<u>LATE</u> REQUEST FOR A SPECIAL PROJECT 2022–2024

MEMBER STATE:	United Kingdom
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Project Title:	Probabilistic Machine Learning models for stochastic cloud parameterisation schemes: development and coupled evaluation within the IFS

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.)	2022	
Would you accept support for 1 year only, if necessary?	YES ☒	NO ☐

Computer resources required for the years: (To make changes to an existing project please submit an amended version of the original form.)		**2022**	**2023**	**2024**
High Performance Computing Facility	(SBU)	100,000	10,200,000	-
Accumulated data storage (total archive volume)[2]	(GB)	380	16,000	-

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 an annual progress report of the project's activities, etc.
[2] 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.

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Extended abstract

The completed form should be submitted/uploaded at https://www.ecmwf.int/en/research/special-projects/special-project-application/special-project-request-submission.

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.

Requests asking for 3,000,000 SBUs or more should be more detailed (3-5 pages).

Following submission by the relevant Member State the Special Project requests the evaluation will be based on the following criteria: Relevance to ECMWF's objectives, scientific and technical quality,and 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.

All accepted project requests will be published on the ECMWF website.

Introduction

Stochastic Parameterisations

A major source of inaccuracies in climate models is due to the parameterisation of unresolved processes. Introducing stochasticity has had benefits including better ensemble forecasts (Buizza et al., 1999; Leutbecher et al., 2017; Palmer, 2012), and improvements to model mean state (Berner et al., 2012) and climate variability (Christensen et al., 2017). The motivation for using stochasticity comes from the understanding that the effects of the unresolved (sub-grid) processes cannot be effectively predicted as a deterministic function of the resolved ones due to a lack of scale separation between them. Adding randomness allows us to capture our uncertainty about those aspects of the unresolved processes which may affect the resolved outcomes. Using correlated noise (such as red noise) is important for modelling temporal correlations, and is used in the stochastically perturbed parameterisation tendencies (SPPT) scheme (Buizza et al., 1999; Palmer et al., 2009) amongst other examples.

Machine Learning for Parameterisation

The machine learning (ML) approach is to learn parameterisation functions from data. Various researchers have proposed ML methods for learning deterministic models (Brenowitz & Bretherton, 2018, 2019; Gentine et al., 2018; Krasnopolsky et al., 2013; O'Gorman & Dwyer, 2018; Rasp et al., 2018; Yuval & O'Gorman, 2020; Yuval et al., 2021). Deterministic models with learnt temporal correlations were proposed by Chattopadhyay, Hassanzadeh, & Subramanian (2020), Chattopadhyay, Subel, & Hassanzadeh (2020) and Vlachas et al. (2018), but these were costly. Gagne et al. (2020) were the first to use a probabilistic approach to learn parameterisations, whilst also including red noise to capture temporal trends.

There are noted issues pertaining to model instability when ML parameterisations are coupled within existing weather and climate models. Good results from testing in an 'offline' capacity do not guarantee good results in a coupled setting. Also, results obtained from studying simpler models such as the Lorenz 96 (Lorenz, 1996), whilst an important step in crafting better parameterisation models, may not hold when these approaches are used on full-scale models such as the IFS. It is therefore essential to ultimately test these ML approaches in a coupled system, such as done by Chantry et al. (2021) in the IFS.

Our Prior Work

In our work preceding this, we combined the benefits of stochasticity and machine learning to create a parameterisation scheme for the Lorenz 96 atmospheric simulation which was competitive and often superior to both a bespoke baseline and an existing probabilistic machine-learning one (GAN). Our model (Parthipan et al., 2022) was a physically-informed recurrent neural network deployed within a probabilistic framework, and its good performance was likely due to a superior ability to model temporal correlations compared to existing approaches.

Coupled testing has only been carried out in the Lorenz 96 model. Further model crafting and evaluation is required following coupling to the IFS.

Objectives

The goal is to develop stochastic machine learning models for the cloud parameterisation scheme in the IFS. We start by modelling the cloud fraction. The training data comprises high-resolution data from IFS runs at TCo1280 which are coarse-grained to the TL159 resolution. Coupled IFS runs at TL159 will be used to assess model stability and diagnose errors. After the models have been developed, we will evaluate their performance from longer runs at TL159. Success may lead to future work creating models for operational resolutions.

Proposed Integrations

All runs will be at the T159 resolution.

Runs for Model Development

We would run short forecasts (0-10 days) for dates within the training/validation regime, multiple times during the debugging stage. This will allow us to diagnose any issues that may arise when including our ML model within the IFS.

Evaluation: Medium Range Forecasting

This involves running 10-day forecasts starting every 5 days between July to December 2021. Given our models are stochastic, a 50-member ensemble forecast is run for each start date to represent the uncertainty.

Evaluation: Year-Long Simulations

1 year-long simulations would be run to assess long-range forecasting. These would start in 2021, and be repeated five times to give uncertainty over the climate distribution.

Technical Requirements

The estimate of resources is based on simulations carried out at TL159 on the Cray system, where a 10 day TL159 coupled atmosphere-ocean forecast costs 1800 SBUs and each 2D field is about 70 KB in size. These numbers are used to estimate the SBUs and storage space required below. This is expected to be similar for the new Atos system.

In the first year, we would plan to do most of the model development and debugging. This is estimated to cost 126,000 SBU (7 days/forecast run * 50 different runs * 2 models [as not all models will be run each time] * 180 SBU/day). Allowing for a 10% increase due to the cost of the ML model brings this to 140,000 SBUs. Allowing for a buffer gives 200,000 SBU. Only a subset of the total output created will need to be stored, estimated at 372 GB (0.5 year of output * 744 GB per year when saving hourly).

In the second year we expect to carry out the bulk of the evaluation experiments. Our medium range forecasts are expected to cost 8.1 million SBUs (10 days/forecast * 30 different starting dates * 3 models to compare * 50 ensemble members * 180 SBU for 1 day). Allowing for a 10% increase due to the cost of the ML model itself brings this to 9 million SBUs. Output will be saved 6-hourly, requiring 15,376 GB (124 years of output * 124 GB per year when saving 6 hourly).

The year-long experiments would cost 1 million SBUs (1 year/forecast * 3 models to compare * 5 ensemble members * 65700 SBU for a year). Allowing for a 10% increase due to the cost of the ML model itself, this brings this to 1.1 million SBUs. Output will be saved daily, requiring 470 GB (15 years of output * 31 GB per year when saving daily).

In all cases, a small buffer is included.

Acknowledgements

Thanks to Paul Dando for his help with estimating the number of SBUs for the TL159 forecasts, as well as the output sizes.

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