REQUEST FOR A SPECIAL PROJECT 2024–2026

MEMBER STATE: Austria……………………………………………………………………………………

Principal Investigator[1]: Prof. Dr. Leopold Haimberger

Affiliation: University of Vienna

Address: Josef Holaubeck Platz 2, 1090 Wien, Austria

Other researchers: Dr. Alexander Bihlo, Susanna Winkelbauer, Ulrich Voggenberger

Project Title: Applying hydrodynamic constraints to coupled energy budget analysis and to physics-informed machine learning based forecasting

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To make changes to an existing project please submit an amended version of the original form.)

If this is a continuation of an existing project, please state the computer project account assigned previously.	**SPATLH00**	
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 ☐	NO X

Computer resources required for project year:		**2024**	**2025**	**2026**
High Performance Computing Facility	[SBU]	10000	10000	10000
Accumulated data storage (total archive volume)[2]	[GB]	500	1000	2000

EWC resources required for project year:		**2024**	**2025**	**2026**
Number of vCPUs	[#]	20	25	30
Total memory	[GB]	160	200	240
Storage	[GB]	1000	2000	2000
Number of vGPUs[3]	[#]	2	2	2

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.
[3] The number of vGPU is referred to the equivalent number of virtualized vGPUs with 8GB memory.

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Extended abstract

Understanding forecast error growth is key to make targeted improvements of the quite complex forecasting system on the medium range as well as for seasonal and decadal predictions. In a previous special project “Mining 5th generation reanalysis data for changes in the global energy cycle and for estimation of forecast uncertainty growth with generative adversarial networks “, novel GANs were developed to predict forecast uncertainty growth with remarkable efficiency and low computational cost. ERA-5 and GREP reanalyses were used for detailed evaluations of the coupled atmospheric+oceanic+cryospheric energy budgets to detect systematic energy and water flux errors in the reanalyses themselves but also in CMIP6 simulations, which often lead to biases in the predicted state quantities.

More comprehensive and detailed archiving policies and higher temporal frequencies of reanalysis data allow for improved and more precise energy budget diagnostics on the monthly to decadal time scales. In the past 3-4 years numerical noise in the energy budget evaluations employing spectral fields on model levels could be substantially improved. An atmospheric energy and water budget data set, considered to be the best derived from ERA5 data, has been published via the C3S (Mayer et al. 2022). Recently we found a way to reduce the noise further (Fig. 1) and we expect to use resources allocated for the new special project to deliver an even more accurate version of this data set. We plan to optimally extract energy budget terms from the IFS in the version to be adopted for the forthcoming Copernicus reanalysis ERA6, for which we hope to have an even more accurate budget evaluation system near the end of this special project.
In the previous SP we have used GREP reanalyses and experimental versions of the ORA system to evaluate detailed budgets also in the oceans. The budget terms, particularly horizontal oceanic transports, are compared with CMIP6 simulations, consequently using data on their respective native grid. This is a demanding task, given the variety of different grids used for CMIP6 ocean models, but the evaluations on the native grids yield high accuracy and quite small residuals even for regional budgets (Fritz et al. 2023; Winkelbauer et al. 2023). We plan to develop these methods further, making them applicable to the next generation of GREP and CMIP models.

As a further part of this special project, we will further investigate the use of machine learning for meteorological applications, in particular for replacing the ensemble prediction system and for physics-informed machine learning based weather forecasting.
We have shown in past work that it is possible to obtain the spread of the geopotential ensemble using just the deterministic control forecast (Brecht and Bihlo 2023a), and that ensemble members for the total precipitation can be generated in a similar way using just the deterministic precipitation forecast (Brecht and Bihlo, 2023b). We plan to further assess the performance of machine learning based ensemble prediction. In particular, we would like to experiment with novel architectures, such as those based of vision transformers or diffusion models, which are being used in state-of-the-art generative AI. We also plan to develop multi-parameter ensemble machine learning systems, which can forecast not only single meteorological parameters as in our previous work, but the entire catalogue of meteorological parameters of interest. This will require some more computational resources, both for storage of the training data, and for training the models themselves.

Replacing deterministic weather forecasting with machine learning has been a field of growing interest in recent years, with some recent results showing that these methods have the potential to outperform classical numerical weather forecasting (Bi et al. 2022). However, to the best of our knowledge, even the most successful models in this regard are mere adaptation of standard video prediction architectures as used in computer science. As such, they ignore the underlying physical constraints inherent in the atmospheric system, such as mass, energy and circulation conservation. In this project, we aim to investigate whether purely data-driven weather forecasting, such as the Pangu-Weather model (Bi et al. 2022), can be ameliorated by taking into account the physical laws of the atmosphere. This should be done using physics-informed machine learning. More concretely, we will train deep operator-based networks (Lu et al. 2021) for physics-informed weather forecasting. We have shown the feasibility of recreating historical weather forecasts using physics-informed machine learning (Brecht and Bihlo 2023c), which crucially do not rely on data alone, but take into account the governing equations of hydro-dynamics. If trained successfully, these operator-based forecasting systems would combine the advantages of data-driven approaches, such as the speed-up of forecasting by several orders of magnitudes, with the physical consistency of classical numerical forecasting models.

The infrastructure provided on ATOS and the European Weather Cloud would greatly facilitate these planned tasks, since it allows to perform the involved data reduction algorithms on premises where the needed analysis data are available with very high bandwidth It is also easier to be aligned with more recent versions of the ECMWF software stack and to exchange ideas and codes with ECMWF staff. Budget evaluations from ERA5 and ERA6 will require HPC resources due to high memory demand, whereas the evaluation of oceanic reanalyses is feasible with cloud computing setups available in the EWC. The ML based part of the project relies on the availability of GPUs, which is reflected in the resources allocated.

References:

K. Bi et al, 2022. Pangu-Weather: A 3D high-resolution model for fast and accurate global weather forecast, arXiv:2211.02556.1]

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