# SPECIAL PROJECT PROGRESS REPORT

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

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|---|---|
| **Reporting year** | 2022 |
| **Project Title:** | Imprecise approaches to accelerate weather forecasts |
| **Computer Project Account:** | spgbtpia |
| **Principal Investigator(s):** | Tim Palmer<br>Beatriz Monge-Sanz |
| **Affiliation:** | University of Oxford |
| **Name of ECMWF scientist(s) collaborating to the project** (if applicable) | Matthew Chantry, Peter Dueben |
| **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 | 12,000,000 | 15,000,000 | 13,000,000 |
| **Data storage capacity** | (Gbytes) | 15,000 | 17,000 | 15,000 | 17,000 |

## 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. Reduced numerical precision is being increasingly supported by new hardware, in particular GPUs and similar machine learning devices. This hardware offers significantly increased performance if the numerical precision errors can be kept below forecast errors and uncertainty. Machine learning offers another approach to accelerate weather forecasting, whereby physical parameterisations can be emulated at reduced cost using deep learning algorithms. Our project explores the tolerance of kernels of weather and climate forecasting to reduced precision calculations and to emulation by machine learning algorithms.

## Summary of problems encountered (10 lines max)

No significant problems encountered.

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

We are developing machine learning based alternatives to emulate parameterisations relevant for coupling to radiation and dynamics. One major focus is the emulation of radiatively active stratospheric species. Comparison with other schemes documented in scientific literature for these species will be completed, an assessment of performance and impact on meteorological fields will employ similar diagnostics to those used by Monge-Sanz et al. (2022). We plan to couple our offline trained neural networks using routines created in IFS to import and run these ML models, following the importing approaches developed by Chantry et al. (2021). Online tests are planned at different spatial resolutions for deterministic medium-range forecasts, and ensemble prediction runs on longer timescales. On the computational side, we will be able to assess potential gains in computational time using GPUs when implementing the ML algorithms. Research lines from this project will continue beyond the current special project's end date and requests for a subsequent special project are contemplated.

## List of publications/reports from the project with complete references

Chantry, M., Hatfield, S., Dueben, P., Polichtchouk, I., & Palmer, T. (2021). Machine learning emulation of gravity wave drag in numerical weather forecasting. Journal of Advances in Modeling Earth Systems, 13, e2021MS002477. https://doi.org/10.1029/2021MS002477

Hatfield, S., Chantry, M., Dueben, P., Lopez, P., Geer, A., & Palmer, T. (2021). Building tangent-linear and adjoint models for data assimilation with neural networks. Journal of Advances in Modeling Earth Systems, 13, e2021MS002521. https://doi.org/10.1029/2021MS002521

Paper on the machine learning emulation of radiative stratospheric species is in preparation.

## Summary of results

If submitted **during the first project year**, please summarise the results achieved during the period from the project start to June of the current year. A few paragraphs might be sufficient. If submitted **during the second project year**, this summary should be more detailed and cover the period from the project start. The length, at most 8 pages, should reflect the complexity of the project. Alternatively, it could be replaced by a short summary plus an existing scientific report on the project attached to this document. If submitted **during the third project year**, please summarise the results achieved during the period from July of the previous year to June of the current year. **A few paragraphs might be sufficient**.

We have developed machine learning algorithms, and in particular feed-forward neural networks, to emulate parameterisations relevant for interaction with radiation in IFS. We have been focusing on the emulation of the behaviour of radiative chemical species in the stratosphere. We have prepared long datasets covering 30-year period (1980-2010) using output from chemistry-resolving models and reanalyses for the offline training and validation of our machine learning algorithms. Results from the offline tests are analysed for different atmospheric regions and periods along this 30-year period, with particular attention to high latitudes.

In the offline tests, our neural network algorithms show the ability to capture the overall behaviour and variability of stratospheric ozone, also when using a limited number of input variables. For our neural networks, we have focused on time periods with good observational and models coverage for the stratosphere. We are also expanding the number of variables and increasing the time frequency in the input datasets, as well as exploring options for training datasets over longer periods that do not compromise on planned number of input variables.

We have started technical steps towards the online implementation of these new emulation algorithms to be tested within IFS runs, building up from online coupling routines developed earlier in the project on gravity-wave drag emulation (Chantry et al., 2021). Comparison of results from the online runs with improvements achieved by other modelling options for stratospheric species recently implemented in IFS (Monge-Sanz et al., 2022) will ideally be performed within the same IFS cycle version. The machine learning online coupling steps are being prepared with the IFS CY47r3 version, this can be adapted to a different or more recent cycle version if necessary.

References:

Chantry, M., Hatfield, S., Dueben, P., Polichtchouk, I., & Palmer, T. (2021). Machine learning emulation of gravity wave drag in numerical weather forecasting. Journal of Advances in Modeling Earth Systems, 13, e2021MS002477. https://doi.org/10.1029/2021MS002477

Hatfield, S., Chantry, M., Dueben, P., Lopez, P., Geer, A., & Palmer, T. (2021). Building tangent-linear and adjoint models for data assimilation with neural networks. Journal of Advances in Modeling Earth Systems, 13, e2021MS002521. https://doi.org/10.1029/2021MS002521

Monge-Sanz, B. M., Bozzo, A., Byrne, N., Chipperfield, M. P., Diamantakis, M., Flemming, J., Gray, L. J., Hogan, R. J., Jones, L., Magnusson, L., Polichtchouk, I., Shepherd, T. G., Wedi, N., and Weisheimer, A.: A stratospheric prognostic ozone for seamless Earth system models: performance, impacts and future, Atmos. Chem. Phys., 22, 4277–4302, https://doi.org/10.5194/acp-22-4277-2022, 2022.