

SPECIAL PROJECT PROGRESS REPORT

All the following mandatory information needs to be provided. The length should *reflect the complexity and duration* of the project.

Reporting year 2020

Project Title: Imprecise approaches to accelerate weather forecasts

Computer Project Account: spgbtpia

Principal Investigator(s): Tim Palmer
Matthew Chantry

Affiliation: University of Oxford

Name of ECMWF scientist(s) collaborating to the project
(if applicable) Peter Dueben
Sam Hatfield

Start date of the project: 2020

Expected end date: 2022

Computer resources allocated/used for the current year and the previous one (if applicable)

Please answer for all project resources

		Previous year		Current year	
		Allocated	Used	Allocated	Used
High Performance Computing Facility	(units)			15,000,000	2,917,827
Data storage capacity	(Gbytes)			15,000	Low

Summary of project objectives (10 lines max)

Investigate the applications of reduced numerical precision and reduced numerical precision hardware to improving the performance of weather and climate modelling. This aims to cover data assimilation, existing modelling approaches and future modelling approaches. Reduced numerical precision is being increasingly supported by new hardware, in particular GPUs and similar machine learning tools. This hardware offers significantly increased performance if the numerical precision errors can be kept below forecast errors and uncertainty.

Summary of problems encountered (10 lines max)

Some issues encountered attempting to output data every timestep to assess emulator performance. Currently we have reduced the output volume which has sidestepped the issue.

Summary of plans for the continuation of the project (10 lines max)

We have developed emulators of several physical parameterisation schemes; these have been tested in weather and climate forecasting mode and have performed well. Our next target is running the data assimilation mode. We will also assess the performance our emulators at reduced numerical precision, therefore fully utilising the reduced precision hardware.

We have also made progress in using machine learning to preprocess the linear solver involved in implicit timestepping, the next step of this project will be to move to larger resolutions and increased complexity models. This testing will take place using our special project resources.

We expect these tasks to consume the remainder of this year's units.

List of publications/reports from the project with complete references

Paper summarising gravity wave drag results in preparation.

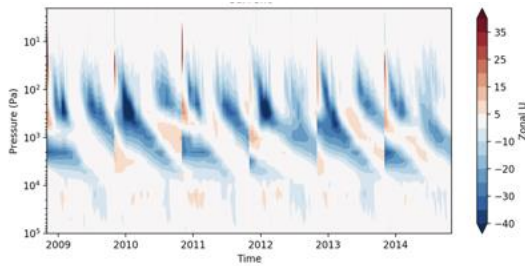
Summary of results

Our major success in the first six months of this project has been the progress towards machine learning emulators of physical parameterisation schemes within the IFS codebase. In particular we have been focussing on the gravity wave drag schemes with IFS. These schemes, while not particularly expensive, have similar structure from the machine learning point of view, in particular the fields inputted and outputted are very similar. By choosing two similarly structured schemes we can evaluate whether machine learning architectures can be shared, i.e. similar network design. If true, this would accelerate a program of building emulators of each of the parameterisation schemes within the IFS. The argument for building these emulators has several strands. Firstly, emulators can easily leverage new machine learning hardware, and therefore accelerate the IFS. Secondly, these schemes are inherently uncertain, as they are closure schemes. Therefore, there is room for inaccurate computation while still producing accurate forecasts. Thirdly, for ECMWF's 4Dvar system of data assimilation it is necessary to maintain tangent-linear and adjoint versions of each parameterisation scheme. By using neural networks as emulators, these versions can be derived at no additional cost, leveraging that the complexity of neural networks lies in the weights rather than complex algebra.

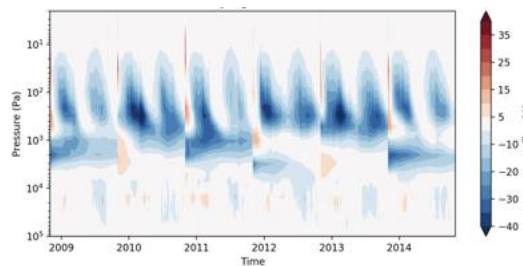
Our results can be highlighted in the figure below, which shows the IFS free-running for 6 consecutive yearly simulations, each initialised from the analysis. Each simulation is running at TL159L91 with cycle 45r1. We plot the equatorial zonal jet speed as a function of pressure level and time, to capture the descent involved in the quasi-biennial oscillation (QBO). When the current

non-orographic gravity wave drag scheme was introduced a main improvement over the previous Rayleigh drag scheme was this descent (Orr et al. 2010). Panel (a) shows the current IFS system, with existing non-orographic gravity wave drag scheme used. Panel (b) shows the previous IFS Rayleigh drag scheme, in which the jet fails to descend. Panel (c) shows our neural network emulator which accurately captures this descent. Correctly recreating this descent in a simulation free running for over 8000 timesteps each year is a major achievement in our emulator's performance, as it demonstrates the both the performance and stability. Beyond this, our emulator also performs well in medium range weather forecasting.

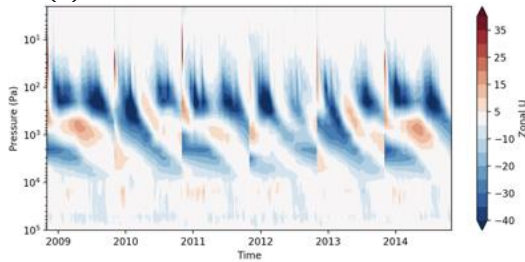
(a) Existing scheme



(b) Rayleigh drag (old scheme)



(c) Neural network emulator



Bibliography

Orr, Andrew, et al. "Improved middle atmosphere climate and forecasts in the ECMWF model through a nonorographic gravity wave drag parameterization." *Journal of climate* 23.22 (2010): 5905-5926.