# REQUEST FOR A SPECIAL PROJECT 2024–2026

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| **MEMBER STATE:** | Belgium |
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| **Project Title:** | Simulation of extremes of Arctic sea ice reduction with a rare event algorithm in EC-Earth3 |

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| If this is a continuation of an existing project, please state the computer project account assigned previously. | | |
| Starting year: (A project can have a duration of up to 3 years, agreed at the beginning of the project.) | 2024 | |
| Would you accept support for 1 year only, if necessary? | YES | |

| **Computer resources required for project year:** | **2024** | **2025** | **2026** |
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| High Performance Computing Facility [SBU] | 32,000,000 | 14,000,000 | 14,000,000 |
| Accumulated data storage (total archive volume)[2] [GB] | 90,000 | 125,000 | 160,000 |

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# Extended Abstract

## 1 Introduction

The Arctic sea ice cover has been shrinking since at least the late 1970s, in large part due to anthropogenic emissions of greenhouse gases. Besides this downward trend, internal variability contributes to the year-to-year variations, and can cause **extreme fluctuations of the annual Arctic sea ice minimum** (Ding et al. 2017, Ono et al. 2019, Francis and Wu 2020). Extreme Arctic sea ice reduction, such as observed in the summers of 2007 and 2012, influences mid-high latitude weather and climate (e.g. Screen and Simmonds 2010, Francis and Vavrus 2012, Delhaye et al. 2022), impacts the integrity of the permafrost (Lawrence et al. 2008, Heijmans et al. 2022), and has repercussions on Arctic Ocean accessibility (Eicken 2013, Smith and Stephenson 2013). A precise understanding of the **physical drivers** of extremes of Arctic sea ice reduction, their **seasonal predictability**, and a quantification of the **relative contribution of anthropogenic and natural variability** on their formation, remain however challenging.

A key issue in studying climate extremes is the **lack of robust statistics** in observations and in numerical simulations with computationally expensive climate models. A possible solution to this problem is given by **rare event algorithms**, computational techniques developed in statistical physics to **increase the sampling efficiency of rare events in numerical simulations** (e.g. Kahn and Harris 1951, Del Moral 2004, Giardina et al 2011, Ragone et al 2018, Grafke and Vanden-Eijnden 2019). Typically they take the form of **genealogical algorithms**, where a set of cloning and suppression rules are applied to the members of an **ensemble simulation** along the numerical integration, in order to focus the computational effort only on trajectories leading to a class of extreme events of interest. **This allows to simulate a number of extreme events orders of magnitude larger than what possible with direct numerical simulations for a given computation cost, and to sample events so rare that they would be impossible to observe otherwise**. Recently, these techniques have been applied to climate science and fluid dynamics to study heatwaves (Ragone et al 2018, Ragone and Bouchet 2020, Ragone and Bouchet 2021), large scale precipitation (Wouters et al 2023), tropical storms (Plotkin et al 2019, Webber et al 2019) and turbulent flows (e.g. Lestang et al 2018, Bouchet et al 2019).

In this project we will study **extremes of Arctic sea ice reduction in the EC-Earth3 Earth system model** (Döscher et al 2022), using a **rare event algorithm designed to study persistent, long lasting events** (Del Moral and Garnier 2005, Giardina et al 2011, Ragone et al 2018). This rare event algorithm has already been used to study midlatitude heatwaves both in intermediate complexity climate models (Plasim, Ragone et al. 2018, Ragone and Bouchet 2020), and in Earth system models of the same complexity as EC-Earth3 (CESM, Ragone and Bouchet 2021). Thanks to the improved sampling, we will perform a **precise analysis of the statistics and of the precursors of extreme Arctic sea ice reduction** in EC-Earth3. This analysis will improve our understanding of the dynamical drivers of extreme sea reduction events, that will allow to improve their seasonal predictability and the assessment of their impacts.

# 2 Scientific description

## 2.1 State of the art

The variability of 44-yr observed record of summer Arctic sea ice extent shows that after a nearly linear decline between 1979 and 2006, **sea ice extent dropped in just one year by 34%** relative to the 1979-2006 average (> 3-sigma event), leading to a record low in September 2007 (Stroeve et al. 2008). A second record low followed five years later, in 2012 (> 4-sigma event). The conditions responsible for these extreme events are not completely understood, and different explanations have been proposed in the literature.

**Ocean-sea ice model studies** attributed the 2007 event to **preconditioning**, that is long-term thinning of the ice leading to low values of the sea ice area already at the beginning of the melting season, and to strengthened transpolar drift caused by **anomalously persistent southerly winds** in the Pacific sector of the Arctic Ocean (Zhang et al. 2008, Lindsay et al. 2009, Kauker et al. 2009). According to these studies, oceanic drivers were of little importance. **Observational studies** based on moorings and ice mass balance instead argue for a **strong role of oceanic processes** through inflow of warm Pacific waters through the Bering Strait, leading to anomalous ice bottom melting (Perovich et al. 2008, Woodgate et al. 2010). The 2012 event was attributed to preconditioning and to a storm that passed over the Arctic in August, breaking the ice and enhancing the ice albedo feedback (Simmonds et al. 2012, Guemas et al. 2013, Zhang et al. 2013, Lukovich et al. 2021)

In general, the factors driving the variability of Arctic sea ice area are 1) **persistence and reemergence** of anomalies, 2) **preconditioning** through the winter-spring sea ice state, and 3) **large-scale oceanic and atmospheric circulation** and associated regional **feedback mechanisms.**

The **memory properties of the sea ice-ocean system** are key in determining persistence and preconditioning. Observational and model studies indicate characteristic e-folding time scales of Arctic sea ice area anomalies of 2-5 months (Blanchard-Wrigglesworth et al. 2011). During the melting season this time scale is smaller in spring and sharply increases in summer, partly due to the sea ice albedo feedback (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 (Chevallier et al. 2012).

The atmospheric and oceanic circulation on the other hand affect sea ice both dynamically and thermodynamically. In particular, the **Arctic Oscillation (AO)** and **Arctic Dipole Anomaly (ADA)** pattern affect sea ice area by modulating the sea ice export out of the marginal Arctic seas into the central Arctic Ocean and the North Atlantic (Wang,et al. 2009), and by affecting cloud cover and thus incoming solar radiation (Ogi et al. 2016). The ocean instead influences sea ice through **heat transport variability** in the North Pacific and North Atlantic (Woodgate et al. 2010, Arthun et al. 2012). A **precise quantification** of the relative importance of these processes is very hard to obtain, in large part due to the lack of robust statistics of Arctic sea ice reduction extremes in observations and simulations with complex numerical models.

## 2.2 Goal of the project and scientific questions

In this project we will use the **Giardina-Kurchan-Lecomte-Tailleur (GKLT) rare event algorithm** (Del Moral and Garnier 2005, Giardina et al 2011, Ragone et al 2018) to improve the sampling efficiency of extreme Arctic sea ice lows in ensemble simulations with EC-Earth3. The GKLT algorithm is designed to improve the sampling of extremes whose dynamics is characterised by **time persistency** (Ragone and Bouchet 2020). The method is therefore very well suited to study extremes of Arctic sea ice reduction.

The application of the algorithm will allow to **simulate events with return times up to tens and hundreds of thousands years**, for computational costs two-three orders of magnitude lower, and to have **hundreds of model trajectories corresponding to events with return time of the order of a few hundred years**. We will exploit these data to address the following scientific questions:

- What is the relative importance of **preconditioning** through winter-spring sea ice-ocean state **vs. thermodynamical and dynamical** processes in spring-summer in determining sea ice lows?
- What is the relative importance and what are the key **oceanic vs. atmospheric processes** contributing to extreme sea ice lows during spring-summer?
- What is the **probability of ultra-rare but high-impact events**, e.g. total disappearance of sea ice for one year in current climate conditions?

# 3 Proposed activities

### 3.2 Description of the rare event algorithm

The GKLT algorithm is a rare event algorithm designed to improve the statistics of rare values of time averaged observables. It is structured as follows - see Ragone et al. (2018), Ragone and Bouchet (2020), Ragone and Bouchet (2021) for a detailed treatment and formulas.

We let evolve in parallel an ensemble of N trajectories of the model starting from different initial conditions, iterating each trajectory for a total time T. During the ensemble run, at regular intervals of a fixed **resampling time $\tau$, some members of the ensemble 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 a **target observable of interest**, for example Arctic sea ice area, during the past resampling time $\tau$. The cloning rule is that each trajectory spawns a random number of copies of itself proportional on average to the value of its weight. A parameter k included in the definition of the weights determines how stringent is the selection of the trajectories, and its sign determines whether low or high values of the time average of the target quantity are favoured by the weights. In our case we are interested in selecting small values of Arctic sea ice cover, so k will be negative and trajectories with high values of the time averaged Arctic sea ice cover (weight close to 0) will likely die, while trajectories with low values (weight larger than 1) will generate multiple copies of themselves. The cloning mechanics takes care of keeping the total number of trajectories in the ensemble constant after each cloning event. The new ensemble is then run again for a resampling time $\tau$. The clones of each trajectory are 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.

Taking a resampling time of the same order of magnitude of the typical decorrelation time of the dynamics (typically 5 model days for applications to climate simulations), one can see that this populates the ensemble of **model trajectories characterised by extreme values of the time average of the target observable over the entire simulation time** T. Additionally, the math of the method gives a formula that relates the probability of observing a trajectory in a normal ensemble simulation to that of observing the same trajectory in a simulation with the algorithm. This allows to compute statistical quantities (return times, composite maps, correlations, etc.) related to the original statistics of the model, using data generated with the algorithm. However, since the algorithm allows to generate a very large number of extreme events, **the accuracy of the estimation of statistical quantities conditional on the occurrence of the extremes is greatly improved**, and much stronger extremes can be observed in the simulations.

### 3.3 Plan of the experiments

We will use EC-Earth3 in TL255L91-ORCA1L75 configuration, corresponding to a spatial resolution of about 1° in the ocean (~50 km in polar regions) and 80 km in the atmosphere. We will generate a **control run** of 1000 years starting from a post-spin up initial condition already at disposal of the UCLouvain group from another project. This control run will serve as reference for the statistics, and to provide initial conditions for the ensembles. We will save restart files on a monthly basis, to be able to start ensembles at any time of the year. Note that we envision using control run and restart files for forthcoming projects with applications of the algorithm to other processes.

We will perform several different types of **experiments with the rare event algorithm,** aimed at providing a complete picture of Arctic sea ice extremes and their physical drivers and precursors

**Type 1 - unconditional probability of extremes of seasonal Arctic sea ice cover**
We will run 5 experiments with the rare event algorithm for different values of the parameter k. Each experiment will consist of an ensemble simulation with 100 ensemble members run for 8 months (February-September). The initial conditions will be sampled uniformly from the control run. The target observable will be the Arctic sea ice cover itself. This will give unconditional estimates of the probability of having very small values of the Arctic sea ice cover averaged over the entire melting season, and data to study precursors, drivers and key processes.

**Type 2 - unconditional probability of extremes of September Arctic sea ice cover**
As Type 1, but using as target observable the time derivative of the Arctic sea ice cover. One can see that integrating the time derivative what will be maximised will be the sea ice reduction during each resampling time, which factorises in reaching extremes of the September Arctic sea ice cover relative to the values at the beginning of the melting season. This will essentially filter out the effect of preconditioning in the selection, and will allow to focus on the effect of seasonal scale oceanic and atmospheric processes instead.

**Type 3 - conditional probability of extremes of Arctic sea ice cover**
As Type 1 or 2 (best choice taken depending on the outcome of the previous experiments), but starting all trajectories in each ensemble from a single, selected initial condition (adding a small perturbation to allow the trajectories to evolve separately). The scientific questions addressed will be the same, but conditionally on starting from a specific initial state. These experiments will provide a testbed for the future viability of the use of the rare event algorithm for actual **seasonal predictions of the risk of ultra-rare high impact extreme events**.

**Type 4 - targeted physical drivers of extremes of Arctic sea ice cover**
Here we will perform 3 sets of 5 experiments each where we will use the algorithm to select trajectories based not on the Arctic sea ice cover or cover reduction itself, but on other quantities and processes identified as physical drivers in the previous experiments. This will allow to test the importance of the processes as direct drivers. The 3 sets of experiments are planned as follows:

- **Preconditioning and long memory**: run the experiments as in Type 1 or 2, but over 2 years for each trajectory, selectively activating the algorithm only during the winter or summer season, and using sea ice thickness as control observable.
- **Atmospheric drivers**: select trajectories based on anomalously strong AO states or on anomalous synoptic activity based on the results of the previous experiments.
- **Oceanic drivers**: select trajectories based on anomalously warm sea surface temperature (SST) over regions and patterns identified in the previous experiments. This in particular will allow to study the impact of marine heatwaves and/or decadal variability of SST on Arctic sea ice.

### 3.4 Technical aspects and justification of computational resources

We will use the standard configuration of EC-Earth3 (TL255L91-ORCA1L75) on Atos. We have planned the project on EC-Earth3 rather than on EC-Earth4, because given the complexity of the application, we prefer to operate with a model for which we have robust informations about the computational performances. If in the coming months more information about the performances of EC-Earth4 will allow to reconsider this choice, we may, with the approval of ECMWF, recalibrate the project on EC-Earth4. This is however not planned at the moment.

We are already working on Atos using the standard allocation of RMI. In the past 18 months we have used the rare event algorithm with the simpler climate model Plasim on Atos, performing Type I experiments as proof of concept. The results show that the algorithm is successful in shifting the distribution of seasonal Arctic sea ice cover towards extreme negative anomalies. This allows to simulate events with return time up to hundreds of thousands of years, as obtained for heatwaves in Ragone et al. (2018), Ragone and Bouchet (2020), and in particular in Ragone and Bouchet (2021), where we used CESM, a model of the same complexity as EC-Earth3. We are therefore confident that the methodology will work equally well for this application.

The extension of the algorithm to EC-Earth3 will be straightforward. The way the method is coded, it uses a climate model as a black box, simply operating on the restart files to realise the cloning. The core of the algorithm is based on Python and bash scripts that we made available for a publication on heatwaves using CESM ([https://zenodo.org/record/4763283](https://zenodo.org/record/4763283)). We expect the algorithm to be up and running with EC-Earth3 within one month from the start of the project, during which we will already start the control run.

Based on existing reports and personal communication with the PIs of currently active ECMWF Special Projects using EC-Earth3 in the same configuration and machines, the optimal setup on Atos is obtained with five nodes (490 cores for IFS and 148 cores for NEMO, and 1 core each for runoff mapper and XIOS server). In this configuration, one model month requires about 1,600 SBU.

We will perform a 1000 model years long control run (12,000 model months) and 30 experiments with the rare event algorithm (5 for Type 1, 5 for Type 2, 5 for Type 3, and 5 each for the three categories of Type 4). Each experiment will run 100 ensemble members for 8 model months, or in the case of the Type 4 preconditioning experiments an equivalent amount of model months (total 24,000 model months). This gives a total of 36,000 model months, that will require about 57,000,000 SBU. An additional 3,000,000 SBU are added for post-processing and short test runs, for a total of 60,000,000 SBU.

The computational resources are distributed over three years as follows:

- **Year 1**: **control run** and **Type 1** and **Type 2** experiments (32,000,000 SBU)
- **Year 2**: **Type 3** experiments and one of the **Type 4** experiments (14,000,000 SBU)
- **Year 3**: remaining two **Type 4** experiments (14,000,000 SBU)

We will generate the output of IFS on a 6-hourly basis. The output of NEMO will be stored with a frequency depending on the resampling time of the algorithm, the standard choice being 5 model days. These figures give an estimate of about 50 GB per model year. This amounts to about 150 TB over the course of the project for the raw output, with an additional 10 TB estimated to store post-processed data (in particular the reconstructed ensembles). This amounts to a total of 160 TB, accumulated over the 3 years proportionally to the consumption of the computational resources.

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