REQUEST FOR A SPECIAL PROJECT 2023–2025

MEMBER STATE: UK

Principal Investigator[1]**:** Hannah Christensen

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Project Title:

Speeding up ocean spin-up using stochastic parametrisations.

If this is a continuation of an existing project, please state the computer project account assigned previously.	**SP** ________________	
Starting year: (A project can have a duration of up to 3 years, agreed at the beginning of the project.)	2023	
Would you accept support for 1 year only, if necessary?	YES X	NO ☐

Computer resources required for 2023-2025: (To make changes to an existing project please submit an amended version of the original form.)		**2023**	**2024**	**2025**
High Performance Computing Facility	(SBU)	2.5 million	50 million	50 million
Accumulated data storage (total archive volume)[2]	(GB)	500	15,500	30,500

Continue overleaf

[1] The Principal Investigator will act as contact person for this Special Project and, in particular, will be asked to register the project, provide annual progress reports of the project's activities, etc.

[2] These figures refer to data archived in ECFS and MARS. If e.g. you archive x GB in year one and y GB in year two and don't delete anything you need to request x + y GB for the second project year etc.

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Extended abstract

All Special Project requests should provide an abstract/project description including a scientific plan, a justification of the computer resources requested and the technical characteristics of the code to be used. The completed form should be submitted/uploaded at https://www.ecmwf.int/en/research/special-projects/special-project-application/special-project-request-submission.

Following submission by the relevant Member State the Special Project requests will be published on the ECMWF website and evaluated by ECMWF and its Scientific Advisory Committee. The requests are evaluated based on their scientific and technical quality, and the justification of the resources requested. Previous Special Project reports and the use of ECMWF software and data infrastructure will also be considered in the evaluation process.

Requests exceeding 5,000,000 SBU should be more detailed (3-5 pages).

A new generation of climate models is under development, which will produce coupled simulations at resolutions of 10 km in both atmosphere and ocean. This represents a step-change in our ability to simulate the ocean mesoscale, including ocean eddies and boundary currents, and allows us to assess their role in the long-term evolution of the Earth System. It is known that ocean mesoscale play an important role in transports of heat and carbon, and in re-distribution of nutrients in the ocean with impacts on bio-productivity. They govern atmospheric phenomena, such as storms and other weather and climate extremes, providing a source of predictability on seasonal to decadal time scales. Finally, mesoscale processes are also central in setting the magnitude of the Atlantic Meridional Overturning Circulation (AMOC) and its sensitivity to global change.

Such models are computationally expensive, so a range of technological advances are required to make climate change experiments at eddy-rich resolutions possible. A formidable challenge involves spinning up the ocean in such models. A thousand years of simulation or more are typically required to spin up an ocean model to a state of equilibrium, and it is simply not feasible to run eddy rich models for this length of time. Novel solutions are required.

As part of the Horizon Europe project "European Eddy-Rich Earth System Models" (EERIE), for which ECMWF is a partner institute, we propose to utilise two new approaches in Earth System Modelling to address this challenge. Our goal is to develop a new atmosphere-ocean coupling approach, whereby a vastly lower resolution atmosphere is coupled to a high-resolution ocean model, substantially reducing the computational cost during ocean model spin-up. The challenges are to ensure the low-resolution atmospheric state does not drift too far from its high-resolution benchmark, and secondly to ensure the low-resolution atmospheric fields returned to the ocean do not dampen the ocean variability.

Stochastic Parametrisations

Stochastic parametrisation schemes have been used for more than two decades in atmospheric models. They represent model uncertainty through representing the variability of unresolved sub-grid processes. They improve the spread and mean-state for medium range and seasonal forecasts (Buizza et al. 1999, Palmer et al. 2009). This is also increasing evidence that stochastic parametrisation schemes benefit climate models, where they reduce model biases (Berner et al. 2008), improve the representation of flow regimes (Dawson and Palmer 2014), and improve modes of internal variability such as the Madden-Julian Oscillation (Davini et al, 2016) and El Nino-Southern Oscillation (Christensen et al, 2017). Importantly, stochastic parametrisations are able to mimic the impact of increasing resolution of the atmospheric model, but with negligible increase in cost [cite, cite].

Stochastic parametrisations have been used with great success in developing coupling approaches for mixed-resolution ocean-atmosphere models. Rackow and Juricke (2020) investigated the coupling between a low-resolution atmospheric model and an ocean model at substantially higher resolution. They found that simply sampling ocean states for the ocean-atmosphere flux calculation instead of using the average ocean state within a coarse atmospheric grid cell leads to substantially improved variability in the atmospheric model.

Machine Learning

There is much interest in using deep learning to emulate complex processes within the climate system. One approach is to train statistical models to emulate the behaviour of high-resolution simulations (Brenowitz et al, 2020) to replace parametrisation schemes. The focus to date has been largely deterministic, but proof-of-concept studies have shown that stochastic approaches have great potential to improve variability at the small scales (Gagne et al, 2020). Of particular interest in this context are generative models such as Generative Adversarial Networks (GANs). These are used for sample generation. Applications to date have included downscaling and nowcasting (Ravuri et al, 2021). Their probabilistic nature makes them suitable for the stochastic parametrisation problem (Gagne et al, 2020). In a GAN, two neural networks (NNs) are trained in parallel. The generator network produces synthetic (state dependent) samples designed to mimic the training data, and the discriminator network judges whether a sample it views is real or synthetic. The discriminator then teaches relevant features to the generator through backpropagation, improving the fidelity of generated samples (Arjovsky et al, 2017).

Project Outline

We will utilise ideas from stochastic parametrisations and machine learning to improve the coupling between the ocean and atmosphere components of the coupled IFS system, with a focus on cases when the ocean resolution is higher than the atmosphere.

We will firstly use ideas from the stochastic parametrisation community to improve the fidelity of the low-resolution atmospheric fields, and to ensure that the atmosphere uses as much information from the high-resolution ocean model as possible. We will take Rackow and Juricke (2020) as a starting point, but will explore alternative ways of using the high-resolution ocean information to improve the quantification of uncertainty in surface fluxes fed to the atmosphere, including developing ideas presented in Bessac et al (2019, 2021). The goal is to develop a stochastic representation of the unresolved variability in surface fluxes to improve the mean state and variability of the low-resolution atmosphere, to compensate for its lower resolution.

We will secondly use ideas from machine learning to downscale the low-resolution atmospheric fields, to statistically add detail when feeding information from the atmosphere back into the ocean. Suitable neural-network (NN) based architectures include GANs or variational autoencoders (VAE), conditioned on the low-resolution atmospheric fields. Both GANs and VAEs are probabilistic approaches, such that this second half of the coupling parametrisation will also be stochastic.

While our goal will ultimately be simulations at 0.1^{o} resolution in the ocean, initial testing will be carried out at 0.25^{o} resolution, before testing the generalisability of techniques to 0.1^{o}. This will also allow us to use SEAS5 forecasts, at a resolution of 0.25^{o} ocean – $T_{CO}320$ atmosphere, as benchmark.

While our focus in the project is on ocean spin-up, we anticipate that the approach we develop will be more widely useful in cases of resolution mis-match, e.g. running a high-resolution atmosphere with a lower resolution ocean.

Resources

Our resource requests are estimated using knowledge of SBUs on the Cray machine using the double precision version of the IFS.

1° – T255	24,000 Cray SBUs per simulated year
0.25° – T255	100,000 Cray SBUs per simulated year
0.25° – T511	310,000 Cray SBUs per simulated year

We also make use of the formulae for Cray and Atos SBUs listed here:
https://confluence.ecmwf.int/display/UDOC/HPC+accounting

We further assume that single precision will be available for these simulations, and will reduce the costs by 50%. The resultant conversion factor from Cray SBUs to Atos SBUs is around 2.5.

In year 1 we plan to carry out preliminary tests using the IFS with differing resolutions in atmosphere and ocean. There may be technical issues at this stage to troubleshoot. These simulations will provide training data for years 2 and 3.

1 million Cray SBUs to cover approx. 10-years of mixed resolution simulation.

In year 2 we plan to develop the stochastic surface flux parametrisation component of the coupling scheme. We will test the scheme in sub-seasonal length ensemble forecasts (45 days, 5 members, Nov 1 start, 20 years = approx. 15 years simulation per experiment) and compare to SEAS5 forecasts

20 million Cray SBUs to cover ten such experiments plus buffer for iterative parametrisation development and testing etc.

In year 3, we plan to develop the ML downscaling component of the coupling scheme. The ML training will be carried out on a different machine before the trained model is tested in forecasts on the ECMWF machine. We will focus on climate-type simulations, with a focus on the spin-up period and final model state.

20 million Cray SBUs to cover 200 years of mixed resolution simulation.

Towards the end of year 3 (and in a possible year 4 of the project), we will perform preliminary tests at 0.1° resolution in the ocean, before handing over the scheme to collaborators at BSC who will test the approach at full resolution.

With our conversion factor of 2.5 (Cray ⇒ Atos), we therefore request:

Year 1: 2.5 million Atos SBU
Year 2: 50 million Atos SBU
Year 3: 50 million Atos SBU

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