic-scale storms may impact the sea ice volume budget, the response of sea ice to storms has been shown to vary according to the timing during the year and according to the position relative to the sea ice edge [Lukovich et al., 2021].

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Compared to the AS- Δ SIA ALG MIN trajectory of the SI-NEUTRAL experiment, the atmospheric and surface conditions during the most extreme sea ice reduction available from the SI-LOW experiment depict a totally different picture (Figure 4.13). A dipole-like structure consisting out of an anticyclonic anomaly around Alaska and a cyclonic one over the eastern Arctic Ocean promotes enhanced transport of moisture and heat from the North Pacific towards the Arctic. Enhanced thermodynamic melting leads to a spatially wide-spread reduction of the surface albedo, explaining the drastic sea ice/snow-albedo feedback in this trajectory compared to the average behavior, while a reduction in the surface albedo in the AS- Δ SIA ALG MIN trajectory of the SI-NEUTRAL experiment is restricted to a smaller area compared to the AS- Δ SIA ALG MIN trajectory of the SI-LOW experiment (Figure 4.13). The fact that the surface albedo in the AS- Δ SIA ALG MIN trajectory of the SI-NEUTRAL experiment is substantially less reduced compared to the AS- Δ SIA ALG MIN trajectory of the SI-LOW experiment is striking given the fact that both trajectories show very similar amplitudes in the sea ice area anomalies. We interpret this by the fact that enhanced export of sea ice out of the central Arctic Ocean towards the marginal seas in the AS- Δ SIA ALG MIN trajectory of the SI-NEUTRAL experiment keeps the surface albedo on a comparatively high level, as the sea ice is spread around and cyclonic conditions might potentially lead to enhanced snow fall, whereas the melting from the Pacific side in the AS- Δ SIA ALG MIN trajectory of the SI-LOW experiment is more efficient in creating open water compared to the SI-NEUTRAL one.

It is noticeable that the mean sea level pressure pattern shown in Figure 4.13 resembles the positive phase of the Arctic Dipole (AD) pattern [Wang et al., 2009]. According to several studies, a positive phase of the Arctic Dipole pattern contributed to the 2007 extreme sea ice low by leading to enhanced inflow of atmospheric and oceanic heat into the Arctic from the North Pacific [Wang et al., 2009; Overland and Wang, 2010; Overland et al., 2012]. Exploiting the access to 15 independent extreme sea ice lows available from the SI-NEUTRAL and SI-LOW experiments, we verified to what extent a positive AD phase is typically associated with extreme sea ice lows. We define the AD as the second leading empirical orthogonal function of square root of cosine of latitude weighted mean sea level pressure anomalies northern of 70°N. Accordingly, we compute the AD index as the projection of unweighted MSLP anomalies northern of 70°N on that second EOF. In May-June, the AD indeed shows a positive phase taking a value of about +1.2 (Supplementary Figure C17(b)). However, in the composite, the AD is not statistically significant and is centered around zero. Among the 15 extremes, we find four independent extremes where the Arctic Dipole index is above a value of +1 (Supplementary Figure C17).

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Table 4.3: SI-NEUTRAL AS- Δ SIA ALG MIN trajectory: sea ice volume anomalies [10^3 km^3] spatially integrated over the domain enclosed by the climatological August-September mean 15% sea ice concentration contour line (black line in Figure 4.4) and integrated in time for three periods. 30 JUNE - 12 JULY encloses the passage of a 2012-like synoptic-scale storm (cf. Figure 4.12 and Supplement Figure C16). The term "DYNAMIC" is the sea ice transport and thus the divergence of the sea ice volume flux. "DIVERGENCE" is the divergence of sea ice velocity.

Δ SEA ICE VOLUME [10^3 km^3]	01 MARCH - 29 JUNE	30 JUNE - 12 JULY	01 MARCH - AUGSEP
TOTAL	-1.77	-1.01	-3.94
THERMODYNAMIC	-0.78	-0.41	-1.93
DYNAMIC (i.e. TRANSPORT)	-0.99	-0.60	-2.02
DIVERGENCE	-1.38	-0.68	-2.63
ADVECTION	+0.39	+0.08	+0.61

4.3.4.4 The role of the ocean

As discussed in section 4.3.1, the statistics of extremely low late summer sea ice area values strongly depends on the late winter sea ice-ocean initial condition (e.g. Figure 4.3(b)). This is in line with numerous studies according to which the state of the wintertime sea ice-ocean system can precondition the occurrence of extreme annual sea ice minima in the Arctic [Parkinson and Comiso, 2013; Guemas et al., 2013; Lindsay et al., 2009; Holland et al., 2006; Döscher and Koenigk, 2013]. The sea ice-ocean preconditioning acts on different time-scales, both including long-term changes due to global warming and low-frequency variability of ocean heat content and ocean heat transport around the global warming signal [Cai and Chen, 2025; Holland et al., 2006; Döscher and Koenigk, 2013]. In particular, the long-term decline of summer Arctic sea ice area is non-linear, and abrupt reductions of sea ice area over several years, so-called rapid ice loss events (RILEs), are anticipated by climate models to occur during the 21st century [Holland et al., 2006; Döscher and Koenigk, 2013]. According to Holland et al. [2006] and Döscher and Koenigk [2013], both sea ice thinning and abrupt increases of meridional ocean heat transport substantially contribute to those RILEs. As introduced in section 1.1, particularly strong decline of late summer sea ice area has been observed between 2007 and 2012. In this context, it is noticeable that 1) winter Arctic sea ice volume during 2007-2012 has been reduced by about 30% compared to the last decade of the 20st century [Tietsche et al., 2017] and 2) North Atlantic subpolar heat content is substantially increased during the period 2005-2012 before re-decreasing after 2012 (Figure 4.14; [Met Office, 2026]).

The ensemble simulations used in this Chapter 4 are not specifically designed for a sophisticated analysis of the role of multi-annual ocean variability in favoring extreme Arctic sea ice lows. Within an ensemble experiment, all trajectories are initialized from identical sea ice-ocean initial conditions. In sections 4.3.2, 4.3.3, 4.3.4.1, 4.3.4.2 and 4.3.4.3, extreme sea ice lows are defined as negative sea ice area anomalies relative to two initial condition-specific climatologies. This means that anomalies in the "SI-NEUTRAL"

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experiment are computed related to the "SI-NEUTRAL" control ensemble mean, while anomalies in the "SI-LOW" experiment are computed related to the "SI-LOW" control ensemble mean. We chose two local baseline climatologies in those sections 4.3.2, 4.3.3, 4.3.4.1, 4.3.4.2 and 4.3.4.3 to focus on sub-seasonal drivers of low sea ice states.

In an absolute sense, i.e., relative to a fixed external baseline climatology, the SI-NEUTRAL and SI-LOW experiments have substantially different mean sea ice-ocean states. Therefore, we compare the ocean heat content and the meridional ocean heat transport between the SI-LOW and the SI-NEUTRAL control ensemble means (Figures 4.15 and 4.16). In the SI-LOW experiment, ocean heat content is increased by about half a standard deviation of the 250-year control run compared to the SI-NEUTRAL experiment in the Arctic Ocean (Figure 4.15; here we use the variability of the 250-year control run as an estimate for the baseline variability because we wish to understand whether the heat content difference between both experiments is large (or not) with respect to an absolute climatology). In this context, it is noticeable that a positive heat content signal occurs southern of Svalbard and in the Barents Sea. In that region, the climatological late summer sea ice edge of the SI-LOW experiment (magenta line in Figure 4.15(a)) is shifted polewards compared to the SI-NEUTRAL control ensemble mean (black line in Figure 4.15(a)). This strongly suggests a contribution of increased ocean heat content to enhanced sea ice reduction on the North Atlantic side of the Arctic Ocean.

Also the heat content in the North Atlantic subpolar gyre is increased in the SI-LOW control ensemble mean compared to the SI-NEUTRAL control ensemble mean, but its signal is relatively small compared to the variability of the 250-year control run (Figure 4.15(b-c)). In contrast to the ocean heat content, we cannot detect a signal in the meridional ocean heat transport in the northern hemispheric mid-high-latitudes in association with enhanced sea ice loss (Figure 4.16). This does, however, not mean that the ocean heat transport does not play a role in driving sea ice loss. As discussed above, the experiments applied in Chapter 4 are simply not designed for a sophisticated analysis of the role of multi-annual ocean variability in driving sea ice loss. For example, ocean heat transport may lead the signal in the sea ice by a few years as for example suggested by [Holland et al., 2006]. In order to investigate this, experiments such as provided in Chapter 2 would be required. In that case, one would be able to investigate the state of the ocean during several years prior to the extremes. Here, instead, we have only access to the state during the initial conditions and the evolution during one single melting season.

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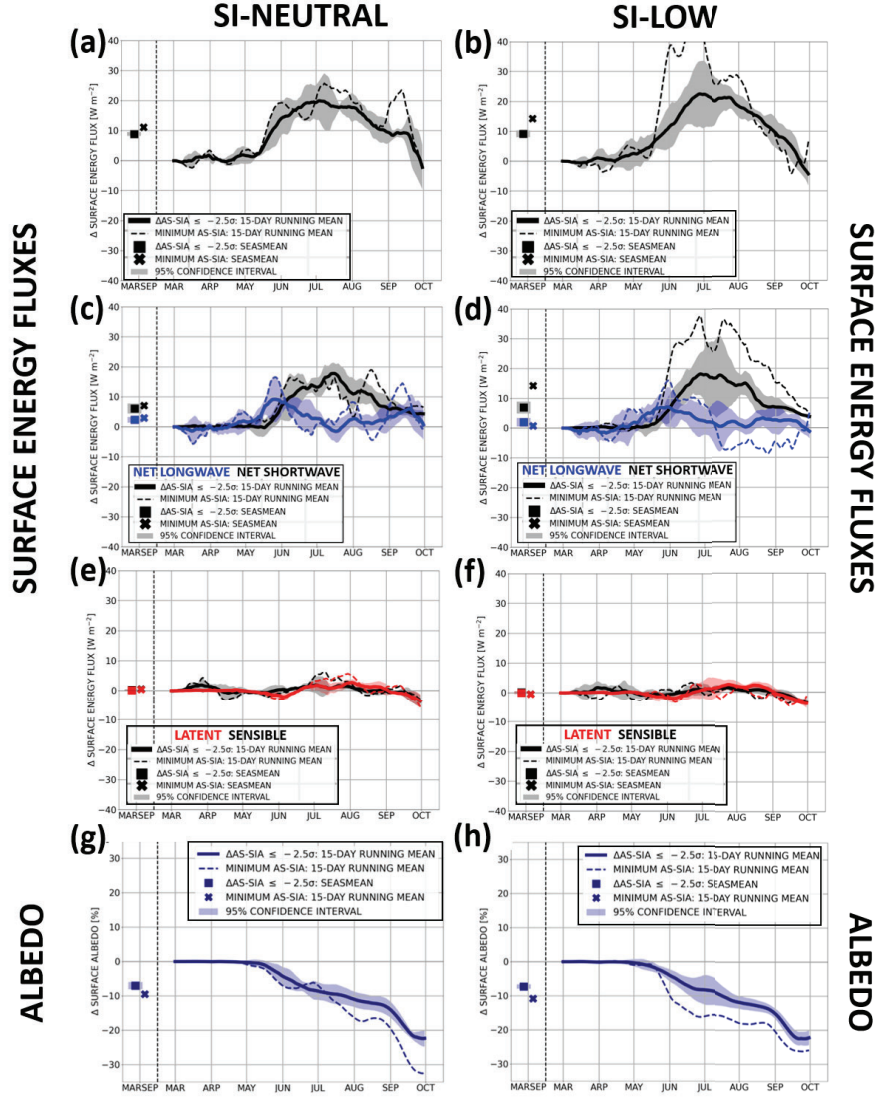


Figure 4.11: (a,c,e,g) "SI-NEUTRAL: ALG(SIV)" and (b,d,f,h) "SI-LOW: ALG(SIV)" experiments: MARSEP and 15-day running mean (a,b) net atmosphere-surface energy flux, (c,d) net surface (black) shortwave and (blue) longwave radiative flux (e-f) surface (black) sensible and (red) latent heat flux and (g-h) surface albedo [%] anomalies relative to the control ensemble means. Energy fluxes [W m⁻²] are positive when they are directed downwards. All quantities are spatially averaged over the domain defined by the union of statistically significant negative thermodynamically-induced sea ice volume anomalies (Figure C13). Thick lines and square markers are composite mean anomalies ($\Delta AS-SIA \leq -2.5\sigma$) and the shading shows 95% confidence intervals around these composite estimates. The thin lines and "x"-markers are the trajectories with the most extreme sea ice reduction available from the two experiments respectively.

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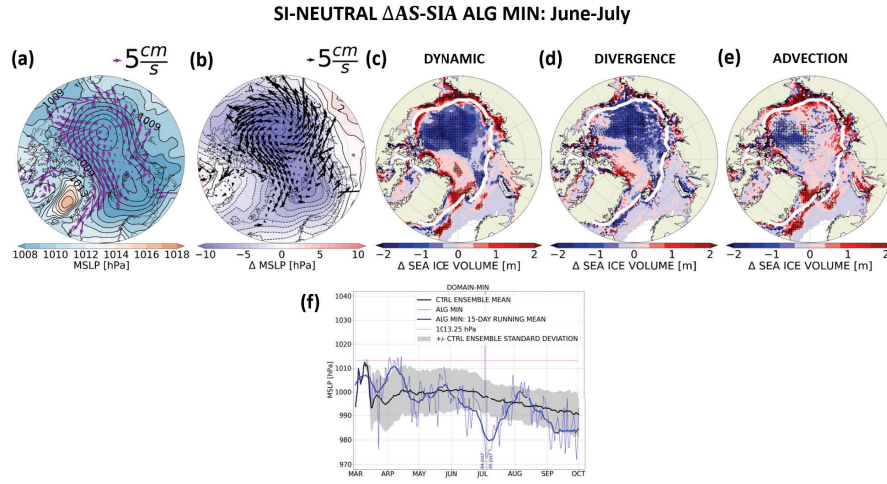


Figure 4.12: Trajectory leading to the most extreme sea ice area reduction available from the "SI-NEUTRAL: ALG(SIV)" experiment (Δ AS-SIA ALG MIN): (a) June-July average mean sea level pressure (MSLP) [hPa] and sea ice motion vectors [cm s^{-1}], (b) as in (a), but expressed as anomalies relative to the SI-NEUTRAL control ensemble mean, (c-e) anomalies of (c) transport-, (d) divergence- and (e) advection-related sea ice volume tendencies integrated from 01 June to 31 July. Hatching indicates where anomalies are larger in magnitude than the SI-NEUTRAL control ensemble standard deviation. The white line shows the AUGSEP mean 15% sea ice concentration line of the control ensemble. (f) Time series of the minimum daily mean sea level pressure of the domain shown in Figure 4.12(c-e) for (blue) the Δ AS-SIA ALG MIN trajectory and (black,gray) the control ensemble mean and control ensemble standard deviation.

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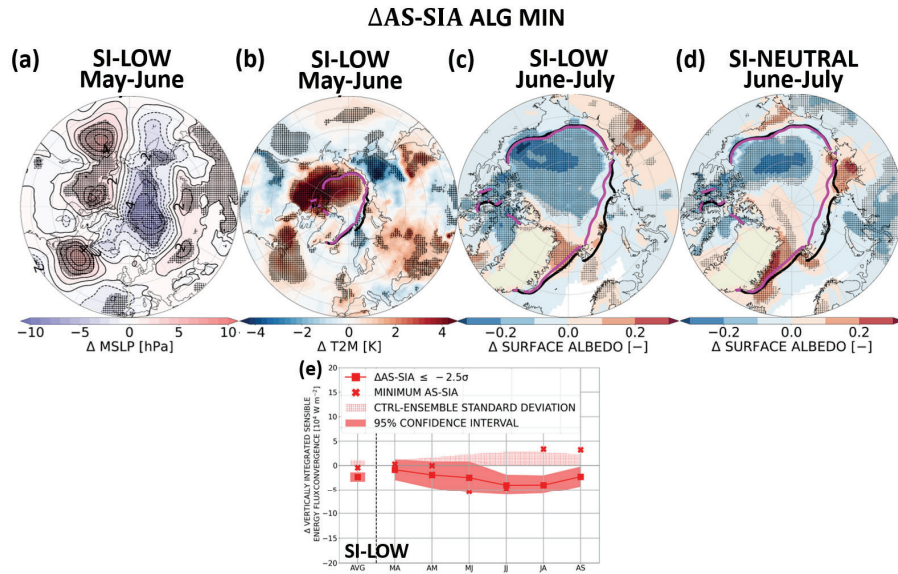


Figure 4.13: (a-c) Trajectory leading to the most extreme sea ice area reduction available from the SI-LOW experiment: (a) May-June mean sea level pressure [hPa], (b) May-June two metre temperature [K] and (c) June-July surface albedo [-] anomalies relative to the SI-LOW control ensemble mean. (d) The same as in (c), but June-July surface albedo anomalies in the most extreme sea ice area reduction trajectory available from the "SI-NEUTRAL: ALG(SIV)" experiment and computed relative to the SI-NEUTRAL control ensemble mean. Hatching in (a-d) indicates anomalies that are larger in magnitude than the control ensemble standard deviations. The black and magenta contour lines indicate the AUGSEP mean 15% SIC line in the SI-NEUTRAL and SI-LOW control ensembles respectively. (e) SI-LOW experiment: seasonal evolution of the horizontal divergence of vertically integrated transport of sensible heat presented as a spatial average over the domain shown in the Supplementary Figure C13 [$10^4\ Wm^{-2}$]. Squares are composites ($\Delta AS-SIA \leq -2.5\sigma$) and stars show the single trajectory leading to the most extreme sea ice area reduction available from the experiment. Hatching indicates 95% confidence intervals and shading the control ensemble standard deviations. Negative anomaly values correspond to a gain of sensible energy in the Arctic atmosphere above the domain defined in Supplementary Figure C13.

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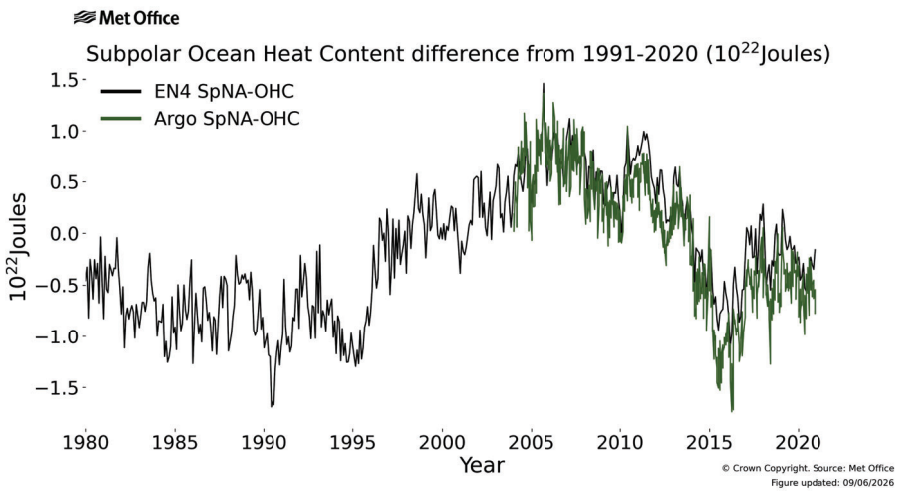


Figure 4.14: North Atlantic subpolar (45°N - 67°N; upper 1000 m) ocean heat content difference compared to the 1991-2020 climatology [10^{22} Joules] [Met Office, 2026].

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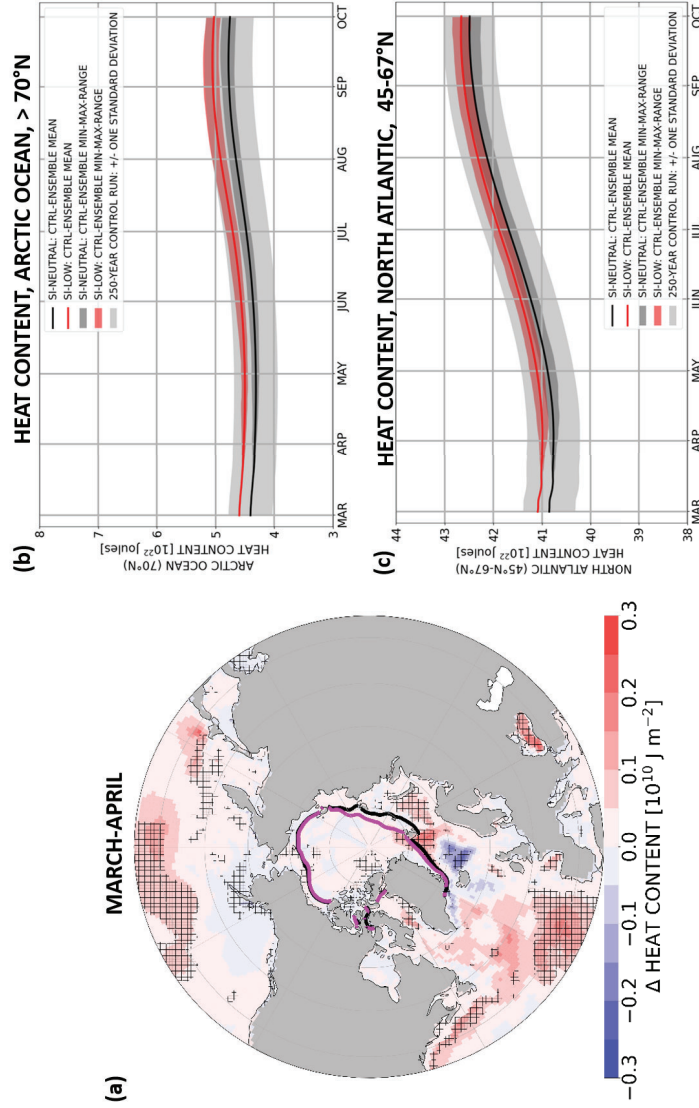


Figure 4.15: (a) March-April mean ocean heat content difference between the SI-NEUTRAL and SI-LOW control ensemble means. Hatching indicates grid cells where the absolute value of these differences is larger in magnitude than 0.5 standard deviations of March-April mean heat content in the 250-year control run. The black and magenta contour lines indicate the August-September mean 15% sea ice concentration contour lines of the SI-NEUTRAL and SI-LOW control ensemble means respectively. (b-c) Seasonal evolution of ocean heat content spatially averaged over (b) the Arctic Ocean (north of 70°N) and (c) over the North Atlantic region between 45°N and 67°N. (b-c) The light shading shows $\pm$ one standard deviation of the 250-year control run around the SI-NEUTRAL control ensemble mean and the dark and red shadings show the minimum-maximum ranges over the SI-NEUTRAL and SI-LOW control ensembles. Solid lines are the control ensemble means.

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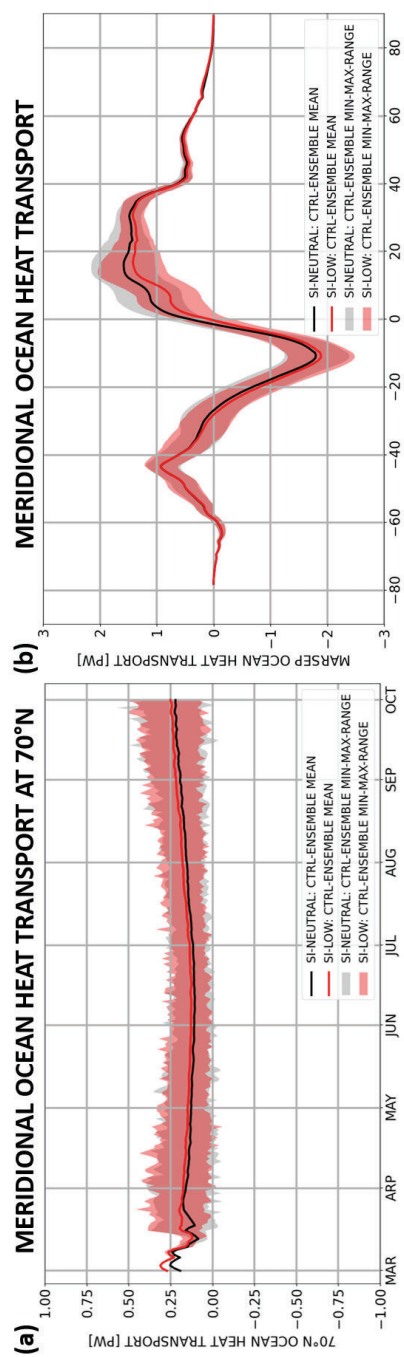


Figure 4.16: (a) Seasonal evolution of meridional ocean heat transport at 70°N and (b) seasonal average of meridional ocean heat transport at different latitudes for (black) the SI-NEUTRAL and (red) the SI-LOW control ensembles. Solid lines are the control ensemble means and shading shows the minimum-maximum range within the control ensembles.

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4.4 Discussion and conclusions

We exploit initialized ensemble simulations to investigate the statistical properties of extremely negative late summer pan-Arctic sea ice area anomalies as a function of two different initial winter sea ice-ocean states. We compute statistically significant composite maps of dynamical quantities conditional on the occurrence of extremes with probabilities of less than 1% (-2.5σ events). Likewise, we study physical processes in two trajectories leading to extreme late summer sea ice lows with larger amplitudes than observed in 2012. In order to circumvent the poor sampling of extreme events from numerical simulations, we use a rare event algorithm to increase the sampling efficiency of trajectories leading to extremely low pan-Arctic sea ice area during the annual sea ice minimum. The simulations with the rare event algorithm produce several dozen of times more extremes than direct sampling for the same computational cost, and they allow to estimate extreme sea ice low probabilities that are two orders of magnitude smaller compared to direct sampling (Figure 4.3).

As in Sauer et al. [2025], the rare event simulations used in this study are performed in a seasonal climate prediction setup, allowing to compute the probabilities of observing an extreme late summer sea ice low as a function of a given initial winter sea ice-ocean state. As all trajectories within one ensemble start from identical sea ice-ocean initial conditions, this approach also allows for a targeted study of the synoptic-scale to sub-seasonal drivers of extreme pan-Arctic sea ice area reduction within one single melting season. While the study of Sauer et al. [2025] makes use of the intermediate complexity coupled climate model Planet Simulator (PlaSim), including a purely thermodynamic sea ice model, we here apply the rare event algorithm to the comprehensive CMIP6-generation European community Earth-System-Model version 3 [Döscher et al., 2022] (EC-Earth3). Notably, the EC-Earth set-up used in this study reasonably represents the 1979-2015 mean sea ice thickness climatology available from PIOMAS (cf. Figure 4.1(b) and page 207 of Chevallier et al. [2019]) and reasonably represents the observed late summer sea ice area variability around a linear trend fitted to the period 1979-2025 (cf. section 4.2.2.2 and Supplement Figure C6).

The statistics of the two different experiments indicates a substantial impact of the winter sea ice-ocean initial condition on the probabilities and amplitudes of extremely negative late summer pan-Arctic sea ice area anomalies computed relative to a fixed baseline climatology (e.g. relative to the SI-NEUTRAL control ensemble mean). Relative to the SI-NEUTRAL control ensemble mean, the SI-LOW control ensemble mean August-September sea ice area anomaly is $-0.81 \cdot 10^6 \text{ km}^2$ and the SI-LOW 1% percentile August-September sea ice area anomaly is $-2.07 \cdot 10^6 \text{ km}^2$ (table 4.1). Thus, about 40% of the magnitude of the anomaly corresponding to the 1% percentile value of August-September mean sea ice area in the SI-LOW experiment is explainable by the impact of the imposed "2012-AVG<1995-2005>" winter sea ice-ocean anomaly on the SI-LOW control ensemble mean. Likewise, the SI-NEUTRAL 1% percentile August-September sea ice area value deviates from the SI-NEUTRAL control ensemble mean by $-0.92 \cdot 10^6 \text{ km}^2$ for the ALG(SIV) and by $-0.98 \cdot 10^6 \text{ km}^2$ for the ALG(SIA) simulation (table 4.2). Consequently, late summer sea ice area anomalies being purely induced by sub-seasonal weather variability approximately correspond in magnitude to the impact

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of the imposed "2012-AVG<1995-2005>" winter sea ice-ocean anomaly on the mean of the distribution of August-September mean sea ice area. This implies that the most extreme sea ice reduction events occur as a consequence both of winter preconditioning and sub-seasonal weather variability.

The rare event simulations can be used to provide an estimate of the probability of 2012-like late summer sea ice area anomaly relative to a linear trend fitted to the period 1979-2025. The observed 2012 August-September mean sea ice area deviated from the 1979-2025 linear trend line by $-1.16 \cdot 10^6 \text{ km}^2$. As described in section 4.2.2.2, the observed 1979-2025 late summer sea ice area variability is reasonably captured by the baseline climatology of the SI-NEUTRAL experiment (i.e. the standard deviation of late summer sea ice area of the SI-NEUTRAL control ensemble corresponds to the one of the observed variability around the 1979-2025 linear trend line). Both the "SI-NEUTRAL: ALG(SIA)" and the "SI-NEUTRAL: ALG(SIV)" experiments suggest that the probability of observing a late summer sea ice area anomaly being more extremely negative than the 2012 deviation from the 1979-2025 trend line is in the order of 10^{-3} . We emphasize, however, that this estimate is sensitive both with respect to sampling uncertainty and with respect to the chosen initial condition. Regarding the sampling uncertainty, the estimated 95% confidence intervals around these probability estimates are $[0, 4.7 \cdot 10^{-3}]$ for the ALG(SIV) experiment and $[0, 1.6 \cdot 10^{-3}]$ for the ALG(SIA) experiment. Consequently, while a reasonable upper bound of plausible estimates of the probability of a 2012-like fluctuation around a linear trend can be derived from these rare event simulations, one realization of the experiment and/or an ensemble size of $N = 300$ trajectories is not sufficient to derive a reasonable lower bound. Regarding the sensitivity with respect to the initial condition, it is noticeable that the estimated probability of a 2012-like sea ice area anomaly relative to a local climatology obtained with the SI-LOW experiment (i.e. relative to the SI-LOW control ensemble mean) is in the order of 10^{-2} instead of 10^{-3} (Supplement Figure C11). As evident from the Supplement Figure C11, the increase of the probability from 10^{-3} to 10^{-2} is formally not statistically significant. Nevertheless, it is consistent with the study of Goosse et al. [2009] according to which a thinning in the winter sea ice may increase the variance of late summer sea ice area. Notably, the standard deviations of the late summer sea ice area in the SI-LOW and SI-NEUTRAL control ensembles are $0.45 \cdot 10^6 \text{ km}^2$ ($[0.41 \cdot 10^6 \text{ km}^2, 0.49 \cdot 10^6 \text{ km}^2]$) and $0.40 \cdot 10^6 \text{ km}^2$ ($[0.37 \cdot 10^6 \text{ km}^2, 0.43 \cdot 10^6 \text{ km}^2]$) (the 95% confidence intervals of the standard deviation estimates are derived by considering the variance as a sample mean of squared differences and by applying the central limit theorem to the uncertainty of the variance).

Thanks to the rare event algorithm, we elaborate common physical properties among various realizations of extreme sea ice loss events (i.e. composite mean anomalies of dynamical quantities conditional on the occurrence of extremes with probabilities of less than 1%). Based on the example of the two most extreme sea ice lows available from the SI-NEUTRAL and SI-LOW experiments, we also highlight possible pathways leading to "ultra-rare" sea ice loss events with estimated probabilities of less than 10^{-4} . Our work includes a sea ice volume and sea ice area budget analysis to assess the relative importance of thermodynamic vs. sea ice-dynamic sea ice loss during extremes of sea ice reduction. On statistical average during the extremes, about 25%-35% and 20%-30% of anomalous

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sea ice volume and sea ice area loss within a domain defined by the climatological late summer sea ice edge can be explained by the export of sea ice out of that domain. The relative importance of thermodynamic vs. sea ice-dynamic processes, however, fluctuates substantially between different realizations of an extreme. Thus, the most extreme sea ice low available from the SI-LOW experiment is almost entirely explained by thermodynamic processes, whereas sea ice-dynamics explains about 50% of enhanced total sea ice volume loss during the most extreme trajectory available from the SI-NEUTRAL experiment. The various realizations of extreme sea ice loss events exhibit several common dynamical properties: 1) Extremely negative late summer sea ice area anomalies are typically preceded by strongly enhanced sea ice volume loss during May-June-July. This behavior is consistent with the studies of Sauer et al. [2025]; Bonan et al. [2019]; Bushuk et al. [2020] and implies that late spring to early summer sea ice volume, but also its time derivative, provides an additional source of predictability of extremely negative late summer sea ice area anomalies relative to a fixed baseline climatology in addition to the predictability associated with the late winter sea ice-ocean initial condition. 2) On statistical average, enhanced late spring-early summer sea ice volume loss typically occurs in association with cyclonic anomalies in the mean sea level pressure over the central to eastern Arctic Ocean, promoting enhanced convergence of vertically integrated water vapor flux, water vapor, cloudiness and therefore enhanced downward longwave radiation. 3) During the melting season, two distinct phases can be detected. Typically, both thermodynamic and dynamic processes contribute to enhanced sea ice loss during May-June and June-July, while thermodynamic processes, in particular the sea ice-albedo feedback, determine enhanced sea ice loss towards the end of summer.

The physical characteristics in the two most extreme trajectories (AS- Δ SIA ALG MIN) of the SI-LOW and SI-NEUTRAL experiments substantially differ from each other. Compared to the "typical extremes" (i.e. compared to the composite), the AS- Δ SIA ALG MIN trajectory in the SI-NEUTRAL experiment exhibits additional sea ice volume loss during May-June-July and an additional pulse of sea ice volume and sea ice area loss in September (Figure 4.5(a)). The latter is associated with more positive late summer net surface energy flux anomalies compared to the composite, partly due to an amplified sea ice-albedo feedback in August and partly due to more positive longwave radiative flux and integrated water vapor anomalies in September (cf. Figure 4.5(a), Figure 4.6(a,c,g) and Supplement Figure C19(a)). The particularly strong sea ice loss during the spring-summer transition (i.e. more sea ice loss compared to the composite) is associated with persistent strongly cyclonic mean sea level pressure anomalies over the central Arctic Ocean, including a synoptic-scale storm with a minimum core pressure of about 972 hPa and a duration of about 10 days. Substantial Ekman drift leads to drastically increased export of sea ice out the central Arctic Ocean into regions of warmer water masses where the sea ice is more likely to be melt away compared to the high Arctic. The total sea ice volume anomaly developed during the storm between 30 June and 12 July is $-1.01 \cdot 10^3 \text{ km}^3$ and thus explains about 25% of March-September total sea ice volume anomalies of $-4 \cdot 10^3 \text{ km}^3$. While the temporal rate of the sea ice loss during the storm is striking, the storm alone cannot fully explain the extreme. In line with for example Kapsch et al. [2019]; Liang et al. [2022]; Guemas et al. [2013]; Zhang et al. [2013], extreme late summer

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sea ice lows result from the superposition of different processes, in which synoptic-scale storms may be embedded, providing a forcing on the sea ice with a duration substantially larger compared to the synoptic time-scale.

The extreme in the SI-LOW AS- Δ SIA ALG MIN trajectory, instead, is dominated by thermodynamic processes. Enhanced southerly winds transport enhanced moisture and heat from the Pacific Ocean into the Arctic, resulting in a long-lasting episode of more positive May-June-July net longwave radiative flux anomalies compared to the composite (cf. Figure 4.11 and Figure 4.13). Compared to the composite (i.e. compared to the situation of a "typical extreme" or of an "average extreme"), the surface albedo is substantially reduced from late May throughout the entire summer, resulting in a drastically increased sea ice-albedo feedback and therefore drastically increased absorption of energy in the sea ice-ocean system due to shortwave radiative fluxes (cf. Figure 4.11(b,d,h) and Figure 4.13(c-d)). The mean sea level pressure during May-June (Figure 4.13(a)) resembles the positive phase of the Arctic Dipole (AD) pattern, a suggested key ingredient of the observed 2007 sea ice low [Wang et al., 2009; Overland and Wang, 2010; Overland et al., 2012]. In May-June, the AD indeed shows a positive phase taking a value of about +1.2 (Supplementary Figure C16(b)). However, in the composite, the AD is not statistically significant and is centered around zero. Among the 15 extremes, we find four independent extremes where the AD is above a value of +1 (Supplementary Figure C16). From that point of view, our result suggests that the mechanism behind the 2007 event is rather unusual, whereas extreme sea ice lows with cyclonic anomalies over the central Arctic Ocean represent a more typically mechanism behind the extremes than the Arctic Dipole pattern.

In closing, we would like to point out a few limitations and indicate future prospects. The present work investigates synoptic-scale to sub-seasonal drivers of low sea ice states for two initial conditions and using one single model. Pre-existing large ensembles of the models of the Phases 5 and 6 of the Coupled Model Intercomparison Project provide a possibility to complement this study by an analysis of extreme sea ice lows using multiple models and using multiple sea ice-ocean initial conditions. In contrast to our present work, using pre-existing large-ensembles also allows to investigate processes favoring low late summer sea ice states that act on multi-annual time scales. In this context, we also remind the fact that using the 1° resolution in the ocean requires the parameterization of mesoscale and sub-mesoscale ocean eddies, likely impacting the meridional ocean heat transport and potentially impacting the high-latitude atmospheric circulation and the sea ice [Hewitt et al., 2017, 2022]. Nevertheless, for two different winter sea ice-ocean states, our composite analyses are based on 15 independent realizations of the state of the atmosphere that lead to late summer Arctic sea ice area values being at least 2.5 standard deviations below a given initial condition-dependent climatology (i.e. Δ AS-SIA $\leq -0.99 \cdot 10^6 \text{ km}^2$ for the SI-NEUTRAL experiment and Δ AS-SIA $\leq -1.12 \cdot 10^6 \text{ km}^2$ for the SI-LOW experiment). For comparison, the three most extremely negative observed August-September mean sea ice area anomalies relative to a linear trend fitted to the period 1979-2025 are $-1.16 \cdot 10^6 \text{ km}^2$ (year 2012), $-0.98 \cdot 10^6 \text{ km}^2$ (year 2007) and $-0.53 \cdot 10^6 \text{ km}^2$ (year 2008; Supplement Figure C6), yielding only two events with amplitudes comparable to the ones used for the composite analyses in this study.

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We also emphasize that the provided estimates of the probability to observe a sea ice area fluctuation larger in magnitude compared to the deviation in 2012 from the 1979-2025 linear trend line are sensitive with respect to sampling uncertainty and with respect to the chosen initial condition. The probabilities in the order of 10^{-2} to 10^{-3} for a climate state being representative of the observed late summer sea ice area variability provide a first plausible estimate. In the future, however, another step forward towards comparing the probabilities of sea ice low extremes between different climate states would consist in initializing two ensembles with various initial conditions being representative of the two given climate states. This can be achieved by initializing an ensemble with late winter initial conditions sampled from, for example the period 2016-2025 (i.e. an ensemble of 300 trajectories could be generated by producing 30 perturbed replicates of one initial condition per year respectively) where the initial conditions are obtained from a large-ensemble. This could then be repeated with another climate state, for example the period 1986-1995. We recommend, however, to use an ensemble size beyond 300 trajectories, or, alternatively to use multiple experiments with 300 trajectories.

Finally, a new set of experiments can be designed from the existing rare event ensemble simulations of this work. Firstly, continuing the rare event simulations without using the rare event algorithm (i.e. setting $k = 0$) for another two years allows to study the recovery time of extreme sea ice anomalies to go back to a neutral state, similar to the study of Tietsche et al. [2011], but without the need to prescribe anomalous open water conditions. Secondly, the second experiment could consist in re-activating the rare event algorithm starting from 01 March after having switched off the algorithm for five months. This experiment allows to investigate how extreme sea ice lows may become under the very unlikely, but plausible situation of a strong multi-year forcing of anomalous atmospheric and oceanic forcing on the sea ice. Moreover, the data can be used to perform a quantitative statistical analysis of the atmospheric response to extremely low sea ice states. As for the recovery experiment, the advantage of using the data from the algorithm over other techniques to prescribe low sea ice states, such as e.g. ghost flux, nudging and albedo modification [England et al., 2022], is that the "imposed" low sea ice states occur as a natural consequence of the dynamics of the system. In this context, England et al. [2022] argue that common techniques used to impose sea ice loss add to an artificial warming on top of the warming induced by the sea ice loss itself and thereby lead to an overestimation of the atmospheric response to anomalously low sea ice states.

Finally, while our approach has been applied to study low states of the pan-Arctic sea ice area, it can easily be adjusted to focus on specific regions of the Arctic, depending on the required need of a specific stakeholder. An improved sampling of extremely low sea ice states and a better understanding of the drivers of those events can be used in multiple ways: Firstly, an advanced understanding of the precursors of extreme Arctic sea ice lows can be used for initialized forecasts and for statistical models. Secondly, machine learning models can be trained on a large amount of extreme events available through the rare event algorithm, which may potentially improve their skill in predicting events with extremely low sea ice cover [cf. Jacques-Dumas et al., 2022; Miloshevich et al., 2023]. And thirdly, the rare event algorithm may be used in operational probabilistic forecasts

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to accurately assess the risk of occurrence of an extreme sea ice reduction conditional on starting from a known initial state.

Chapter 5

Discussion, conclusion and future perspectives

5.1 Discussion and conclusion

In this thesis, we study extremes of Arctic sea ice reduction in the coupled climate models PlaSim-LSG [Fraedrich et al., 2005; Maier-Reimer et al., 1993] and EC-Earth3 [Döscher et al., 2022] under present-day climate conditions. To circumvent the lack of robust statistics on extreme events related to computational cost limitations, we apply the Giardina-Kurchan-Lecomte-Tailleur (GKLT) rare event algorithm [Del Moral and Garnier, 2005; Giardina et al., 2011; Ragone et al., 2018; Ragone and Bouchet, 2020, 2021] to increase the sampling efficiency of extreme sea ice lows in ensemble simulations with these two models. The GKLT algorithm is designed to improve the sampling of extremes whose dynamics is characterized by time-persistency [Ragone and Bouchet, 2020]. From a practical point of view, it is designed to improve the statistics of extreme anomalies of an observable on time-average over the length of a simulation, delivers both the dynamical trajectories that lead to extreme events of interest and enables to estimate their probabilities of occurrence. We apply this method using two complementary approaches:

1) Sampling extremes from the full phase space (Chapter 2): Using PlaSim-LSG, we initialize several $N = 600$ trajectory ensembles with independent initial conditions sampled from a long stationary control run. This approach allows to improve the sampling of extremes in an absolute sense and is suitable to compute the unconditional probabilities of rare events for a given climate state. In that second chapter, we investigate extremes of the seasonally averaged pan-Arctic sea ice area (i.e. the average over the melting season or extended summer season from February to September). The algorithm produces several hundreds of times more extremes with return times of 200 years than the control run for the same computational cost (Figure A5), and allows us to compute return times up to 10^5 years with computational cost of 10^3 years (Figure 2.3). We explicitly demonstrate that the statistical uncertainty of composites of dynamical quantities conditional on the occurrence of extremes with return times of 200 years is reduced when the algorithm is

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used instead of the control run (Figure 2.4). In this context, we also provide an analysis of a couple of indicators judging the adequacy of the rare event simulations in terms of a sufficiently large number of independent extreme events and trajectories (Figure A5 and Figure A6). Thus, each of the ten effective ensembles contain between 51 and 133 independent initial-time ancestors and between 6 and 14 independent extreme events with return times of more than 200 years (Figure A5 and A6). Finally, we compare the statistics of extremely negative sea ice area anomalies between rare event simulations performed with a resampling time of $\tau_r = 5$ days vs. a resampling time of $\tau_r = 30$ days (Figure 2.3). In contrast to the latter, the former is not larger than the persistence time scale of the large-scale atmospheric circulation and is only slightly larger than the typical persistence of synoptic-scale atmospheric fluctuations [Hoven, 1957]. We find that the return curve obtained with the 5-days resampling time experiments extends only to marginally larger amplitudes of February-September mean sea ice area anomalies than the one obtained with the 30-days resampling time experiments. This suggests that the most relevant processes driving extremely low Arctic sea ice states act on time scales that are substantially longer than the synoptic one. As explained below, this interpretation is qualitatively consistent with the results obtained with the comprehensive climate model EC-Earth3 in application to extremes of the August-September mean sea ice area.

2) Rare event sampling in seasonal climate prediction setup (Chapters 3 and 4): The second approach of using the rare event algorithm conceptually corresponds to the setup used in ensemble weather and seasonal climate predictions. Ensemble simulations are initialized from slightly perturbed identical initial conditions, and the purpose of using the rare event algorithm is to improve the sampling of the areas of the phase space populated by extreme events conditional on starting from that initial condition. Probabilities and expectation values have to be interpreted as conditional on the selected initial state. Using $N = 600$ trajectory ensembles with PlaSim-LSG (Chapter 3) and $N = 300$ trajectories with EC-Earth3, we demonstrate the feasibility of using this approach to study extremes of intra-seasonal pan-Arctic sea ice area reduction. This approach is therefore suitable to investigate extremely negative sea ice area anomalies during the late summer annual Arctic sea ice minimum. The selected observable for the rare event simulations with PlaSim-LSG is the pan-Arctic sea ice area itself (Chapter 3). However, the results with EC-Earth3 suggest that using the pan-Arctic sea ice volume as an observable is potentially more efficient in sampling extremely negative late summer sea ice area anomalies than using the pan-Arctic sea ice area itself (Figures 4.2 and 4.3 and Table 5.1). While this thesis does not include a systematic investigation of the extreme event sampling efficiency as a function of two different observables, this behavior is physically still plausible. As shown in Sauer et al. [2025] (Chapter 3) and in Chevallier and Salas-Mélia [2012], the late summer sea ice area is better anticipated by the spring-summer sea ice volume than by the sea ice area itself. Therefore, using the sea ice volume as an observable is an efficient way to improve the sampling of trajectories characterized by an anomalously strong spring-summer sea ice thinning and thus of trajectories that are particularly favorable for the development of extremely low late summer sea ice area. In Table 5.1, we summarize the number of extreme events sampled with the different control and rare event algorithm ensembles in EC-Earth3:

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Table 5.1: EC-Earth3: Number of events with August-September mean sea ice area values of 2.0σ , 2.5σ , 3.0σ , 3.5σ and 4.0σ below the initial condition-dependent control ensemble means of the SI-NEUTRAL and SI-LOW experiments. The parameter σ is the initial condition-dependent control ensemble standard deviation of August-September mean sea ice area values in the two experiments. Note that the standard deviation in the SI-LOW control ensemble is slightly larger than the one in the SI-NEUTRAL control ensemble (see table 4.2). Therefore, the thresholds in the "Amplitude" column correspond to slightly different amplitudes in the SI-LOW compared to the SI-NEUTRAL experiment. In the "ALG()" columns, the numbers in round brackets denote the full number of extremes, while the numbers in front of these brackets denote the number different initial-time ancestors that lead to extremes of the given amplitude. The latter provides a conservative estimate of the number of extreme events that are independent with respect to the dynamics within one single melting season between March and September. The term "independence" needs to be interpreted as conditional on starting from the selected initial state.

	SI-NEUTRAL			SI-LOW	
Amplitude	control ensemble	ALG(SIA)	ALG(SIV)	control ensemble	ALG(SIV)
-2.0σ	12	16(97)	13(122)	9	16(195)
-2.5σ	2	7(20)	5(48)	2	10(133)
-3.0σ	0	0	1(30)	0	4(34)
-3.5σ	0	0	1(23)	0	0
-4.0σ	0	0	1(7)	0	0

We exploit the improved statistics of extremely negative pan-Arctic sea ice area anomalies available from the simulations with the rare event algorithm to address the three questions presented in section 1.5 (Chapter 1):

How likely (in a statistical sense) is a 2012-like sea ice low under present-day climate conditions, and what are the physical bounds to the most extreme sea ice reduction in one single melting season?

The Arctic sea ice cover fluctuates across a wide range of time scales [Dörr et al., 2023]. In contrast to a stationary state, the transient nature of the current climate hampers a clear definition of a baseline sea ice climatology. In Chapter 4, we consider a "2012-like sea ice low" as an event where the August-September mean sea ice area anomaly relative to a local climatology (defined by the initial condition-specific control ensemble mean) is more extremely negative than the deviation of the observed 2012 August-September mean sea ice area from a linear trend fitted to the period 1979-2025 ($-1.16 \cdot 10^6 \text{ km}^2$ as illustrated in the Supplementary Figure C6(b)). As shown in Figure 4.3 (Chapter 4), all three rare event simulations with EC-Earth3 produce trajectories that meet this condition.

In this context, two rare event simulations, one using the pan-Arctic sea ice area as an observable (ALG(SIA)) and one using the pan-Arctic sea ice volume as an observable (ALG(SIV)), are initialized from an initial condition where the late winter sea ice thickness is approximately representative of the 1979-2015 mean sea ice thickness climatology available from PIOMAS (called "SI-NEUTRAL" in Chapter 4). For this initial condition, the late summer sea ice area variability produced by the EC-Earth3 SI-NEUTRAL control

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ensemble is representative of the observed August-September mean sea ice area variability around a linear trend both fitted to the period 1979-2015 and to the period 1979-2025 in EUMETSAT-OSISAF data (EUMETSAT Ocean and Sea Ice Satellite Application Facility [2024]; see Supplementary Figure C6). Thus, the estimated standard deviations of August-September mean sea ice area values and of the values of the difference between August-September and late winter sea ice area in the control ensemble are $0.40 \cdot 10^6 \text{ km}^2$ (95% confidence interval: $[0.37 \cdot 10^6 \text{ km}^2, 0.43 \cdot 10^6 \text{ km}^2]$). For these two metrics, the standard deviations of the observed residuals around a linear trend fitted to the periods 1979-2015 and 1979-2025 in the EUMETSAT-OSISAF data are $0.38 \cdot 10^6 \text{ km}^2$ and $0.42 \cdot 10^6 \text{ km}^2$ respectively. **For this specific initial condition and climate state, both the ALG(SIA) and ALG(SIV) experiments consistently suggest that the probability of occurrence of a 2012-like sea ice low is in the order of 10^{-3} (Figure 4.3).**

A second experiment, called "SI-LOW", is conducted after using "anomaly initialization" [Tian et al., 2021] to add to the initial condition of the SI-NEUTRAL experiment on a grid point level the observed differences of selected snow-sea ice-ocean variables between 2012 and the 1995-2005 climatology ("2012-AVG<1995-2005>"; see Chapter 4 for more technical details). For the SI-LOW initial condition, the value of the standard deviation in the control ensemble is $0.45 \cdot 10^6 \text{ km}^2$ and the 95% confidence interval around this estimate is $[0.41 \cdot 10^6 \text{ km}^2, 0.49 \cdot 10^6 \text{ km}^2]$. Consequently, the late summer sea ice area variability in the SI-LOW experiment tends to be slightly increased compared to the one of the SI-NEUTRAL experiment. This behavior is consistent with the study of Goosse et al. [2009]. Goosse et al. [2009] demonstrated that - for a certain range of basic sea ice states - a sea ice thinning in the Arctic leads to an increase of the late summer sea ice area variance. **Notably, the probability of a 2012-like sea ice low estimated with the SI-LOW rare event simulation is 10^{-2} , i.e., one order of magnitude larger compared to the estimate obtained with the SI-NEUTRAL experiment (cf. Figure 4.3 and Figure C11).**

We acknowledge that the probability of occurrence of a 2012-like sea ice low may not only be sensitive with respect to the initial condition, but that the 95% confidence intervals around the estimated probabilities provided in this study are relatively large (Figure 4.3). Typically, the lower probability limits of these confidence intervals are at zero: $[0, 4.7 \cdot 10^{-3}]$ for the "SI-NEUTRAL: ALG(SIV)", $[0, 1.6 \cdot 10^{-3}]$ for the "SI-NEUTRAL: ALG(SIA)" and $[0, 3 \cdot 10^{-3}]$ for the "SI-LOW: ALG(SIV)" experiments (Figure 4.3). Hence, increasing the ensemble size and/or conducting multiple experiments would be required to substantially reduce the statistical uncertainties of these probability estimates. Nevertheless, the ability of the rare event algorithm to simulate extreme sea ice lows with larger amplitudes than observed in 2012 implies that this method can be very useful for attribution studies in the future, to better compare the probabilities of drastic sea ice loss events between different climate states.

Finally, the method can be used to anticipate a lower bound of possible sea ice area values that can be reached for a given climate state or for a given initial condition (Figure 4.3). In this project, the simulations with EC-Earth3 are run for one single melting season. Consequently, based on the example of two initial conditions with present-day sea ice conditions, these experiments provide an estimate of how extreme a late summer

sea ice low can become through processes occurring within one single melting season. In these experiments, the most extremely negative August-September mean sea ice area anomalies relative to the initial-condition specific control ensemble means are $-1.67 \cdot 10^6$ km² (SI-NEUTRAL) and $-1.53 \cdot 10^6$ km² (SI-LOW; Figure 4.3). In terms of absolute values, the late summer sea ice area in these two trajectories remains substantially above $1 \cdot 10^6$ km² and thus above the threshold used to define a practically sea ice-free Arctic Ocean (Figure 4.3) [Jahn et al., 2024; Notz and Community, 2020]. Continuing the rare event simulations for another few years, selectively activating the algorithm only during the summer season, could clarify to what extent a sea ice-free Arctic Ocean is in principle possible under present-day climate conditions. We emphasize, however, that the two most extreme sea ice low trajectories available from the SI-NEUTRAL and SI-LOW experiments have very small probabilities in the order of 10^{-4} . They therefore correspond already to very rare realizations of the system (Figure 4.3). Even if a multi-year rare event simulation produced a trajectory with a total disappearance of summer sea ice after a few years, the probability of observation such a dynamical pathway would be even smaller than 10^{-4} . Physical limits, for example sea ice northern of the Canadian Archipelago that is too thick to be melt away within a reasonable amount of time, may impose a lower threshold of possible sea ice area values under the present-day climate state used in this study.

What are the precursors of extreme Arctic sea ice lows and how does an extreme become an ultra-rare event?

We investigate both composites of dynamical quantities conditional on the occurrence of extremes of sea ice reduction and analyze the physical properties in single trajectories leading to the most extreme states available from the experiments. Regarding the composites, the amplitude levels used as a threshold to define the extremes is -2.5σ , i.e., events where the sea ice area is at least 2.5 standard deviations below (Chapter 2) the mean of the control run and (Chapter 4) the means of the control ensembles (Chapter 4). This corresponds to events with return times ≥ 200 years (probabilities of less than 0.5%) in Chapter 2 and probabilities of less than approximately 1% in Chapter 4. While the composites indicate common physical characteristics emerging on statistical average over various extreme events, the single trajectory analyses allow to identify a set of ingredients that favor the development of ultra-rare but high impact events with probabilities in the order of 10^{-3} - 10^{-4} or smaller.

As an intermediate complexity climate model, PlaSim-LSG inherently involves a couple of simplifications compared to comprehensive climate models that may impact the interpretation of the results of Chapter 2 and Chapter 3. Apart from the extremely coarse atmospheric and oceanic resolutions and the binary representation of the sea ice concentration (SIC; i.e. $SIC \in \{0, 1\}$), the two most obvious limitations of PlaSim-LSG is the lack of dynamic sea ice and biases in the sea ice thickness and sea ice concentration fields (Figure 1.3 in Chapter 1). Due to the former, PlaSim-LSG does not capture the dynamical impacts of synoptic-scale storms and large-scale wind patterns, for example associated with the dominant modes of atmospheric circulation variability, on the sea

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ice. Regarding the latter and in contrast to observations and EC-Earth3, PlaSim-LSG simulates the presence of sea ice in the Barents Sea during late summer (Figure 1.3). Consequently, PlaSim-LSG likely overestimates the relative importance of positive two metre temperature anomalies and thermodynamic melting in the European-Russian sector of the Arctic Ocean in driving extreme annual sea ice minima (Figures 3.4 and 3.5 in Chapter 3 and Figure 2.6 in Chapter 2). The study of Liang et al. [2022] demonstrated that the observed 2020 record minimum July sea ice extent was associated with enhanced thermodynamic melting on the Eurasian side of the Arctic Ocean, similar to Figure 3.5(c). However, extreme minima of the sea ice cover in late summer instead of July do not necessarily require an anomalously melting in that region as the Eurasian coast of the Arctic Ocean and the Barents Sea are sea ice-free during late summer on climatological average (Figure 1.3). Supported by a sea ice volume and sea ice area budget analysis (Chapter 4), our work with EC-Earth3 demonstrates that extremely low late summer sea ice states are indeed predominately associated with enhanced thermodynamic melting on the Pacific side of the Arctic Ocean, but not systematically on the Eurasian side (Figure 4.7).

Despite its simplifications compared to comprehensive climate models, PlaSim-LSG represents the present-day climate realistically enough (cf. Chapter 1 and Angeloni [2022]) to study the main large-scale thermodynamic ingredients involved in the formation of extreme Arctic sea ice lows. Notably, several of these ingredients are found to be valid both in PlaSim-LSG and the comprehensive climate model EC-Earth3:

(A) General sources of predictability of extremely low late summer sea ice area:

All three chapters reveal that extremely negative late summer sea ice area anomalies evaluated relative to an external absolute climatology (e.g. of a stationary long control run) exhibit two levels of predictability in a probabilistic sense: firstly, the late winter sea ice-ocean state substantially impacts the probabilities of occurrence of an extreme late summer sea ice low of a certain amplitude level (Figure 2.5, Figures 3.2, 3.3, 4.2, 4.3 and Tables 3.2, 4.2). This initial condition-predictability is particularly given by the state of the cumulative area with sea ice thickness equal or larger than a certain threshold (1.80 m in EC-Earth3 and about 1.90 m in PlaSim-LSG; Figure 3.1 and Supplementary Figure C3(a)). Initialized ensemble simulations with PlaSim-LSG indicate that the late winter sea ice area imprints on the February-September mean sea ice area through persistence, but that the late winter sea ice area does not impact the late summer sea ice area (Figure 3.3 and Table 3.2). This is in line with the fact that the memory of late winter sea ice area is typically lost after a few months (cf. Figure 1.6 and Blanchard-Wrigglesworth et al. [2011]). Regarding the two initialized ensembles with EC-Earth3 (Chapter 4), the interpretation of the role of late winter sea ice area for the statistics of late summer sea ice area is less straightforward compared to the results with PlaSim-LSG. As shown in Figure 4.2(e) and in the Supplementary Figure C8, imposed negative winter sea ice cover anomalies prevail in the Nordic Seas and lead to slightly negative pan-Arctic sea ice area anomalies that persist and amplify until the end of summer. We hypothesize, however, that the connection between late summer sea ice area and late winter sea ice area is indirect by the fact that imposed positive near-surface ocean temperatures in the northeastern North Atlantic help to maintain the signal in the sea ice area (Figure C8). Apart from a possible role through the ocean temperatures, a key factor leading to the

initial condition-predictability in the EC-Earth3 experiments is related to sea ice thickness information as in PlaSim-LSG.

The second source of predictability of extreme late summer sea ice lows emerges from that fact that these lows are systematically preceded by anomalously strong sea ice thinning, i.e. sea ice volume reduction, between May and July, both in PlaSim-LSG and in EC-Earth3 (cf. Figures 4.5, Figure 3.4 and Figure 2.5). This is in line with the concept of late-spring predictability barrier of late summer sea ice area discussed in Bonan et al. [2019] and Bushuk et al. [2020]. According to these studies, predictions initialized on 01 July are expected to provide a substantially better prediction of late summer sea ice area compared to the ones initialized on 01 May.

(B) Atmospheric drivers of extreme Arctic sea ice reduction:

In terms of causes of enhanced sea ice loss, the results partly depend on the considered time scales and on the considered target quantity. In Chapter 2, we investigate the drivers of extremely negative February-September mean sea ice area anomalies evaluated relative to an absolute climatology defined by the 3000-year control run in PlaSim-LSG. In this approach, both sub-seasonal processes and multi-annual variability, including a possible feedback of the atmosphere to multi-annual oceanic processes, can affect the state of the sea ice. The fact that February-September instead of late summer averaged sea ice area extremes are investigated makes the relative importance of multi-annual time scales compared to short time scales even more substantial. Apart from the persistence of sea ice area and sea ice volume anomalies originating from the previous winter, the main ingredients of low February-September mean sea ice states in PlaSim-LSG are 1) enhanced downward longwave radiative fluxes associated with increased atmospheric moisture, cloudiness and temperatures in spring 2) enhanced downward May-June sensible heat fluxes associated with a reinforcement of positive 500 hPa geopotential height anomalies compared to earlier months (referred to as "Arctic heatwave" in Chapter 2) and 3) the sea ice-albedo feedback. While the sea ice-albedo feedback acts as a pure amplifier of pre-existing sea ice anomalies starting during April-May, it explains, compared to the remaining terms of the surface energy budget, the largest amount of anomalous Arctic Ocean net energy accumulation during extremely low sea ice summers (Figures 2.7 and 2.8). The latter is consistent with the results obtained with EC-Earth3 (Figure 4.11).

In contrast to Chapter 2, the ensembles in Chapter 3 and Chapter 4 are initialized from single initial conditions and therefore the triggers of enhanced sea ice reduction are related to sub-seasonal processes. Moreover, extremes of August-September mean sea ice area reduction are investigated instead of the February-September mean sea ice area. Both a single trajectory analysis performed with PlaSim-LSG (Chapter 3: Figures 3.4, 3.5, 3.6, 3.7) and the statistical analysis using EC-Earth3 (Chapter 4: Figures 4.11, 4.9, 4.6(e,f,g,h) and Supplementary Figure C19) demonstrate that extremes of intra-seasonal sea ice area reduction are systematically associated with two different thermodynamic states over the course of the melting season: 1) enhanced energy accumulation in the sea ice-ocean system via longwave radiative fluxes within an anomalously moist, cloudy and warm Arctic atmosphere in May-June and 2) strongly enhanced energy accumulation in the sea ice-ocean system via shortwave radiative fluxes due to the sea ice-albedo feedback starting at the end of May and lasting until the end of summer. Regarding this

5. Discussion, conclusion and future perspectives

second phase, longwave fluxes are in a relatively neutral state on statistical average over the various extremes starting from July. These two thermodynamic phases are consistent with the results of Chapter 2. However, compared to Chapter 2, they are temporally more precisely defined in the single initial condition ensembles used in Chapters 3 and 4 as the multi-annual variability related to the ocean is by construction excluded from the analysis. Consequently, an atmospheric feedback to an anomalously warm surface in early spring, such as observed in Figure 2.7 of Chapter 2, is by construction excluded from the analyses in Chapters 3 and 4.

A key difference between the results obtained with PlaSim-LSG in Chapter 2 and the results with EC-Earth3 in Chapter 4 is the state of the atmospheric circulation during late spring. According to the analyses with EC-Earth3, extreme annual sea ice minima are preceded by cyclonic mean sea level pressure anomalies during the spring-summer transition over the central to eastern Arctic Ocean (Figure 4.6). Cyclonic anomalies in the atmospheric circulation favor increased water vapor and cloudiness (Figure 4.9) and therefore the positive surface net longwave radiative flux anomalies (Figure 4.11; positive radiative flux anomalies correspond to enhanced energy accumulation in the sea ice-ocean system). While the former is related to enhanced vertically integrated moisture flux convergence (cf. Figure 4.10 and text in section 4.3.4.1), enhanced cloudiness likely results both from enhanced atmospheric water vapor and from frontal systems in the environment of low pressure systems. Apart from the thermodynamic impacts, cyclonic mean sea level pressure anomalies also favor enhanced sea ice transport out of the central Arctic Ocean via Ekman drift (Figures 4.6 and 4.8).

Finally, using EC-Earth3, we demonstrate two possible ways by which specific conditions in the atmosphere-sea ice-ocean system lead to ultra-rare events. One pathway includes strong transport-related sea ice loss in association with persistent strongly cyclonic conditions over the central Arctic Ocean, including a synoptic-scale storm of the type of the one observed in August 2012 (Figure 4.8 and 4.12 and Supplementary Figure C15). The storm lasts about 13 days (30 JUNE - 12 JULY; Table 4.3) and explains about 25% percent of total enhanced sea ice volume loss in that trajectory, compared to the local climatology of that ensemble. While 25% within 13 days is a strong rate of sea ice loss, about 45 % of total anomalous sea ice volume loss are already explained by the period before the storm. In accordance with the comparison between the 5-days and 30-days resampling time experiments in Chapter 2, this is another line of evidence that the most relevant time scales determining low late summer sea ice states are beyond the synoptic time scale. The second ultra-rare sea ice low is dominated by thermodynamic processes associated with very persistent enhanced meridional flow transporting heat and moisture from the Pacific into the Arctic Ocean and triggering a much more pronounced sea ice albedo feedback compared to the typical extremes (Figure 4.13). The late spring mean sea level pressure pattern of that trajectory resembles the one of the observed 2007 event, including a positive phase of the Arctic Dipole (AD) pattern (Figure 4.13(a)). Indeed, the May-June Arctic Dipole index shows a positive value of +1.2 (dimensionless; Figure C16). However, an investigation of 15 independent extreme events reveals that the AD is in a substantial positive phase only in four out of 15 events. Consequently, the

atmospheric circulation of the 2007 event does not appear to be a very typical behavior with respect to a broad climate context.

What is the relative importance of preconditioning through the winter sea ice-ocean state vs. thermodynamical and dynamical processes during spring-summer?

This question implicitly contains two aspects. The first aspect addresses the relative importance of winter sea ice-ocean preconditioning vs. sub-seasonal weather variability for the development of extremely negative late summer sea ice area anomalies. The second aspect entirely refers to sub-seasonal weather variability and addresses the relative contributions of thermodynamic vs. dynamic forcing to the development of extremely negative sea ice area and sea ice volume anomalies within one single melting season. We discuss these two aspects based on simulations with EC-Earth3:

Regarding the first aspect, we compare the amplitudes and probabilities of extremely negative late summer sea ice area anomalies between two ensemble simulations initialized from two different initial sea ice-ocean states (the two experiments are denoted "SI-NEUTRAL" and "SI-LOW" in Chapter 4). The late winter sea ice thickness in the initial condition of the SI-NEUTRAL experiment is approximately representative of the PIOMAS 1979-2015 mean sea ice thickness state. For the SI-LOW experiment, instead, we use "anomaly initialization" [Tian et al., 2021] to add to the initial condition of the SI-NEUTRAL experiment on a grid point level the observed differences of selected snow-sea ice-ocean variables between 2012 and the 1995-2005 climatology ("2012-AVG<1995-2005>"). In both experiments respectively, an order of magnitude of the amplitudes of strong weather-related sea ice area fluctuations can be obtained from the experiment-specific 1% percentile sea ice area anomalies relative to the experiment-specific control ensemble means [Sauer et al., 2025].

The results in Chapter 4 demonstrate that the imposed "2012-AVG<1995-2005>" sea ice-ocean changes substantially impact the statistics of extremely negative late summer sea ice area anomalies. This is particularly evident in the impact of the initial condition on the mean of the distribution. Thus, the August-September average control ensemble mean sea ice area in the SI-LOW experiment is by $0.81 \cdot 10^6 \text{ km}^2$ reduced compared to August-September average control ensemble mean sea ice area of the SI-NEUTRAL experiment (Table 4.2). In contrast, the 1% percentile sea ice area values estimated with the "SI-NEUTRAL: ALG(SIV)" and "SI-NEUTRAL: ALG(SIA)" simulations are reduced by $0.92 \cdot 10^6 \text{ km}^2$ and $0.98 \cdot 10^6 \text{ km}^2$ compared to the SI-NEUTRAL control ensemble mean (Table 4.2). Consequently, sea ice area anomalies related to the impact of the imposed "2012-AVG<1995-2005>" sea ice-ocean changes on the mean of the distribution and sea ice area anomalies related to strong weather-related fluctuations are of similar order of magnitude. As shown in Table 4.2, the 1% percentile August-September mean sea ice area value in the SI-LOW experiment is reduced by $2.07 \cdot 10^6 \text{ km}^2$ compared to the SI-NEUTRAL control ensemble mean and therefore reduced by $1.26 \cdot 10^6 \text{ km}^2$ compared to the SI-LOW control ensemble mean. In line with the discussion on the estimated probabilities of 2012-like sea ice lows and consistent with Goosse et al. [2009], this aspect further suggests that the imposed "2012-AVG<1995-2005>" sea ice-ocean changes do not only impact the mean, but also the variance of the distribution of late

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summer sea ice area. This implies that the Arctic sea ice area responds more heavily to a given atmospheric forcing in the SI-LOW compared to the SI-NEUTRAL experiment.

Regarding the second aspect, we apply a sea ice area and sea ice volume budget analysis [Holland and Kwok, 2012] to the SI-NEUTRAL and the SI-LOW experiments. This serves to decompose late summer sea ice area and sea ice volume anomalies into a contribution of local thermodynamic melting within a domain defined by the climatological mean late summer sea ice edge vs. a contribution of sea ice export (i.e. sea ice transport) out of that domain into regions of warmer water masses compared to the interior of the domain. For this analysis, we focus exclusively on time scales of at most one melting season (i.e. anomalies are computed relative to the local experiment-specific control ensemble means). Integrated over the entire melting season and on statistical average over numerous independent extreme sea ice loss events, sea ice transport explains about 25%-35% of anomalously increased March-September sea ice volume loss and about 20%-30% of anomalously increased March-September sea ice area loss (cf. Figure 4.7, Figure 4.8 and Figure C12). Regarding the spatial distribution, the contribution of thermodynamic vs. dynamic forcing to enhanced sea ice loss shows a dipole-like structure: significantly enhanced thermodynamic sea ice volume and sea ice area loss occurs from the Canadian Archipelago over the Pacific side of the Arctic to Siberia (Figure 4.7(b,e,h,k)) and is therefore located downstream of the negative mean sea level pressure anomalies shown in Figure 4.6(a-d). Dynamics-related sea ice anomalies are smaller in magnitude than the thermodynamic ones, but statistically significant enhanced sea ice loss is noticeable on the Eurasian side of the Arctic and thus spatially coincides with the center of the anomalously negative mean sea level pressure anomalies. Individual trajectories, however, the relative contributions of transport-related sea ice loss anomalies to the total anomalies can substantially deviate from the statistical mean value. For example, anomalous sea ice volume loss in the most extreme sea ice low trajectory of the SI-NEUTRAL experiment is to 50% explained by the transport, whereas the most extreme sea ice low available from the SI-LOW experiment is almost entirely explained by thermodynamic processes (cf. Figure 4.8 and Figure C12).

5.2 Future perspectives

The methodological, technical and scientific achievements of this project provide several perspectives for the future:

Predicting the late Arctic summer sea ice state on a seasonal time scale:

- The advanced understanding of the precursors of extreme Arctic sea ice reduction may be used for data-based statistical models and for climate model-based initialized forecast. The latter may be improved in terms of informing of the ensemble initialization strategies by the identification of important physical drivers of the extremes. A part from a source of predictability through the late winter sea ice-ocean initial condition (in particular through the cumulative area with sea ice thickness larger than a certain

threshold), the project demonstrates that the sea ice volume during early summer provides an additional source of predictability of late summer sea ice area on top of the initial condition-predictability. We hypothesize that precise information about the early summer sea ice thickness state, including the cumulative area with sea ice thickness larger than a certain threshold and sea ice thickness anomalies in specific regions of the Arctic, provide more predictability of late summer sea ice area than the pan-Arctic sea ice volume itself.

- Potentially relevant for policy-makers, the application of the rare event algorithm to initialized ensemble simulations may help to better assess possible worst-case scenarios for a given initial state of the system.
- Machine learning models may be trained on a large amount of extreme events available through the rare event algorithm, which potentially improves their skill in predicting events with extremely low sea ice cover. The idea of improving machine learning-based forecasts via rare event simulations, though in application to heat waves instead of sea ice, has been suggested by Jacques-Dumas et al. [2022] and Miloshevich et al. [2023].

Attribution studies:

- The approach can be used to better quantify the relative contribution of a given initial condition to specific extreme sea ice loss events such as observed in 2007 and 2012. This could be achieved by comparing an ensemble initialized with the state of, for example, 01 March 2012 of a historical simulation with an ensemble using various initial conditions taken from a 11-year period centered around the desired year.
- The experimental design can be adapted to make quantitative statements about the relative contributions of global warming vs. internal climate variability to the probabilities and amplitudes of extreme sea ice loss events, and to quantify the probability of observing a sea ice-free Arctic within a given period of time. This can be achieved by initializing an ensemble with late winter initial conditions sampled from e.g. the period 2016-2025 (i.e. an ensemble of 300 trajectories could be generated by producing 30 perturbed replicates of one initial condition per year respectively) and comparing the statistics with another ensemble initialized with data drawn from e.g. the period 1986-1995 of a historical simulation.

Recovery and impact studies:

- The existing rare event simulations can be used as starting point for a new set of experiments. Firstly, continuing the rare event simulations without using the rare event algorithm (i.e. setting $k = 0$) for another few years allows to study the recovery time of extreme sea ice anomalies to go back to a neutral state, similar to the study of Tietsche et al. [2011]. In contrast to Tietsche et al. [2011], extremely low sea ice states in the rare event simulations with EC-Earth3 result naturally from the dynamics of the system, and therefore the sea ice is in thermodynamic equilibrium with the atmosphere and the ocean. For example, prescribing an sea ice-free Arctic Ocean,

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but keeping the atmospheric and oceanic temperatures unchanged, implies that the atmospheric (and likely also the oceanic) temperatures are too low for a sea ice-free Arctic Ocean. This may potentially lead to an underestimation of the recovery time required by the sea ice to go back to its original state. Likewise, the study of Tietsche et al. [2011] may underestimate the role played by the sea ice-albedo feedback as the sea ice disappearance is imposed on 01 July, whereas this project demonstrates that extreme late summer sea ice lows are typically preceded by enhanced melting and enhanced sea ice-albedo feedback already during May-June, the annual maximum of downward solar radiation (e.g. Figure 4.11). Consequently, the ensembles with EC-Earth3 provide a possibility to re-assess the recovery time after drastic sea ice loss events using a realistic set-up with a comprehensive climate model.

- Secondly, the second experiment could consist in re-activating the rare event algorithm starting from 01 March after having switched off the algorithm for five months. This experiment allows to investigate how extreme sea ice lows may become under the very unlikely, but plausible situation of a strong multi-year forcing of anomalous atmospheric and oceanic forcing on the sea ice. Moreover, the data can be used to perform a quantitative statistical analysis of the atmospheric response to extremely low sea ice states. As for the recovery experiment, the advantage of using the data from the algorithm over other techniques to prescribe low sea ice states, such as e.g. ghost flux, nudging and albedo modification [England et al., 2022], is that the "imposed" low sea ice states occur as a natural consequence of the dynamics of the system. In this context, England et al. [2022] argue that common techniques used to impose sea ice loss add to an artificial warming on top of the warming induced by the sea ice loss itself and thereby lead to an overestimation of the atmospheric response to anomalously low sea ice states.

As a starting point, we compute composite mean late summer 500 hPa geopotential height and two metre temperature anomalies conditional on the occurrence of August-September mean sea ice area values of at least 2.5 standard deviations below the control ensemble means (Figure 5.1). During July-August, no substantial signal in the thermal state of the atmosphere is visible. However, in August-September, positive two metre temperature anomalies emerge over the central Arctic Ocean and are associated with enhanced latent and sensible heat release from the ocean to the atmosphere (cf. Figure 5.1(e-h) and Figure 4.11(e-f)). Statistical significant positive 500 hPa geopotential height anomalies over the Pacific-North American side of the Arctic Ocean in August-September suggest that the atmospheric circulation is potentially re-acting to the anomalously large open water during extreme sea ice lows. Notably, the amplitudes of the Z500 anomalies are comparable or even larger in magnitude compared to the atmospheric response to low 2007 and 2008 sea ice conditions discussed in Balmaseda et al. [2010]. A systematic investigation of the atmospheric autumn response to the simulated extreme annual sea ice minima in EC-Earth3 will be performed in the future.

Regional predictability and Antarctic sea ice:

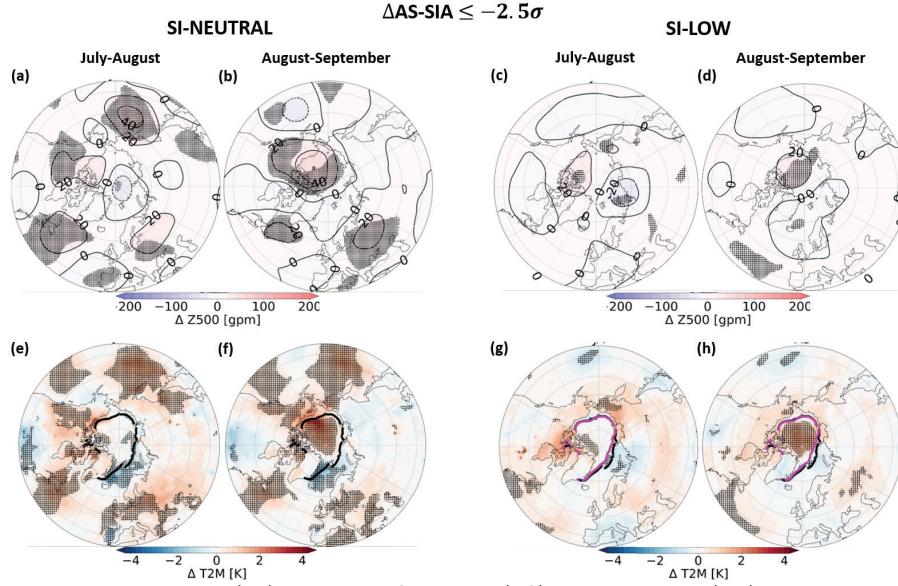


Figure 5.1: July-August (JA) and August-September (AS) composite mean (a-d) 500 hPa geopotential height [gpm] and (e-h) two metre temperature [K] anomalies conditional on the occurrence of an August-September sea ice area of at least 2.5 control ensemble standard deviations below the control ensemble means. The hatching indicates statistical significance at the 5% level (see section 4.2.2.3). The results are based on (a,b,e,f) the "SI-NEUTRAL: ALG(SIV)" and (c,d,g,h) the "SI-LOW: ALG(SIV)" experiments. The black and magenta contour lines indicate the August-September mean 15% sea ice concentration line in the SI-NEUTRAL and SI-LOW control ensembles respectively.

- The approach used in this project can easily be adapted to study the predictability of anomalous sea ice conditions in specific regions of the Arctic instead of investigating the pan-Arctic sea ice area. For certain applications, such as shipping, exploitation of natural resources or understanding the atmospheric response to sea ice loss in a specific part of the Arctic, for example in the Barents-Kara Sea, the regional sea ice may be of larger interest than the Arctic-wide sea ice state.
- In contrast to the Arctic, Antarctic sea ice had been slightly expanding on average from 1979 to 2015 [Docquier et al., 2025]. Afterwards, Antarctic sea ice experienced a series of record sea ice lows. To what extent these extreme Antarctic sea ice minima are part of the climate system's internal variability or whether they anticipate more profound changes to come, remains unclear. As for the Arctic, ensemble simulations with the rare event algorithm constitute a possibility to improve our understanding of the drivers of Antarctic sea ice lows in a quantitative statistical sense (i.e., to identify a range of possible processes and conditions that favor these lows going beyond an analysis of the individual records observed in 2017 and 2022) and to quantify the probabilities of these events for a given climate state.

CMIP5/CMIP6 large ensembles:

The results in Chapter 4 are based on one single comprehensive climate model. Meanwhile, CMIP5 and CMIP6 large ensembles exist [Maher et al., 2025]. These include multiple models with 100 ensemble members and provide an exciting opportunity to expand our analyses on multiple models. This will allow to further investigate the following aspects:

- **Necessary vs. sufficient conditions for extreme late summer sea ice lows:**
In the thesis, we extensively investigated the physical properties of the atmosphere-sea ice-ocean system conditional on the occurrence of an extreme sea ice low. Key for better understanding the predictability of these extremes would consist in also quantifying their probabilities conditional on the occurrence of an anomalous atmosphere-sea ice-ocean state during spring-summer. Apart from using CMIP5/CMIP6 data, we can run the ensemble simulations with the rare event algorithm by choosing an observable that represents a potentially important atmospheric or oceanic driver of low sea ice states. Synoptic activity, the AO/AD indices or ocean heat content/SSTs in a specific region of interest are examples of possible observables for simulations with the rare event algorithm.
- Composites, such as for example presented in Figure 4.6 and Figure 2.4, allow to extract the average physical properties over multiple realizations of an event. However, as evident from Figures 4.12 and 4.13, different realizations of an extreme may be associated with different weather patterns. The systematic **clustering** of different weather patterns leading to extreme sea ice loss, combining EC-Earth3 output with the output of pre-existing large ensembles, represents an interesting future research opportunity.

Appendix A

Appendix to Chapter 2

S2A: Statistical significance

We use a two-sided t-test to estimate the statistical significance of composite maps and we use the t-distribution to construct confidence intervals. We use the 5% significance level. We subdivide the control run in several ensembles and perform multiple experiments with the rare event algorithm. We denote M the number of independent experiments in which extreme events of interest occur. We compute the t-value as $t = \sqrt{M} \frac{\mathbb{E}_0(f)}{\sigma(f)}$, where $\mathbb{E}_0(f)$ is the empirical average of a quantity, e.g. the average over composite mean values obtained from multiple experiments, and $\sigma(f)$ is the empirical standard deviation of that quantity, e.g. the standard deviation over composite mean values obtained from multiple experiments. We denote a composite mean value $\mathbb{E}_0(f)$ as statistically significant at the 5% level if the absolute value of t is larger than 2.776 for $M = 5$, 3.182 for $M = 4$ and 4.303 for $M = 3$. We likewise construct 95% confidence intervals from the student's t-distribution. In the present work, we have $M = 5$ for all composite analyses and $M \in \{3, 4, 5\}$ for the return time estimates. The variable sample size regarding the return times estimated with the rare event algorithm is due to the fact that the rare event algorithm experiments with different biasing parameters k cover slightly different ranges of pan-Arctic sea ice area anomalies. Hence, the estimates of the return times and of their confidence intervals is based on the output of five rare event algorithm experiments in a broad range of sea ice area anomalies and on the output of three or four experiments in the upper and lower amplitude range of sea ice area anomalies.

S2B: Adequacy of the rare event simulations

One problem potentially occurring in rare event simulations is degeneracy. Degeneracy means that the entire ensemble is effectively shrunk to a small number of ensemble members that are distinguishable only in a small last part of the simulation. The degeneracy level in the simulations performed for this work, however, is relatively low (Figures A5 and A6). For each resampling step, the fraction of surviving trajectories with respect to the ensemble size is larger than 90% for the 5-days resampling time and between about

A. Appendix to Chapter 2

60% and 90% for the 30-days resampling time experiments (Figure A5(a-b); note that the decrease of the survival fraction in July consistently coincides with an increase in the interannual variability of sea ice area anomalies (cf. Figure A5(a-b) and Figures 1(c), 2(a,b) of the main text)). The comparatively high rate of surviving trajectories per resampling step results in a relatively large number of different initial-time ancestors that lead to at least one final-time descendant (between 51 and 133; Figure A5(c-d)). Furthermore, the number of different initial-time ancestors that lead to at least one (or more) extreme negative February-September pan-Arctic sea ice area anomaly equal or smaller than -2.5 standard deviations of the control ensembles is substantially larger than the number of extreme events sampled in the control ensembles (Figure A5(c-d); note that the total number of extreme events counted over partially or fully overlapping trajectories in the rare event simulations is in the order of several hundreds per ensemble). Finally, the low degeneracy level in the rare event simulations becomes evident from the distribution of the number of final-time descendants that are associated with the different initial-time ancestors. Most of the initial-time ancestors lead to between 1 and less than 50 final-time descendants (Figure A6). The present study does not contain a situation where one single initial-time ancestor dominates the entire ensemble.

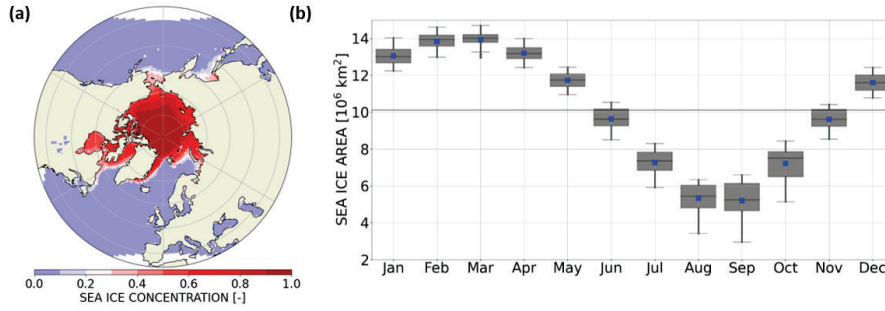


Figure A1: (a) 1979-2015 mean sea ice concentration from European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Ocean and Sea Ice Satellite Application Facility (OSI SAF) data [EUMETSAT Ocean and Sea Ice Satellite Application Facility, 2017] and (b) monthly mean pan-Arctic sea ice area [10^6 km²] from EUMETSAT OSI SAF data between 1979 and 2015 [EUMETSAT Ocean and Sea Ice Satellite Application Facility, 2023]. The horizontal gray line shows the annual mean pan-Arctic sea ice area.

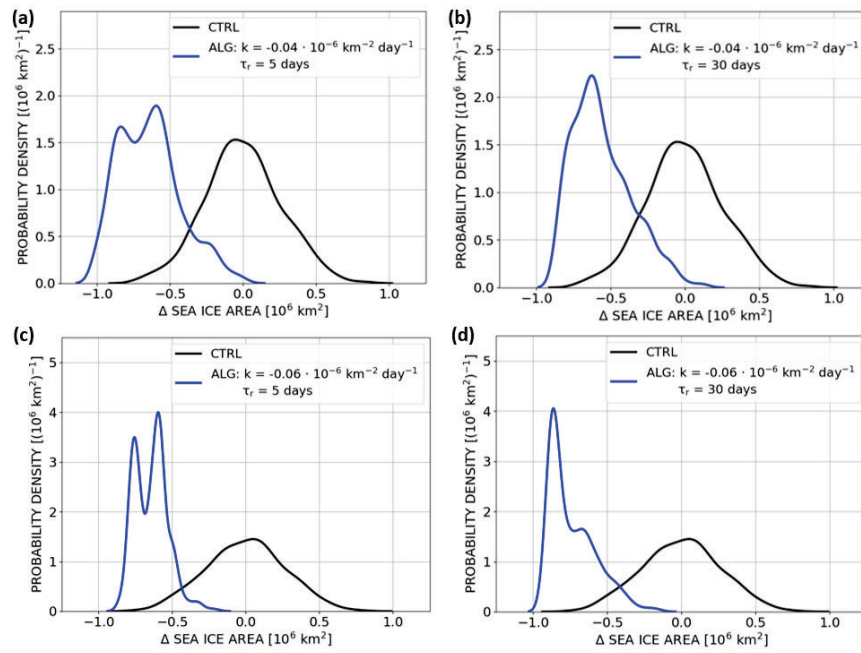


Figure A2: Probability distribution functions of February-September mean pan-Arctic sea ice area anomalies relative to the control climatology for (black) the control run itself and (blue) experiments with the rare event algorithm for (a,c) a resampling time of 5 days and (b,d) a resampling time of 30 days. (a,b) Control ensembles three and five and rare event algorithm experiments corresponding to ensembles three and five, i.e. with $k = -0.04 \cdot 10^{-6} \text{ km}^{-2} \text{ day}^{-1}$. (c,d) Control ensemble one and rare event algorithm experiment corresponding to ensemble one, i.e. with $k = -0.06 \cdot 10^{-6} \text{ km}^{-2} \text{ day}^{-1}$.

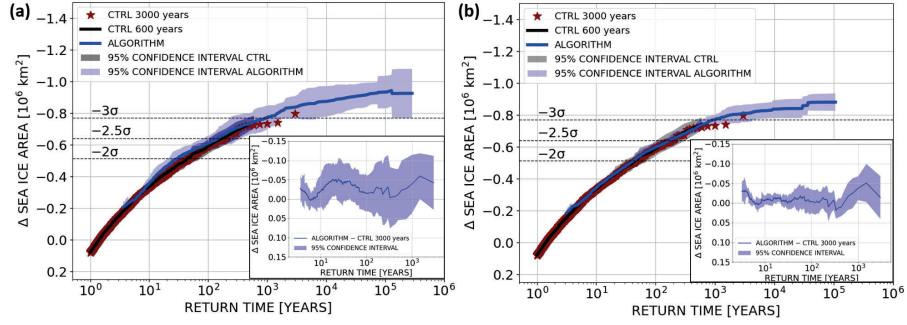


Figure A3: Return curves for February-September mean pan-Arctic sea ice area anomalies relative to the control run. (Red stars) The direct estimate of return times from the 3000 year control run, (black line) the average estimate over the five 600-member ensembles of the control run and (blue line) the average estimate over the overlap of at least three out of five 600-member rare event algorithm experiments. Shading denotes the 95% confidence interval obtained from the statistics of the three to five estimates assuming a student's t-distributed estimator (see Supplementary Information S2A). (a) Rare event algorithm with 5-days resampling time and (b) with 30-days resampling time. The dashed lines in (a) and (b) indicate anomalies of minus two and a half and minus three standard deviations with respect to the control run. (a-b) The insets show the difference between the return level estimates obtained with the rare event algorithm and the ones directly estimated from the 3000 year control run together with the 95% confidence intervals of these differences (the confidence intervals of the differences neglect the uncertainty of the control estimates).

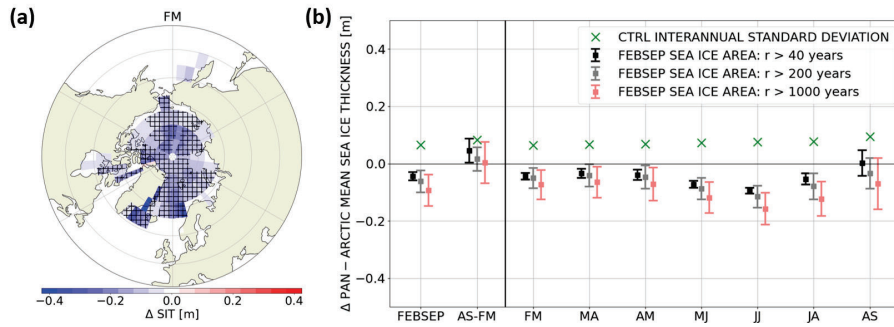


Figure A4: Composite mean sea ice thickness anomalies [m] conditional on extreme negative February-September mean pan-Arctic sea ice area anomalies equal or smaller than (a) -2.5 standard deviations and (b) (black) -2 standard deviations, (gray) -2.5 standard deviations and (red) -3 standard deviations of the control run (roughly corresponds to extremes with return times of more than 40, 200 and 1000 years). (a,b) The composite estimates are presented as an average over the five rare event algorithm ensembles and the hatching in (a) and error bars in (b) represent statistical significance at the 5% level and 95% confidence intervals respectively (see Supplementary Information S2A). The anomalies are computed with respect to the control climatologies of the five control ensembles. (a) Spatial field of February-March sea ice thickness anomalies and (b) spatial average of mean SIT anomalies over all grid boxes north of 40°N conditional on the presence of sea ice. "AS-FM" denotes the difference between August-September and February-March and the green "x" markers indicate the climatological standard deviation in the control run.

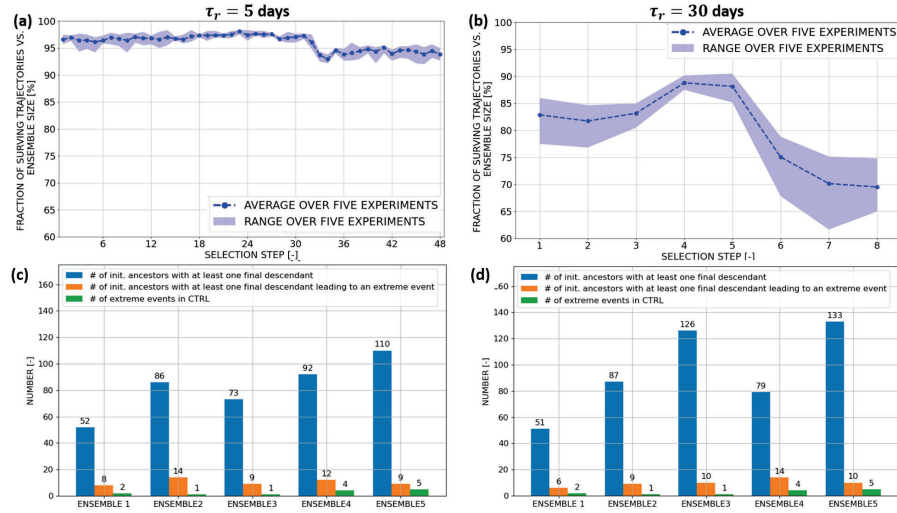


Figure A5: (a-b) Fraction of surviving trajectories with respect to the ensemble size for each selection step [%] shown as (markers) the average and (shading) the minimum-maximum range over five experiments with the rare event algorithm. (c-d) Number of (blue) different initial-time ancestors with a non-zero number of final-time descendants, (orange) different initial-time ancestors with a non-zero number of final-time descendants leading to an extreme negative February-September mean pan-Arctic sea ice area anomaly equal or smaller than -2.5 standard deviations of the control ensembles and (green) the number of extreme events in the control ensembles (same extreme event definition as for (orange)). (a,c) show the experiments with a resampling time of 5 days and (b,d) the ones with a resampling time of 30 days.

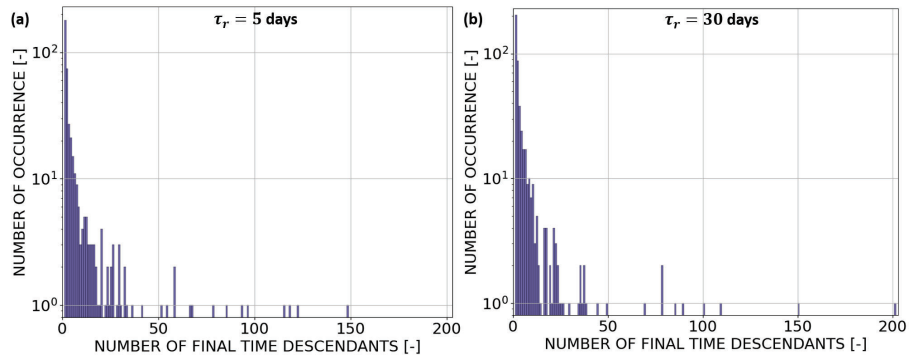


Figure A6: : Histograms of the number of final-time descendants for the different initial-time ancestors presented in Figure A5(c-d) aggregated over the five experiments with a resampling time of (a) 5 days and (b) 30 days.

Appendix B

Appendix to Chapter 3

S3A: Climatological properties of sea ice in the Planet Simulator



Figure B1: Model years 501-3500 of PlaSim-LSG control run [Sauer et al., 2024]: (a) Monthly mean pan-Arctic sea ice area anomalies in the PlaSim-T21-LSG control run with fixed pre-industrial greenhouse gas conditions. Lagged correlations applied to monthly mean pan-Arctic sea ice area anomalies in PlaSim-T21-LSG with increasing lag from top to bottom up to a lag of 23 months.

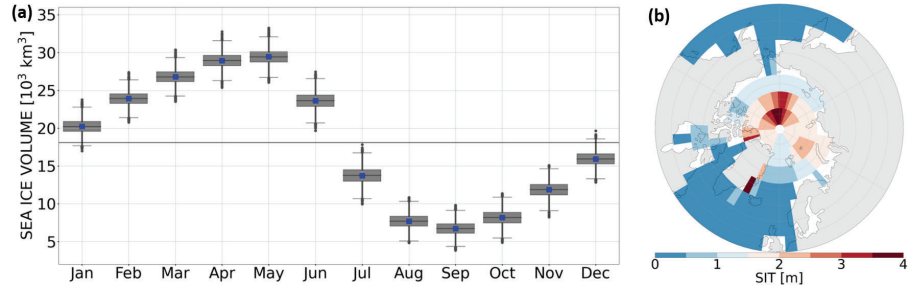


Figure B2: Model years 501-3500 of PlaSim-LSG control run [Sauer et al., 2024]: (a) Distributions of monthly mean pan-Arctic sea ice volume [10^3 km^3] with respect to the 3000 control run model years. The averages and medians are given by the blue squares and the horizontal lines in the boxes. The boxes denote interquartile ranges and the maximum whisker length is defined as 1.5 times the interquartile range. The horizontal gray line shows the annual mean pan-Arctic sea ice volume. (b) Annual mean sea ice thickness [m].

S3B: Observational data

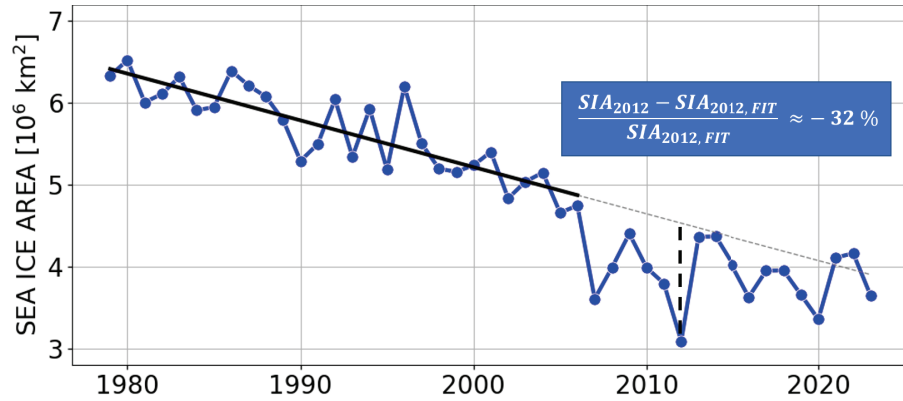


Figure B3: August-September mean pan-Arctic sea ice area [10^6 km^2] from European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Ocean and Sea Ice Satellite Application Facility (OSI SAF) data [EUMETSAT Ocean and Sea Ice Satellite Application Facility, 2024]. The black solid and dashed gray lines show a linear trend fitted (FIT) to the data of the period 1979 and 2006. Compared to the entire time series, the period 1979-2006 shows the most linear decline of the sea ice area.

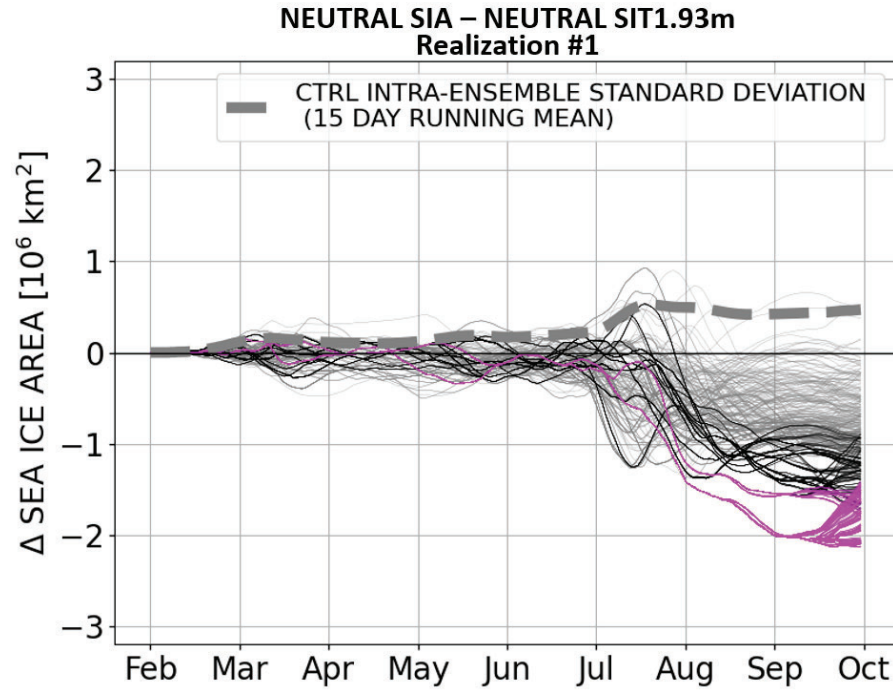
S3C: Bimodality in the rare event simulation

Figure B4: Rare event ensemble simulations initialized on 01 February 1930 of the control run. 15-day running mean of daily pan-Arctic sea ice area anomalies [10^6 km^2] relative to the control ensemble mean. The magenta lines show trajectories leading to the lower peak of the bimodal distribution of Figure 2(e) of the main manuscript and the dark black lines the trajectories leading to August-September mean sea ice area anomalies below -2.5 control ensemble standard deviations excluding the lowest peak. The gray dashed line shows the 15-day running mean of the intra-ensemble standard deviation.

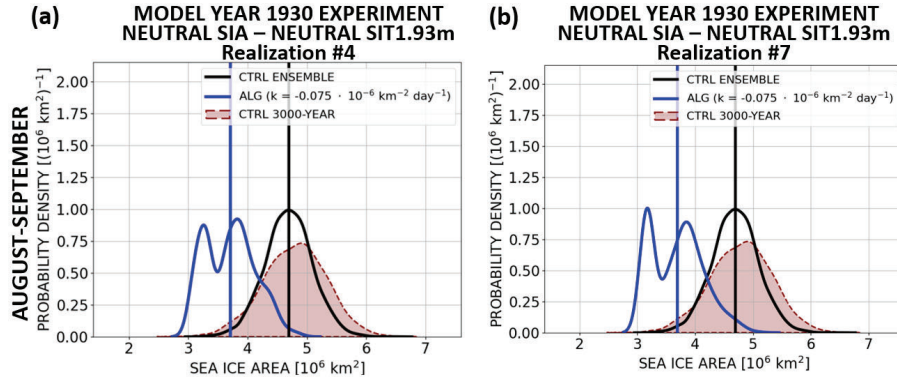


Figure B5: Ensemble simulations initialized on 01 February 1930 of the control run. August-September mean pan-Arctic sea ice area for (blue) the rare event simulation, (black) the control ensembles ($N = 6000$ trajectories) and (red) the 3000-year control run for (a) rare event simulation realization #4 and (b) rare event simulation realization #7. The vertical lines show the mean of the distributions. The black and blue values indicate the smallest August-September mean sea ice area value in the control and rare event ensemble simulations respectively.

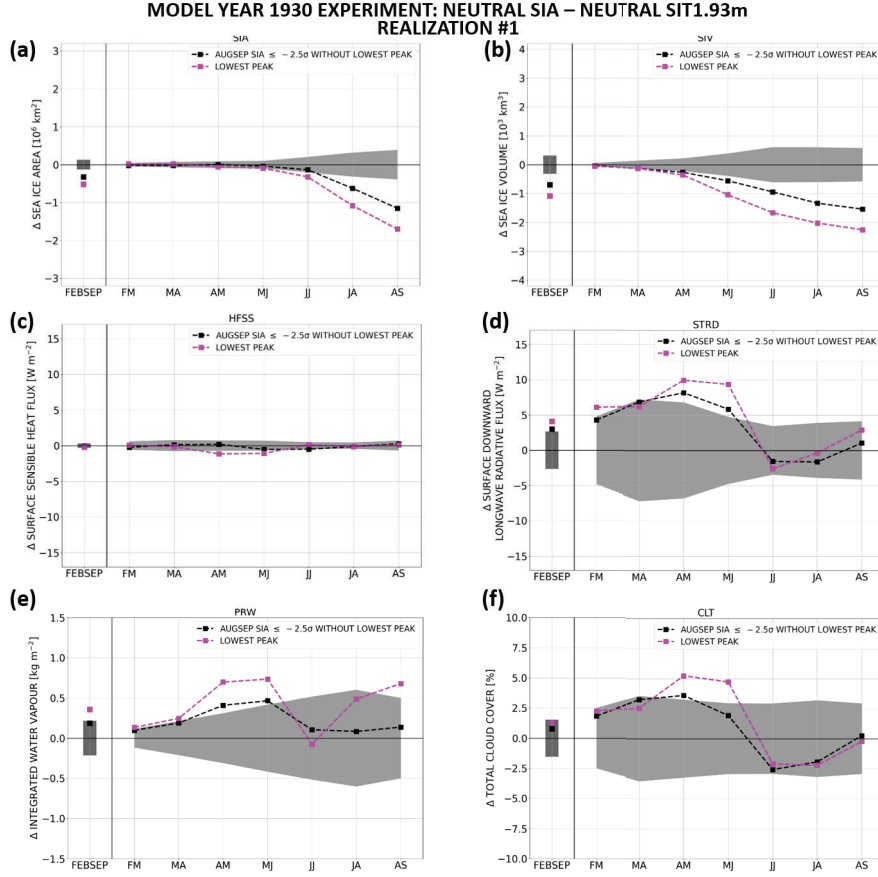


Figure B6: Rare event simulation realization #1 starting from a neutral winter initial condition. Composite mean anomalies of different quantities for all trajectories leading to an August-September mean sea ice area value belonging to (magenta) the “lower peak” of the rare event algorithm probability distribution function of Figure 2(e) and (black) for all trajectories leading to an August-September mean sea ice area anomaly equal or smaller than -2.5 standard deviations of the control ensemble excluding the magenta trajectories (see Figure S4 for the selected trajectories). The composites are computed using the estimator in Equation (3) of the main manuscript (see Sauer et al. [2024] for details about the computation of composites with the output of the algorithm). (a-b) Pan-Arctic sea ice (a) area and (b) volume. (c-f) Spatially averaged composite mean anomalies over all ocean grid boxes northern of 70°N . (c) Surface sensible heat flux and (W m^{-2} ; positive upwards) (d) downward longwave radiative flux anomalies [W m^{-2}] (Direction-independent absolute values of the downward and upward fluxes are considered, i.e., a positive (negative) anomaly indicates a radiative flux that is stronger (weaker) in magnitude than the climatology). (e) Integrated water vapour [kg m^{-2}] and (f) total cloud cover [%] anomalies. (a-f) Shading indicates the intra-ensemble standard deviation of the control ensemble and anomalies are computed with respect to the climatology of the control ensemble.

S3D: Statistical significance

Confidence intervals for probability estimates

We exploit $M \in \{4, 5, 6, 7, 8, 9, 10\}$ rare event algorithm ensemble simulations to derive 95% confidence intervals around the estimate of a sea ice area anomaly amplitudes for a given probability level, i.e., we derive the confidence interval from M t-distributed sea ice area amplitude estimates available from the M experiments. We compute the confidence intervals as $[\mathbb{E}_0(f) - t \frac{\sigma(f)}{\sqrt{M}}, \mathbb{E}_0(f) + t \frac{\sigma(f)}{\sqrt{M}}]$, where $\mathbb{E}_0(f)$ and $\sigma(f)$ are the empirical average and standard deviation over M estimates and t takes the values $t = 3.182$ for $M = 4$, $t = 2.776$ for $M = 5$, $t = 2.571$ for $M = 6$, $t = 2.447$ for $M = 7$, $t = 2.356$ for $M = 8$, $t = 2.306$ for $M = 9$ and $t = 2.262$ for $M = 10$. The variable sample size of amplitude-probability levels estimated with the rare event algorithm is due to the fact that the smallest probabilities obtained with a rare event simulation vary from one realization to the next due to sampling. Hence, the estimates of the probabilities and of their confidence intervals is based on the output of ten rare event algorithm experiments in a broad range of sea ice area values and on the output of four to nine experiments in the upper and lower amplitude range of sea ice area values. We only show estimates where at least four experiments are overlapping.

Statistical significance of composite estimates

We use a two-sided t-test to estimate the statistical significance of the composite estimates presented in Figure 1(a) of the main manuscript. We use the 5% significance level. We subdivide the 3000-year control run Sauer et al. [2024] in $M = 5$ ensembles with $N = 600$ trajectories. We compute the t-value as $t = \sqrt{M} \frac{\mathbb{E}_0(f)}{\sigma(f)}$, where $\mathbb{E}_0(f)$ is the empirical average of a quantity, i.e., the average over composite mean values obtained from the five ensembles, and $\sigma(f)$ is the empirical standard deviation of that quantity, i.e., the standard deviation over composite mean values obtained from the five ensembles. We denote a composite mean value $\mathbb{E}_0(f)$ as statistically significant at the 5% level if the absolute value of t is larger than 2.776.

S3E: Adequacy of the rare event simulations

As discussed in Chapter 2, one problem potentially occurring in rare event simulations is degeneracy. Degeneracy means that a large portion of the trajectories of an ensemble are distinguishable only in a small last part of a simulation. In such a situation, the rare event simulations would not allow for a quantitative statistical analysis of the extremes. Here we evaluate the level of degeneracy 1) in terms of different initial-time ancestors leading to at least one final-time descendant and 2) in terms of different initial-time ancestors leading to at least one extreme event of interest:

1) Different initial-time ancestors leading to at least one final-time descendant: The fraction of surviving trajectories with respect to the ensemble size is typically in the order of 97.5% until the end of June (selection step 30) and decreases to values between about 87% and 96% during late summer (Figure B7). The sudden decrease in the survival rate is consistent with the sudden increase of intra-ensemble sea ice area variability at the beginning of July (cf. Figure B7 and Figure 3.2(a,b) of the main text). The relatively high rate of surviving trajectories per resampling step leads to a relatively large number of different initial-time ancestors that lead to at least one final-time descendant (between 64 and 131; Figure B8). For this metric, the degeneracy level is therefore low.

2) Different initial-time ancestors leading to at least one extreme event of interest: The number of different initial-time ancestors that lead to at least one (or more) extreme late summer sea ice low (i.e. August-September mean sea ice area anomaly ≤ -2.5 control ensemble standard deviations) is not larger than the number of extreme events sampled by the control ensembles. In contrast to Chapter 2, the rare event simulations in Chapter 3 therefore do not systematically provide more independent extreme events than the control ensembles. According to this metric, the level of degeneracy is therefore relatively large. We hypothesize, however, that using the pan-Arctic sea ice volume as the observable instead of using the sea ice area as the observable would allow to circumvent this issue. In this context, rare event simulations performed with EC-Earth3 and presented in Chapter 4 strongly suggest that using the sea ice volume as an observable is more efficient in improving the sampling of low states of late summer sea ice area than using the sea ice area as an observable. We hypothesize that this behavior would also hold for PlaSim-LSG as PlaSim-LSG captures a pronounced connection between extremely low late summer sea ice area and enhanced sea ice thinning during late spring (Figures 3.2 and 3.4 of the main text).

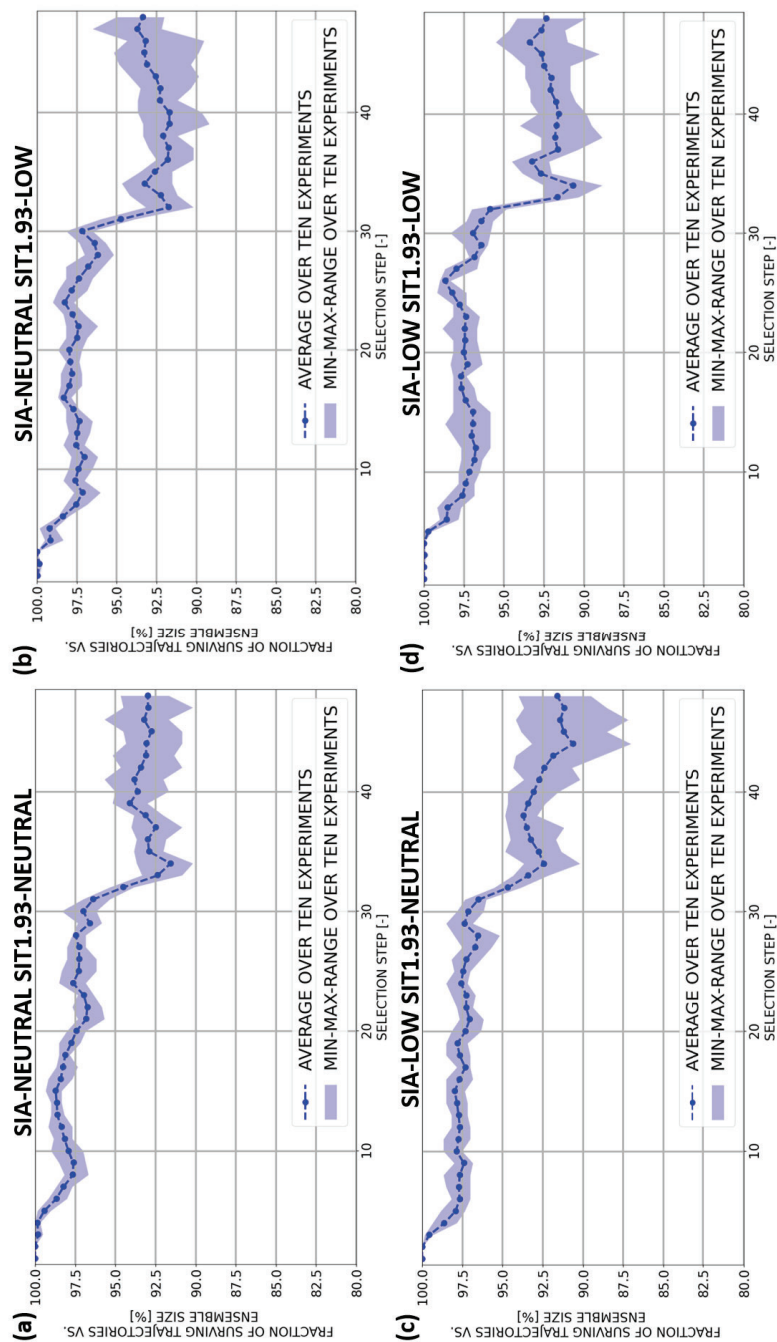


Figure B7: (a) SIA-NEUTRAL SIT1.93-NEUTRAL, (b) SIA-NEUTRAL SIT1.93-LOW, (c) SIA-LOW SIT1.93-NEUTRAL and (d) SIA-LOW SIT1.93-LOW experiments: fraction of surviving trajectories with respect to the ensemble size for selection step [%] shown as (markers) the average and (shading) the minimum-maximum range over ten experiments with the rare event algorithm.

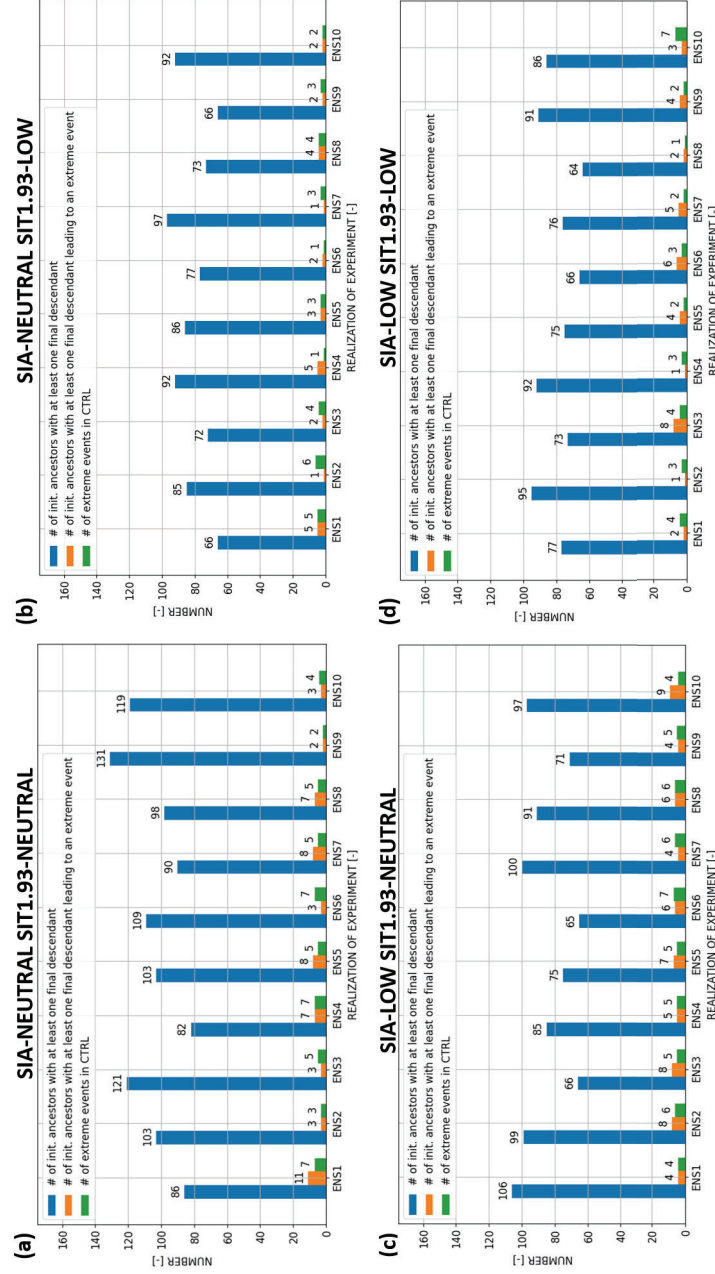


Figure B8: (a) SIA-NEUTRAL SIT1.93-NEUTRAL, (b) SIA-NEUTRAL SIT1.93-LOW, (c) SIA-LOW SIT1.93-NEUTRAL and (d) SIA-LOW SIT1.93-LOW experiments: number of (blue) different initial-time ancestors with a non-zero number of final-time descendants, (orange) different initial-time ancestors with a non-zero number of final-time descendants leading to an extreme negative August-September mean pan-Arctic sea ice area anomaly equal or smaller than -2.5 standard deviations of the control ensembles and (green) the number of extreme events in the control ensembles (same extreme event definition as for (orange))

Appendix C

Appendix to Chapter 4

S4A: Mean atmospheric circulation and sea ice motion in EC-Earth3.3.1

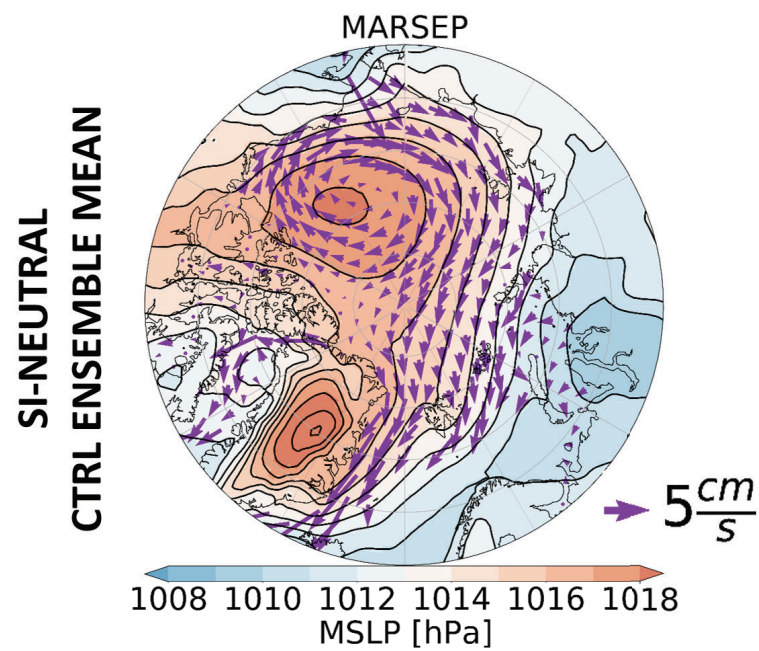


Figure C1: March-September average mean sea level pressure [hPa] and sea ice motion vectors [$m s^{-1}$] in the SI-NEUTRAL control ensemble mean.

Modes of atmospheric circulation variability: Both in winter and summer, the Arctic Oscillation represents the leading mode of climate variability in the extratropical latitudes of the northern hemisphere [Thompson and Wallace, 1998; Ogi et al., 2016]. The summer AO can impact sea ice by modulating the sea ice export from the marginal Arctic seas into the central Arctic Ocean and via Fram Strait into the North Atlantic [Ogi et al., 2016]. It affects sea ice also indirectly by modulating cloudiness and hence the amount of solar radiation [Ogi and Wallace, 2012]. The Arctic Dipole pattern, instead, often considered as the second leading mode of Arctic mean sea level pressure variability, influences sea ice through changes of the meridional flow and hence of the northward heat transport and poleward sea ice advection on the Pacific-side of the Arctic [Wang et al., 2009; Overland et al., 2012; Lee et al., 2025]. The AD has been suggested to play a key role for the formation of the 2007 extreme sea ice loss event [Wang et al., 2009; Overland et al., 2012; Lee et al., 2025].

To verify the capability of EC-Earth3 in capturing these modes, we apply an empirical orthogonal function analysis to compare the representation of the summer Arctic Oscillation and Arctic Dipole pattern in the EC-Earth3 "SI-NEUTRAL" 300-trajectory control ensemble with ERA5 [Hersbach et al., 2020] (Figures C2 and C3). We compute the Arctic Oscillation (Arctic Dipole pattern) as the first (second/third) empirical orthogonal function of square root of cosine of latitude weighted mean sea level pressure anomalies northern of 20°N (70°N) [Thompson and Wallace, 2000; Wang et al., 2009; Lee et al., 2025]. According to Lee et al. [2025], the ordering of the second and third EOF modes of Arctic mean sea level pressure have not been stable in time between 1980 and 2020. Therefore, the Arctic Dipole pattern may potentially also emerge as the third EOF mode of Arctic mean sea level pressure.

The patterns in Figures C2 and C3 are presented as a linear regression of mean sea level pressure anomalies on the principle components (normalized to one standard deviation) associated with these three EOFs. In ERA5, the second mode is characterized by a dipole-like structure with opposing centers of action over Greenland and the east Siberian Sea, both in May-June-July (MJJ) and June-July-August (JJA). The third mode in ERA5 is given by opposing centers of action between the Beaufort Sea and the Russian coast, both in May-June-July and June-July-August. In EC-Earth3, the ordering of the modes is less straightforward compared to ERA5. In JJA, the second (third) mode in EC-Earth3 looks similar to the third (second) mode in ERA5. However, the Greenland center of action of the EC-Earth3 third mode in JJA is shifted towards the North Atlantic compared to the second mode in ERA5, likely reducing the strength of the relationship between this mode and sea ice export through Fram Strait. In May-June-July, instead, the second EC-Earth3 mode seems to correspond to the second ERA5 mode, though again the centers of action seem to be slightly rotated compared to ERA5. In particular in MJJ, the second mode still appears to be the potentially relevant mode for sea ice loss. The precise link between this mode and sea ice transport may, however, vary between ERA5 and EC-Earth3. Investigating the role of the different modes for sea ice loss, including an analysis of CMIP6 large-ensembles, constitutes an exciting line of research for the future.

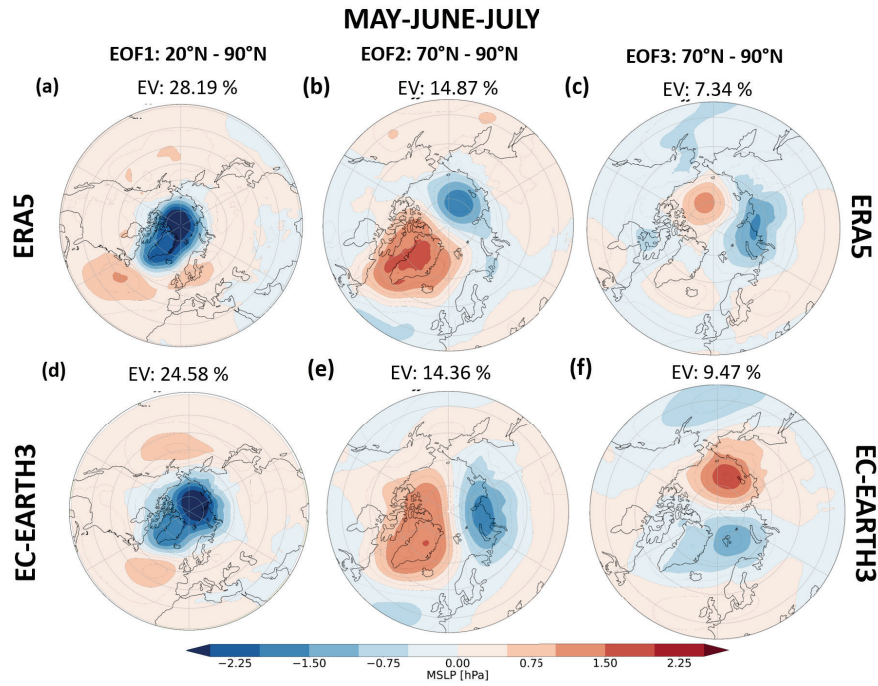


Figure C2: May-June-July averaged data: linear regression of mean sea level pressure (MSLP) on the principle component associated with (a,d) the first EOF applied to MSLP anomalies northern of 20° N and (b,e) the second EOF of MSLP anomalies northern of 70° N and (c,f) the third EOF of MSLP anomalies northern of 70° N for (a-b) the "SI-NEUTRAL" EC-Earth3 300-trajectory control ensemble and (d-f) ERA5 for the period 1979-2021 [Hersbach et al., 2020]. (a-f) All mean sea level pressure anomalies are weighted by the square root of cosine of latitude before the EOFs are computed to ensure that equal grid cell areas have equal weights in the analysis [Thompson and Wallace, 2000].

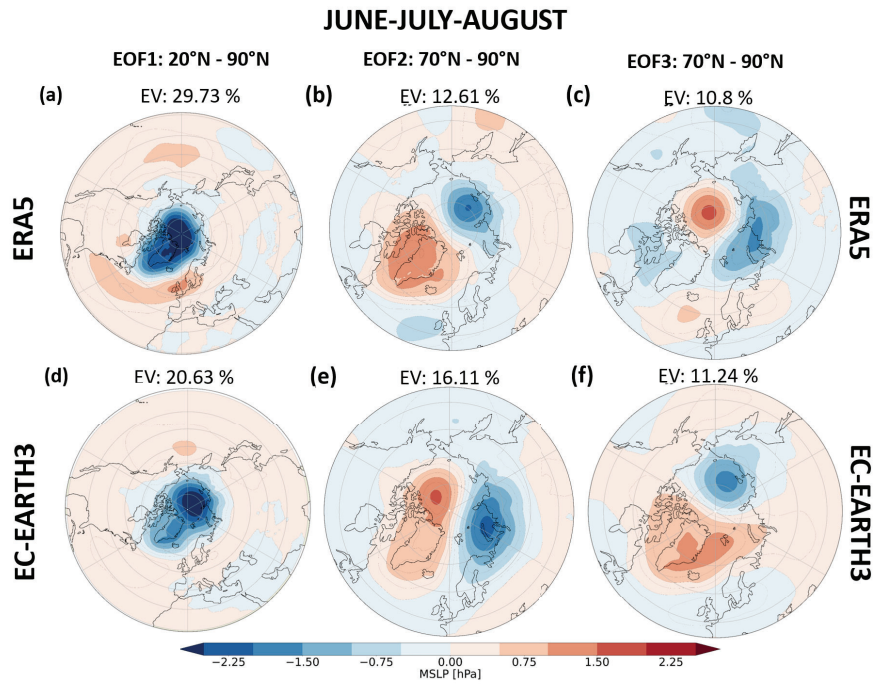


Figure C3: June-July-August averaged data: linear regression of mean sea level pressure (MSLP) on the principle component associated with (a,d) the first EOF applied to MSLP anomalies northern of 20° N and (b,e) the second EOF of MSLP anomalies northern of 70° N and (c,f) the third EOF of MSLP anomalies northern of 70° N for (a-b) the "SI-NEUTRAL" EC-Earth3 300-trajectory control ensemble and (d-f) ERA5 for the period 1979-2021 [Hersbach et al., 2020]. (a-f) All mean sea level pressure anomalies are weighted by the square root of cosine of latitude before the EOFs are computed to ensure that equal grid cell areas have equal weights in the analysis [Thompson and Wallace, 2000].

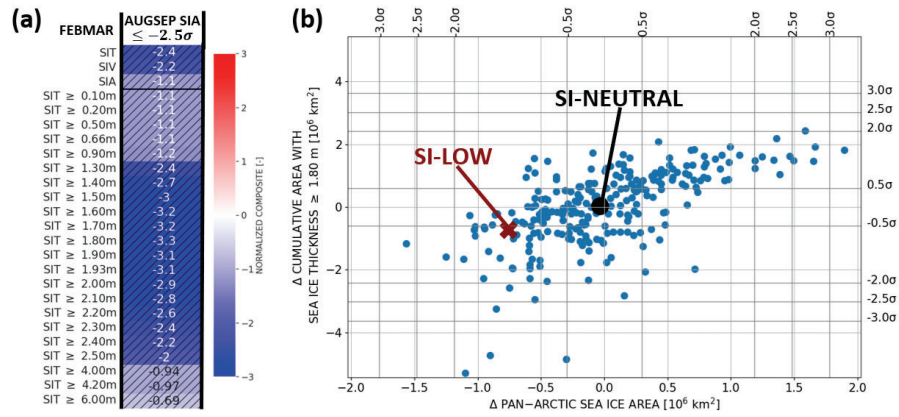


Figure C4: EC-Earth3 250-year control run: (a) Normalized mean anomalies of February-March mean quantities conditional on extreme August-September (AUGSEP) mean pan-Arctic sea ice area anomalies equal or smaller than -2.5 standard deviations. "SIV", "SIA" and "SIT" are the pan-Arctic sea ice volume, sea ice area and mean sea ice thickness. "SIT $\leq$ threshold" are anomalies in the cumulative area with sea ice thickness equal or larger than a critical threshold. Hatching denotes statistical significance at the 5% level assessed from a two-sided t-test applied to five composite estimates after subdividing the 250-year control run into five 50-member ensembles. (b) Scatter plot of February-March mean anomalies of the cumulative area with sea ice thickness equal or larger than 1.80 m vs. pan-Arctic sea ice area. The labels SI-NEUTRAL and SI-LOW show the anomaly values of the two quantities on the 01 March, i.e., during the initialization, of the two experiments described in Chapter 4.

C. Appendix to Chapter 4

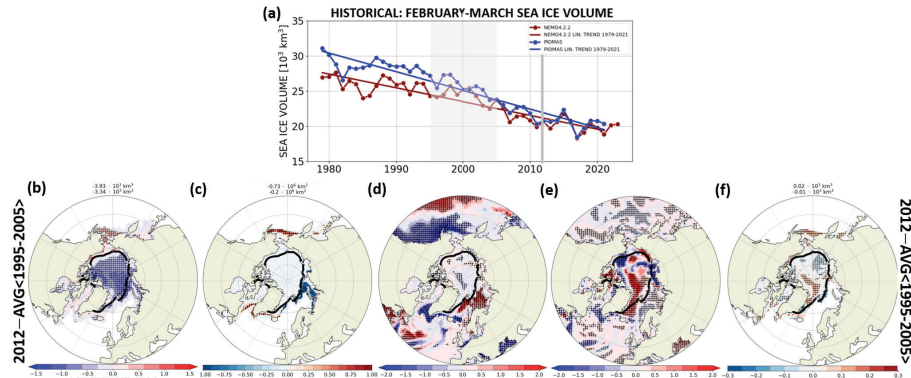


Figure C5: February-March mean pan-Arctic sea ice volume [10^3 km^3] for (red) a historical NEMO4.2.2 integration and (blue) PIOMAS. The gray shading shows the period 1995-2005 and the vertical bar the year 2012. As described in Chapter 4, the initial condition of the SI-LOW experiment is constructed by adding to the initial condition of the SI-NEUTRAL experiment the difference of selected snow-sea ice-ocean variables between 2012 and the 1995-2005 average ($2012 - \text{AVG}<1995-2005>$). Panels (b)-(f) show the imposed $2012 - \text{AVG}<1995-2005>$ anomalies for (b) sea ice thickness [m], (c) sea ice concentration [-], (d) mean ocean temperatures [$^{\circ}\text{C}$] over the upper most five layers of the ocean and (e) as (d), but for the sea water salinity [10^{-3}]. Hatching indicates where anomalies are larger in magnitude compared to one standard deviation of the NEMO4.2.2 variability around a linear trend fitted to the period 1979-2021 in that data product.

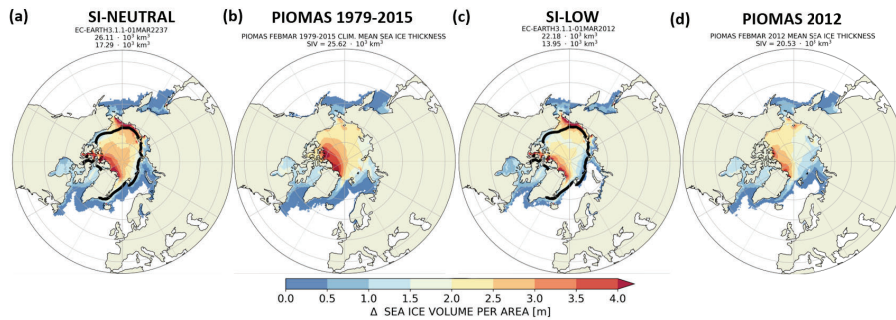


Figure C6: Sea ice thickness [m] in (a,c) the 01 March initial conditions of the (a) SI-NEUTRAL and (c) SI-LOW experiments and (b,d) on February-March average in PIOMAS (b) between 1979-2015 and (d) in 2012. The black contour line shows the August-September mean 15% sea ice concentration line in the SI-NEUTRAL control ensemble simulation.

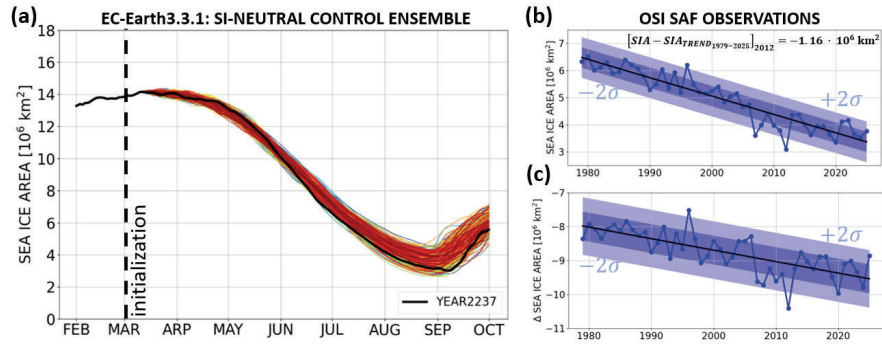


Figure C7: (a) Pan-Arctic sea ice area in the SI-NEUTRAL control ensemble with $N=300$ trajectories. (b-c) European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Ocean and Sea Ice Satellite Application Facility (OSI SAF) data EUMETSAT Ocean and Sea Ice Satellite Application Facility [2024]. (b) August-September mean pan-Arctic sea ice area and (c) the difference between August-September and February-March mean sea ice area (i.e. the reduction of sea ice area from the annual maximum to the annual minimum).

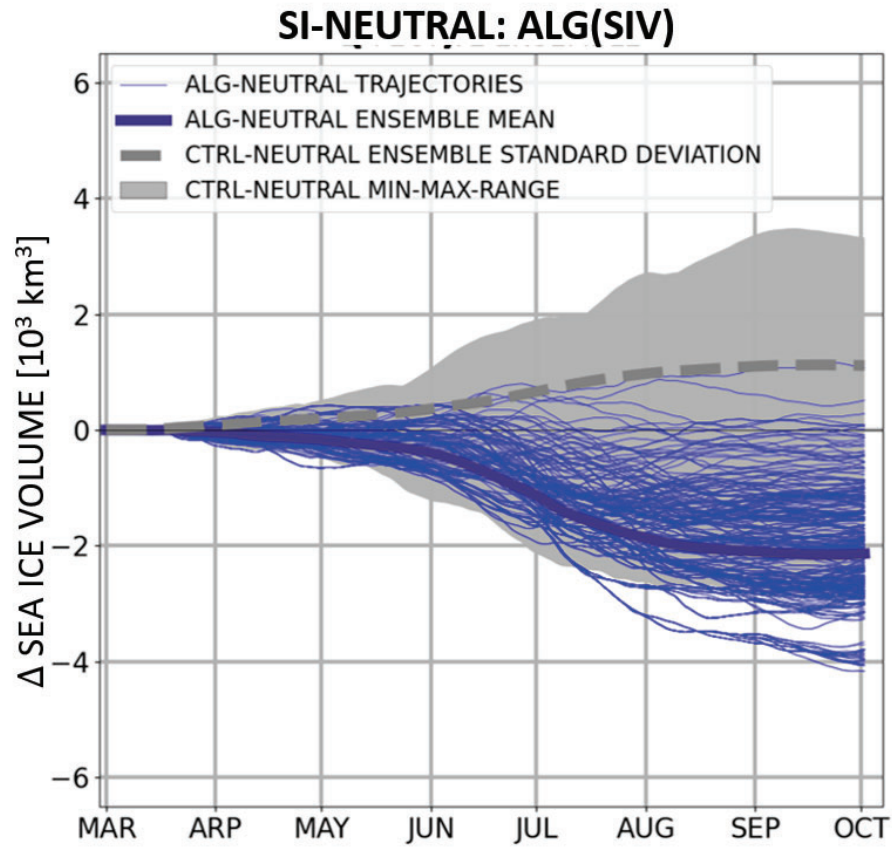


Figure C8: Pair of $N = 300$ trajectory control and rare event algorithm ensemble simulations initialized from the SI-NEUTRAL sea ice-ocean initial condition. The algorithm observable is the pan-Arctic sea ice volume. Trajectories (thin lines) and ensemble mean (blue thick line) of 15-day running mean sea ice volume anomalies [10^3 km^3] obtained with the algorithm and computed relative to the SI-NEUTRAL control ensemble mean. The gray dashed lines and shadings are the SI-NEUTRAL control ensemble standard deviations and minimum-maximum ranges.

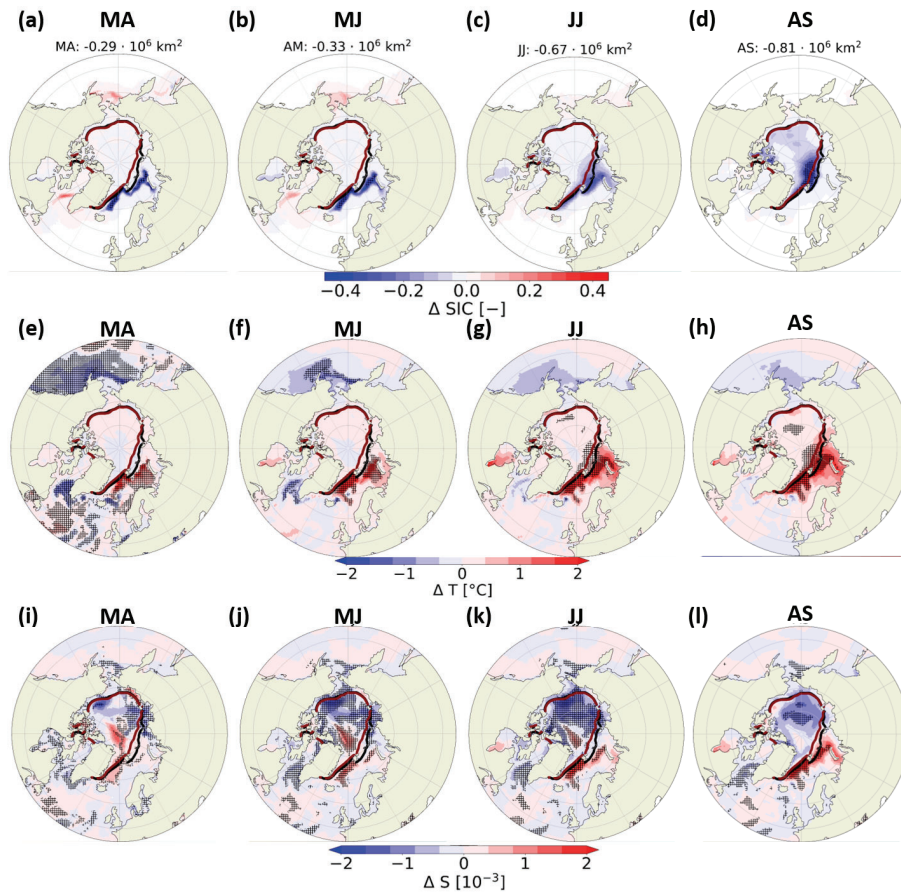


Figure C9: Seasonal evolution of the differences between the SI-LOW and SI-NEUTRAL control ensemble means: (a-d) SIC anomalies $[-]$, (e-h) ocean temperature anomalies $[\text{°C}]$ on average over the upper five ocean layers and (i-l) as (e-h), but for the salinity $[10^{-3}]$. Hatching indicates regions where the anomalies are larger in magnitude than the SI-NEUTRAL control ensemble standard deviation.

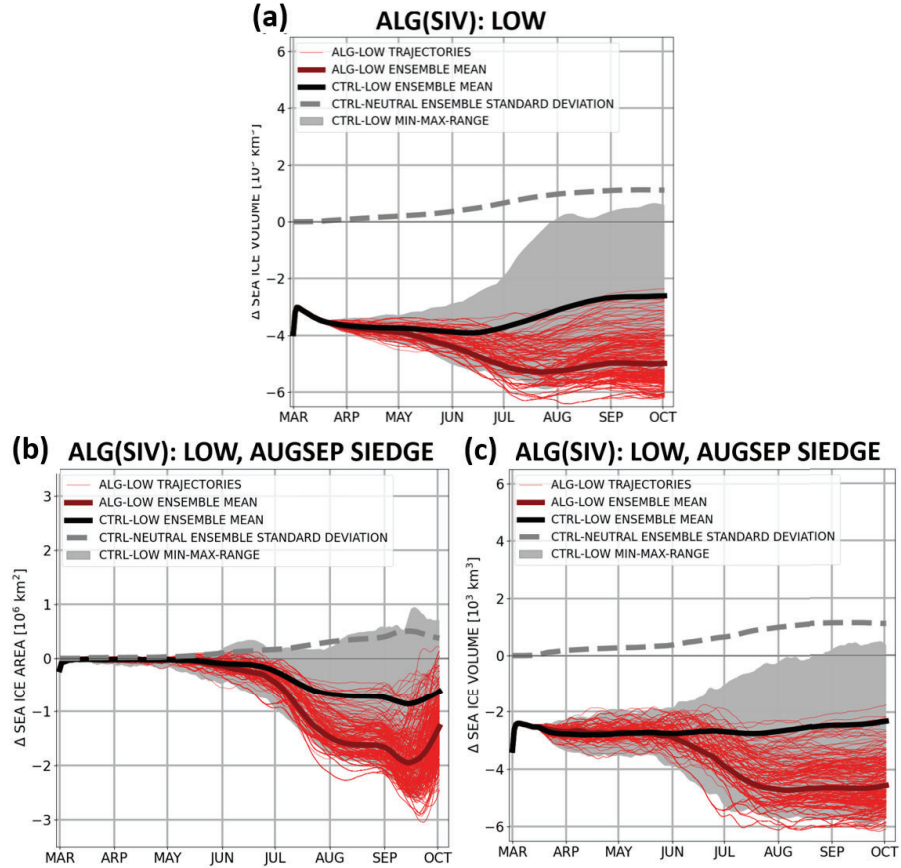


Figure C10: Pair of $N = 300$ trajectory control and rare event algorithm ensemble simulations initialized from the SI-LOW sea ice-ocean initial condition. The algorithm observable is the pan-Arctic sea ice volume. Trajectories (thin lines) and ensemble mean (red thick line) of 15-day running mean (a,c) sea ice volume anomalies [10^3 km^3] and (b) sea ice area anomalies [10^6 km^2] obtained with the algorithm and computed relative to the SI-NEUTRAL control ensemble mean. The gray dashed lines and shadings are the SI-LOW control ensemble standard deviations and minimum-maximum ranges. The dark black line shows the difference between the SI-LOW and the SI-NEUTRAL control ensemble means. (a) Pan-Arctic sea ice volume and (b-c) the (b) sea ice area and the (c) sea ice volume computed within the domain enclosed by the AUGSEP mean 15% sea ice concentration line of the SI-NEUTRAL control ensemble mean.

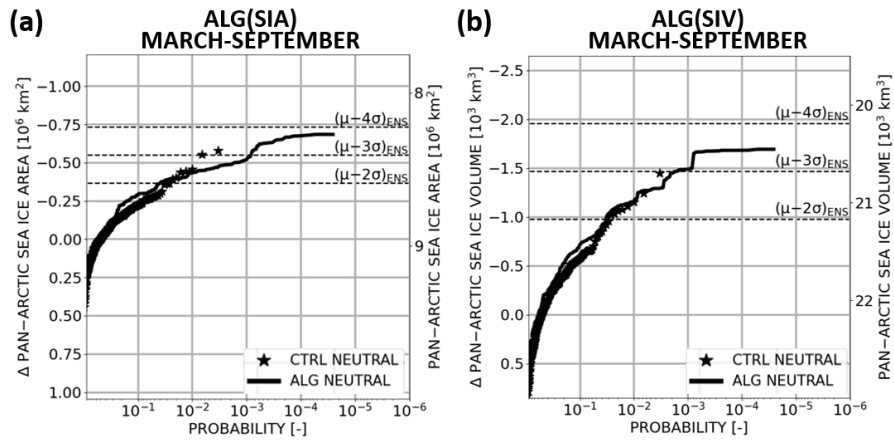


Figure C11: Probabilities (x -axes) of March-September mean pan-Arctic (a) sea ice area and (b) sea ice volume equal or smaller than a given threshold (y -axes) for (a) the "SI-NEUTRAL: ALG(SIA)" and (b) the "SI-NEUTRAL: ALG(SIV)" experiment. While the right y -axis shows absolute sea ice area (sea ice volume) values, the left y -axis expresses these as anomalies relative to the SI-NEUTRAL control ensemble mean. Both are displayed in reverse order. The gray dashed lines indicate how many standard deviations a sea ice area value is below the mean of the SI-NEUTRAL control ensemble.

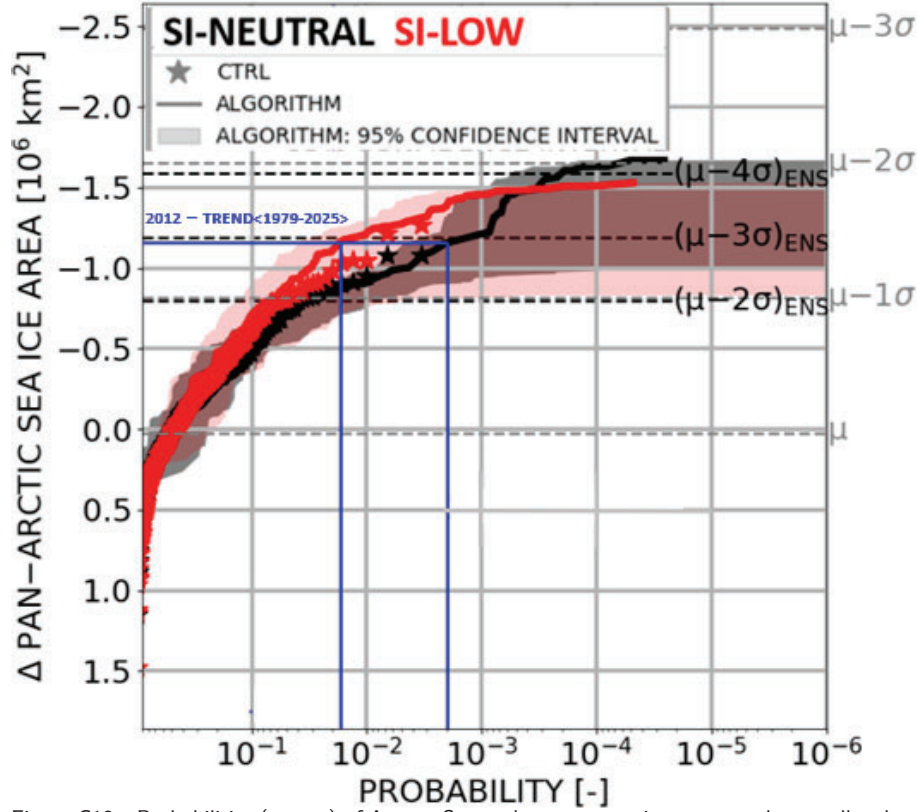


Figure C12: Probabilities (x -axes) of August-September mean sea ice area equal or smaller than a given threshold (y -axes) as a function of two different sea ice-ocean initial conditions for two pairs of $N = 300$ trajectory (stars) control and (solid lines) rare event algorithm ensembles. The Figure is the same as in Figure 4.3(b), but the impact of the imposed 2012-AVG<1995-2005> sea ice-ocean changes on the mean of the distribution, i.e., an offset of $-0.81 \cdot 10^6 \text{ km}^2$ (table 4.2), is removed from the red curve (this means that the SI-LOW ensemble mean is adjusted to have the same value as the SI-NEUTRAL control ensemble mean). The observable used for the simulations with the algorithm is the pan-Arctic sea ice volume. The left y -axes shows sea ice area anomalies relative to the SI-NEUTRAL control ensemble mean. The latter is identical with the adjusted SI-LOW control ensemble mean. Both are displayed in reverse order. The shading in direction of the x -axes shows $\pm 2\sigma$ intervals around the probability estimates using Equation (4.4) in section 4.2.2.3. The blue lines indicate the 2012 observed August-September mean sea ice area anomaly relative to the 1979-2025 linear trend line.

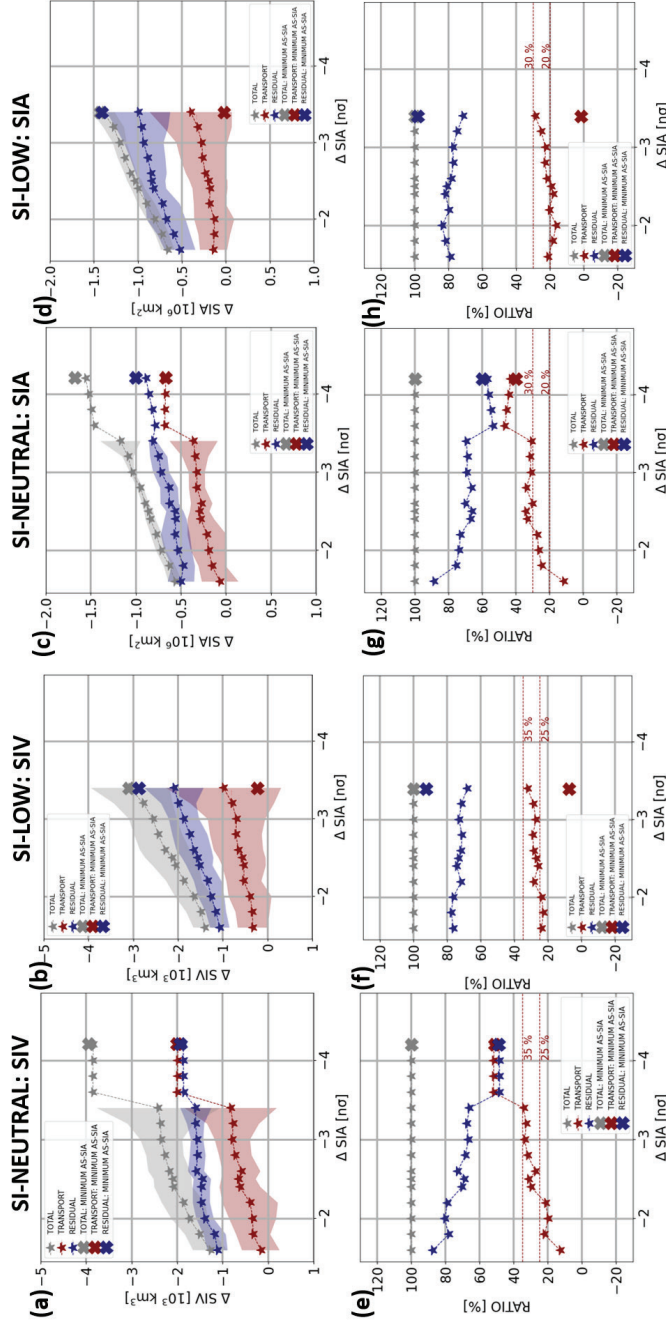


Figure C13: The results are based on (a,e,c,g) the "SI-NEUTRAL: ALG(SIV)" and (b,f,d,h) the "SI-LOW: ALG(SIV) experiments": (a-d) Composite mean anomalies (dashed lines with star markers) of the seasonally-integrated ($\text{AVG} < 01 \text{ March-01 August, } 01 \text{ March-02 August, } \dots, 01 \text{ March-30 September} >$) terms of (a-b) the sea ice volume [m] and (c-d) the sea ice area [-] budget analysis (Equation (4.8)) conditional on trajectories with an AUGSEP sea ice area of between $n\sigma$ and $(n + 0.5)\sigma$ ($n \in \{1.6, 1.8, 2.0, \dots, 4.2\}$) control ensemble standard deviations below the control ensemble means. The shading denotes 95% confidence intervals (see section 4.2.2.3). The "X"-marker indicates the sea ice anomalies for the most extreme sea ice area reduction trajectories available from the two ensembles respectively. (e-h) As (a-d), but showing the ratio [%] of the total, transport-induced and thermodynamically-induced sea ice volume anomalies with respect to the total sea ice volume anomalies.

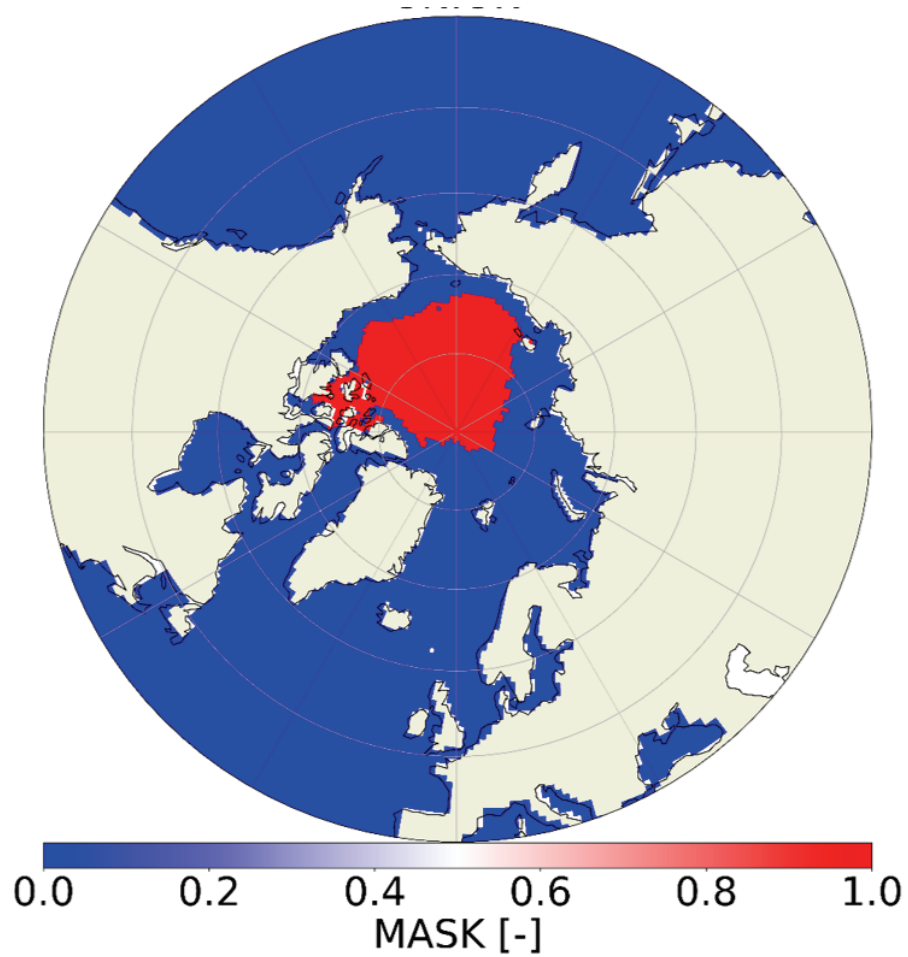


Figure C14: Domain (red area) defined via all grid cells where thermodynamically-induced sea ice volume anomalies in the SI-NEUTRAL and SI-LOW experiments (Figure 4.7(b,e)) are significantly negative in at least one of the two of these experiments, i.e., the union of the regions of statistically significant negative thermodynamically-induced sea ice volume anomalies over both experiments.

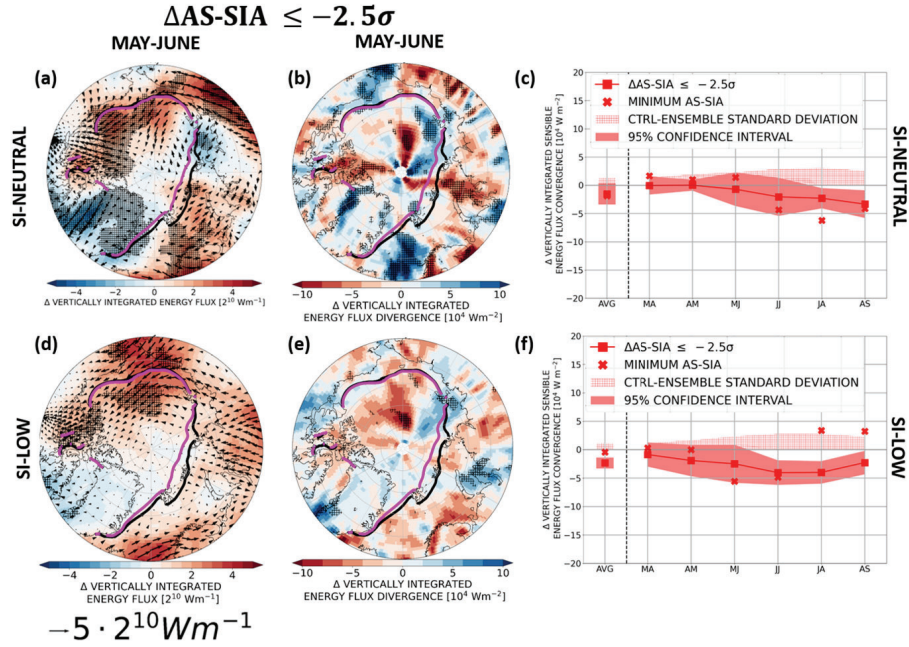


Figure C15: (a-c) "SI-NEUTRAL: ALG(SIV)" and (d-f) "SI-LOW: ALG(SIV)" experiments: (a,b,d,e) May-June composite mean anomalies ($\Delta AS-SIA \leq -2.5\sigma$) of (a,d) the vertically integrated horizontal sensible energy flux [2^{10} W m^{-1}] (vectors and magnitude) and (b,e) the horizontal divergence of the vertically integrated horizontal sensible energy flux [10^4 W m^{-2}] computed relative to the control ensemble means. Hatching denotes statistical significance at the 5% level. (c,f) Seasonal evolution of the vertically integrated horizontal sensible flux divergence presented as a spatial average over the domain shown in Figure C13 [10^4 W m^{-2}]. Squares are composites as in (a,b,d,e) and stars show the single trajectories leading to the most extreme sea ice area reductions available from the two experiments. Hatching indicates 95% confidence intervals and shading the control ensemble standard deviations. In (b,c,e,f), negative anomalies imply enhanced accumulation of sensible energy. The black and magenta contour lines in (a,b,d,e) show the August-September mean 15% sea ice concentration line in the SI-NEUTRAL and SI-LOW control ensemble simulation.

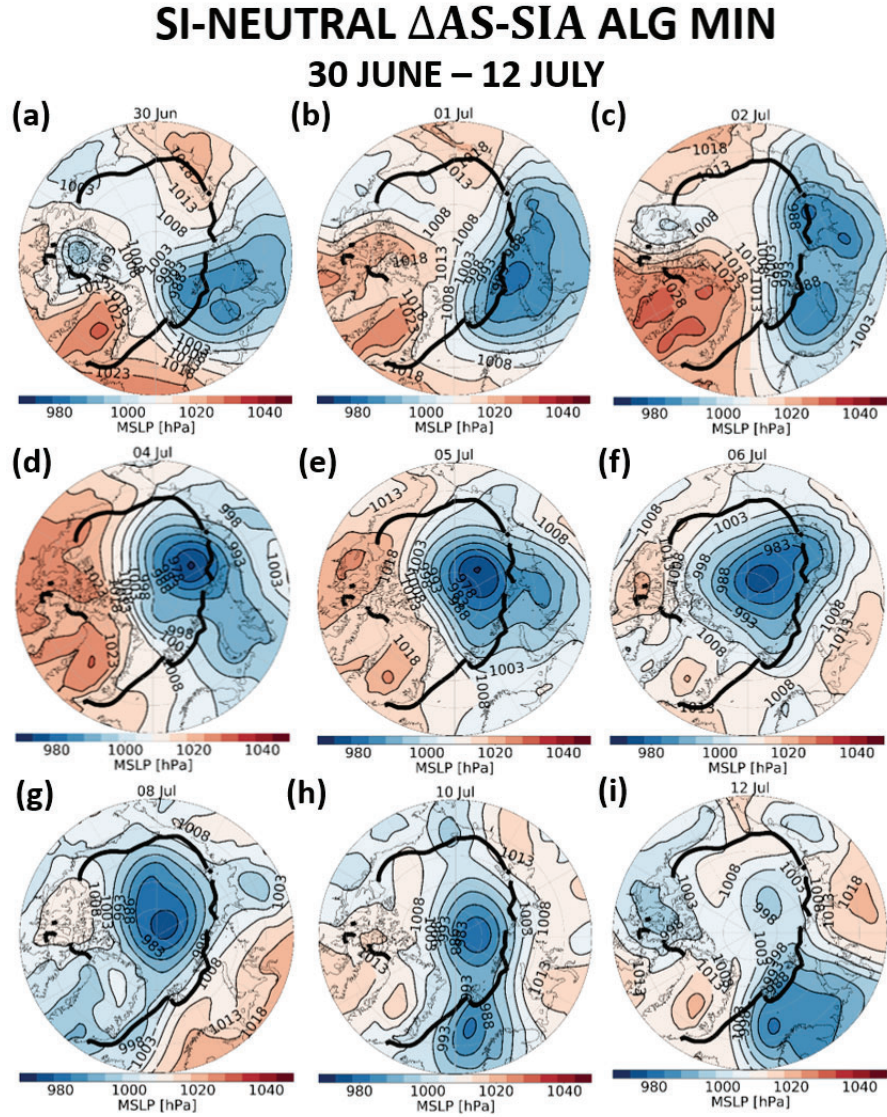


Figure C16: Trajectory leading to the most extreme sea ice area reduction available from the "SI-NEUTRAL: ALG(SIV)" experiment: daily average mean sea level pressure [hPa] from 30 June to 12 July. The black contour line shows the August-September mean 15% sea ice concentration line in the SI-NEUTRAL control ensemble simulation.

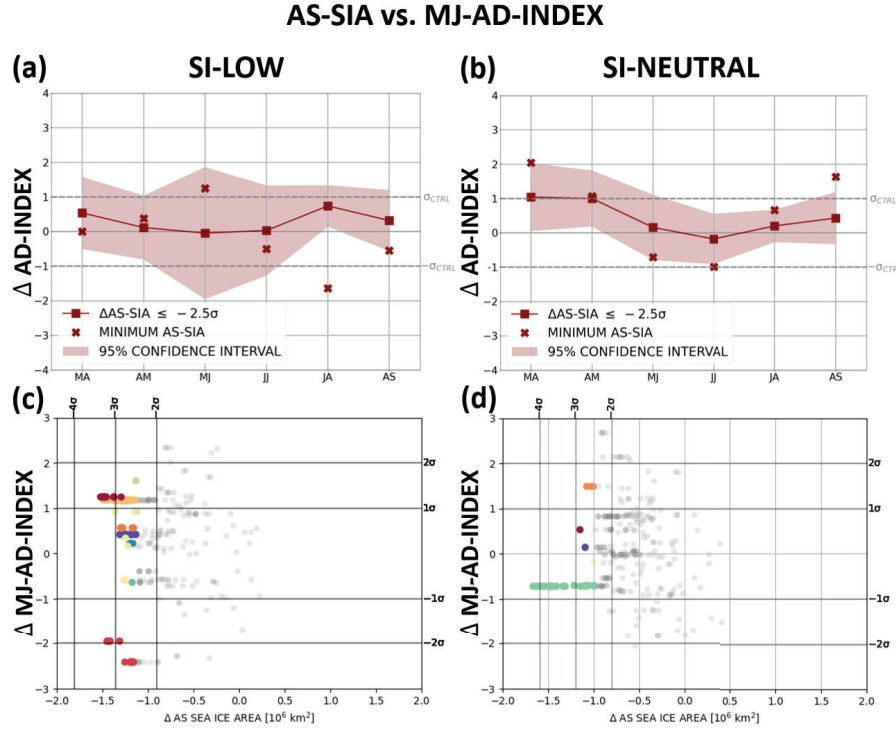


Figure C17: Arctic Dipole (AD) index (a,b) over the course of the season and (c-d) in May-June for (a,c) the "SI-NEUTRAL: ALG(SIV)" and (b,d) the "SI-LOW: ALG(SIV)" experiments. The AD index is computed by projecting the bimonthly averaged mean sea level pressure anomalies northern of 70° N on the second empirical orthogonal function applied to square root of cosine of latitude weighted mean sea level pressure anomalies northern of 70° N. (a,b) shows (squares) composite mean anomalies of the AD index conditional on trajectories leading to an August-September mean sea ice area of at least 2.5 control ensemble standard deviations below the control ensemble mean and (stars) the AD index for the most extreme sea ice area reduction trajectories available from the two experiments respectively. Hatching shows 95% confidence intervals (see section 4.2.2.3). (c-d) The May-June Arctic Dipole index (y -axes) vs. August-September (AUGSEP) mean sea ice area anomalies (x -axes) for all trajectories from the algorithm ensembles. Data points associated with an AUGSEP sea ice area value of more than 2.5 standard deviations below the control ensemble means are shown in colors. Extreme trajectories sharing the same ancestor at the initialization time have the same color.

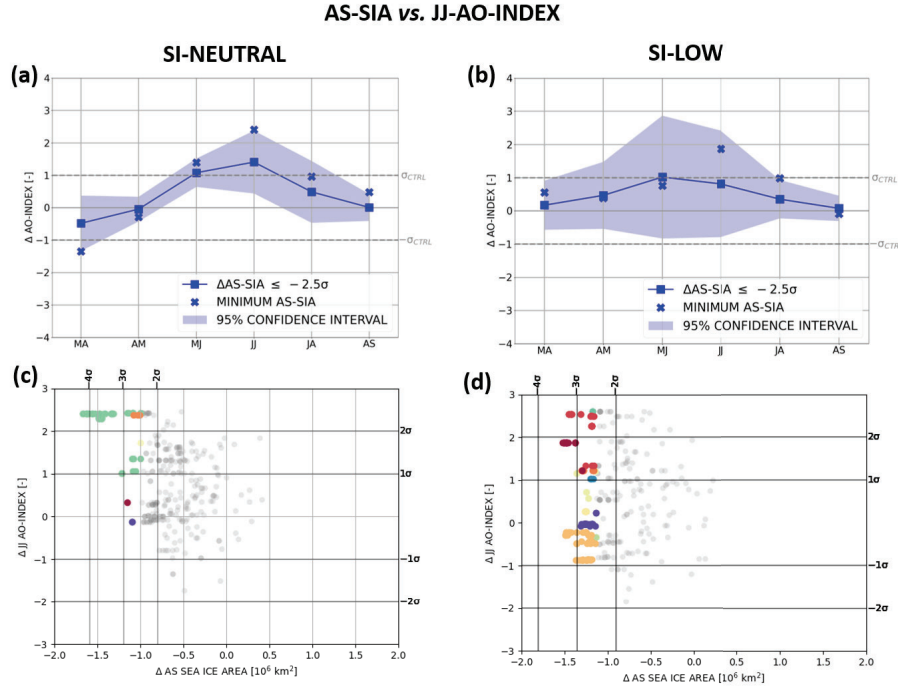


Figure C18: Arctic Oscillation (AO) index (a,b) over the course of the season and (c-d) in June-July for (a,c) the "SI-NEUTRAL: ALG(SIV)" and (b,d) the "SI-LOW: ALG(SIV)" experiments. The AO index is computed by projecting the bimonthly averaged mean sea level pressure anomalies northern of 20° N on the first empirical orthogonal function applied to square root of cosine of latitude weighted mean sea level pressure anomalies northern of 20° N. (a,b) shows (squares) composite mean anomalies of the AO index conditional on trajectories leading to an August-September mean sea ice area of at least 2.5 control ensemble standard deviations below the control ensemble mean and (stars) the AO index for the most extreme sea ice area reduction trajectories available from the two experiments respectively. Hatching shows 95% confidence intervals (see section 4.2.2.3). (c-d) The June-July Arctic Oscillation index (y -axes) vs. August-September (AUGSEP) mean sea ice area anomalies (x -axes) for all trajectories from the algorithm ensembles. Data points associated with an AUGSEP sea ice area value of more than 2.5 standard deviations below the control ensemble means are shown in colors. Extreme trajectories sharing the same ancestor at the initialization time have the same color.

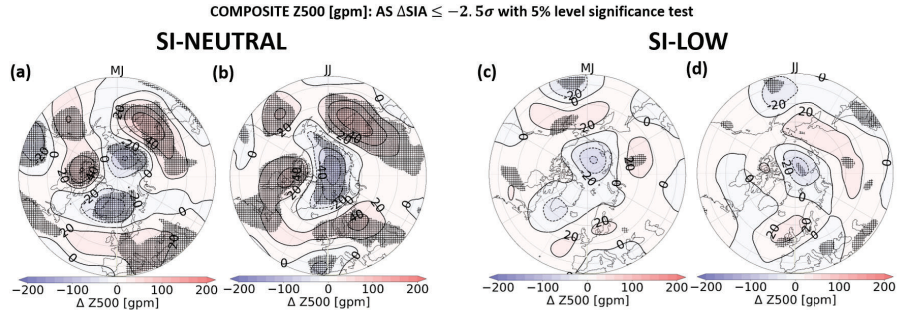


Figure C19: (a,c) May-June and (b,d) June-July composite mean anomalies of 500 hPa geopotential height anomalies [gpm] conditional on all trajectories with an AUGSEP sea ice area of at least 2.5 control ensemble standard deviations below the control ensemble means. The hatching indicates statistical significance at the 5% level. The results are based on (a,b) the "SI-NEUTRAL: ALG(SIV)" and (c,d) the "SI-LOW: ALG(SIV)" experiments.

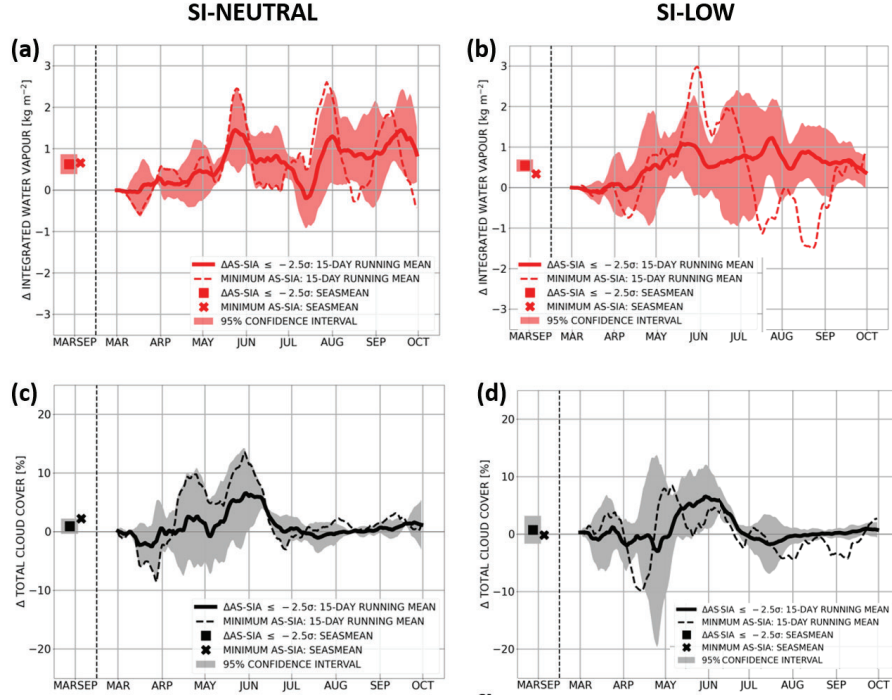


Figure C20: (a,c) "SI-NEUTRAL: ALG(SIV)" and (b,d) "SI-LOW: ALG(SIV)" experiments: MARSEP and 15-day running mean (a,b) integrated water vapor [kg m^{-2}] and (c,d) total cloud cover anomalies [%] relative to the control ensemble means. All quantities are spatially averaged over the domain defined by the union of statistically significant negative thermodynamically-induced sea ice volume anomalies (Figure C13). Thick lines and square markers are composite mean anomalies (Δ AS-SIA $\leq -2.5\sigma$) and the shading shows 95% confidence intervals around these composite estimates. The thin lines and "x"-markers are the trajectories with the most extreme sea ice reduction available from the two experiments respectively.

S4C: Adequacy of the rare event simulations

The degeneracy level (see Supplementary Information S2B for more details about the general problem of degeneracy) in the EC-Earth3 rare event simulations is low (Figures C21, C22, C23). Throughout the simulation period, the survival rate is above 92.5% in all rare event simulations produced for Chapter 4 (Figure C21). Consequently, the number of different initial-time ancestors leading to at least one final-time descendant is relatively large (between 68 and 101; Figure C23). Moreover, the histograms of the number of final-time descendants that are associated with the different initial-time ancestors confirm the low degeneracy level. Most of the initial-time ancestors lead to between 1 and less than 70 final-time descendants. These simulations do not contain a situation where one single initial-time ancestor dominates the entire ensemble (Figure C23).

Finally, the number of different initial-time ancestors leading to extremely negative August-September mean sea ice area anomalies in the EC-Earth3 rare event simulations is systematically increased compared to the control ensembles for the same computational cost (Figure C22). In contrast to the control ensembles, the EC-Earth3 rare event simulations therefore allow to perform a quantitative statistical analysis of the extremes. Figure C22 also shows that a relatively large number of extreme trajectories start to separate near the end of the simulation period (up to 121 extremes in the SI-LOW experiment). Many of these trajectories are strongly dependent on each other as they start to diverge near the end of the melting season. However, these trajectories would continue to diverge if one continued these simulations until the following winter. Therefore, these experiments can provide a relatively large ensemble for studying the autumn-winter response of the atmospheric circulation to extreme late summer sea ice lows.

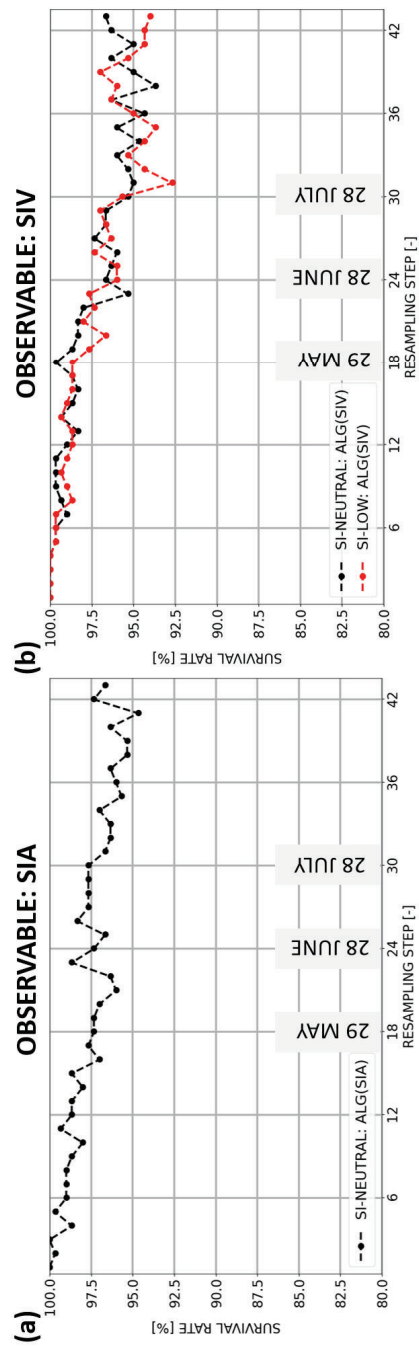


Figure C21: (a) SIA-NEUTRAL: ALG(SIA) and (b) (black) SIA-NEUTRAL: ALG(SIV) and (red) SIA-LOW: ALG(SIV) experiments: fraction of surviving trajectories with respect to the ensemble size for selection step [%].

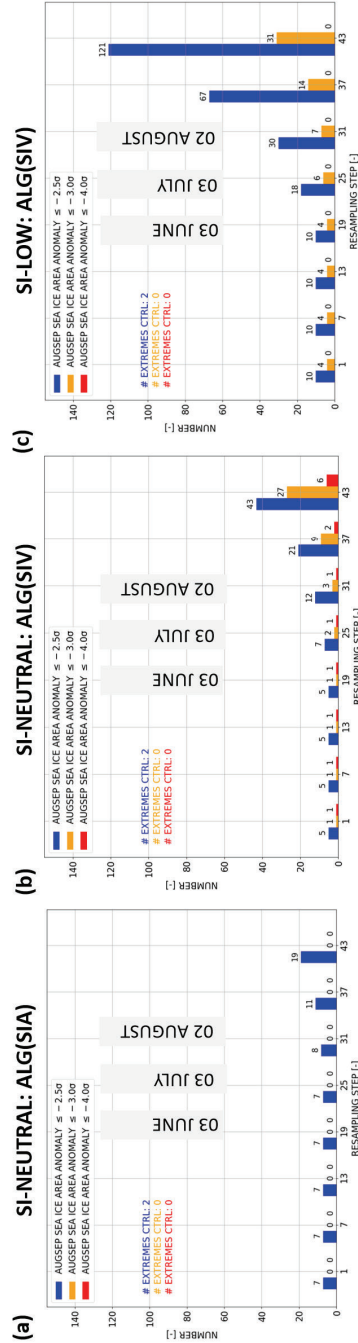


Figure C22: (a) SIA-NEUTRAL: ALG(SIA), (b) SIA-NEUTRAL: ALG(SIV) and (c) SIA-LOW: ALG(SIV) experiments: number of distinct ancestors prior to the indicated resampling step leading extremely negative August-September mean sea ice area anomalies of (blue) -2.5 , (orange) -3 and (red) -4 control ensemble standard deviations. For example, "18" at resampling step "25" in (c) means that one can find 18 extreme events for which the trajectories technically start to separate at least five days before that resampling step (or even earlier). The inset text also shows the number of extremes sampled with the control ensembles. Note that (a) and (b) have exactly the same control ensemble.

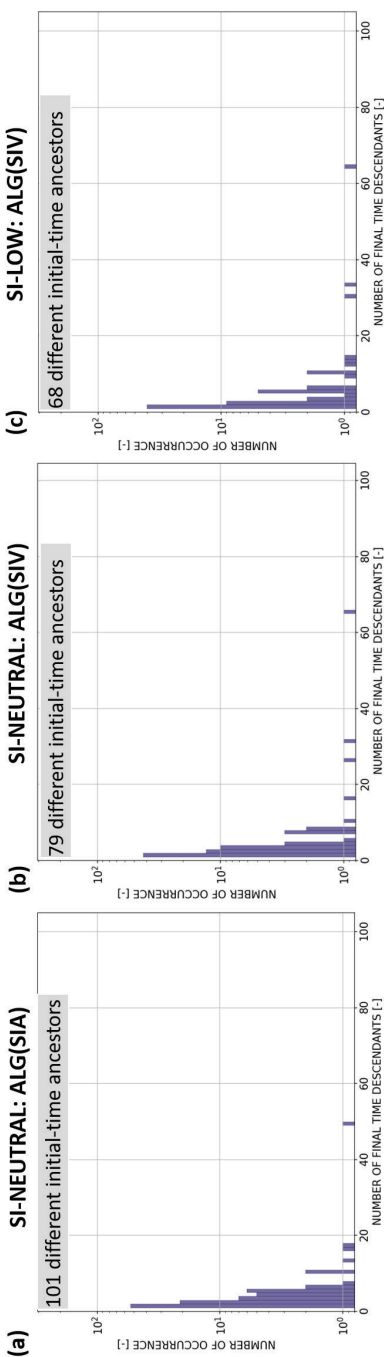


Figure C23: (a) SIA-NEUTRAL: ALG(SIA), (b) SIA-NEUTRAL: ALG(SIA) and (c) SIA-NEUTRAL: ALG(SIV) experiments: histograms of the number of final-time descendants for different initial-time ancestors present in the rare event simulations with EC-Earth3.

Appendix D

List of Publications Related to the Thesis

First author

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*, **62**, 5219-5237, <https://doi.org/10.1007/s00382-024-07160-y> (Chapter 2)

Sauer, J., Massonnet, F., Zappa, G., and Ragone, F., 2025: Ensemble design for seasonal climate predictions: studying extreme Arctic sea ice lows with a rare event algorithm, *Earth System Dynamics*, <https://doi.org/10.5194/esd-16-683-2025>, **16**, 683-702, (Chapter 3).

Sauer, J., Zappa, G., Ragone, F., and Massonnet, F.: Disentangling the thermodynamic vs. dynamic drivers of extreme Arctic sea ice reduction using rare event sampling in EC-Earth3: in preparation, to be submitted to *Journal of Climate* (Chapter 4).

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