Project: **1179**
Project title: **Machine learning-based parameterizations and analysis for the ICON model (ICON-ML)**
Principle investigator: **Veronika Eyring and Julien Savre**
Allocation period: **2025-07-01 to 2026-06-30**

Main achievements and results over the 2025-2026 allocation period

Within project bd1179, we are aiming at developing a Machine Learning (ML)-enhanced multiscale climate modeling framework based on the ICON-XPP Earth System Model (ESM) with the objective to reduce longstanding systematic errors associated with clouds and radiative feedbacks. The project is particularly concerned with the development of robust ML-based parameterizations designed to replace or complement ICON's conventional parameterizations for clouds, convection, radiation or turbulence, and to implement them in an ML-enhanced ICON-XPP model version (ICON-XPP-MLe). All the work accomplished over the past allocation period was summarized in several important research articles (with additional publications currently in preparation): [3, 5, 4, 9, 6]. The project is articulated around three main tasks: Task (i) Development of ICON-XPP-MLe; Task (ii) Improving climate projections across scales; Task (iii) Development of ESMValTool for the evaluation of ICON-XPP-MLe.

Task (i) Develpment of ICON-XPP-MLe

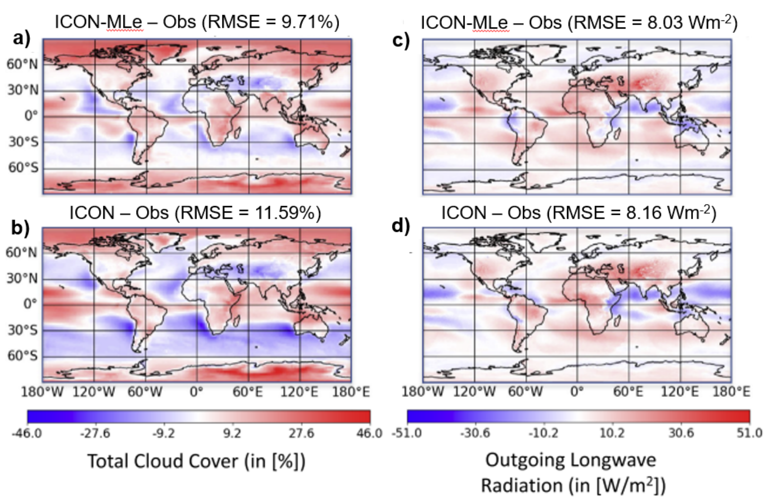

Figure 1: Total cloud cover (left) and outgoing longwave radiation (right) biases is 20-year long AMIP simulations. Panels a) and C) correspond to the ICON-MLe prototype, panels b) and d) to the conventional ICON model (both models have been calibrated following the same procedure).

Part of the resources requested in task (i) were dedicated to the execution of high-resolution ICON simulations (global 5 km and Large Eddy Simulations) to generate ML training datasets. Unfortunately, due to the substantial cuts applied to the CPU resources requested in our previous proposal, we were unable to complete all planned high-resolution simulations. It must be noted however that a thorough automatic pipeline facilitating the configuration and execution of LES simulations with ICON was developed over the period 2025-2026. Furthermore, the first LES simulations (4 of 20 planned) will be carried out before the end of the current allocation period, with the first results available at the end of April 2026.

Significant progress has been made during the past allocation period towards the development of an ML-enhanced version of ICON-XPP (ICON-XPP-MLe). In task (i), several ML-based parameterizations have been successfully developed: a radiation model trained on high-resolution (5 km) global ICON simulations [4], a cloud cover scheme taking the form of a simple diagnostic relationship derived using equation discovery techniques [3], a new parameterization for atmospheric moist convection [5], and a parameterization for atmospheric boundary layer height [6]. The excellent offline performance of these models could be demonstrated, and their practical implementation in ICON-XPP-MLe was achieved. These models are still actively tested in short standard AMIP-like simulations at 80 km resolution (R2B5), but early results are already very promising. In terms of model development, work towards the integration of dedicated parameterizations for turbulence/shallow convection, QML-based cloud cover [8], microphysics [9] and an improved version of the existing deep convection scheme is still ongoing.

Task (i) also focused heavily on the calibration (or tuning) of the hybrid ICON-XPP-MLe prototype considering various combinations of ML-based parameterizations. An efficient calibration workflow making use of objective and automatic methodologies was designed and successfully employed [1, 3, 2]. Calibration of the ICON model equipped with the ML cloud cover scheme was achieved, and the superiority of the hybrid prototype over the conventional physics-based model could be demonstrated for a range of climate metrics (e.g., Figure 1). Tuning of the ICON-XPP model together with ICON's land component (JSBACH) is currently ongoing but will be completed by the end of the current allocation period.

Task (ii) Improving climate projections across scales
In task(ii), the production of downscaled projections using nested ICON-XPP simulations was delayed due to technical issues, and the planned simulations could unfortunately not be carried out. Most of our efforts in task (ii) were thus dedicated to the development of an ML-based downscaling framework based on the existing CorrDiff model [7]. The model was successfully retrained to optimally predict high-resolution (∼6 km) surface temperature (see figure 2), wind speed and precipitation fields from coarse resolution (∼60 km) ICON outputs over a domain centered around Germany and in a perfect model framework (i.e., the coarse data are obtained by coarse graining a given high-resolution dataset, the downscaling algorithm is hence trained and used to recover the original high-resolution fields). Modifications of the input fields (transformations) and loss function were found to be necessary to improve the ability of CorrDiff to predict surface precipitation patterns (publication in preparation). Further model training is currently still ongoing to refine the model's predictions and prepare its application to standard ICON model outputs. Note that this work will be continued as part of a separate computing project.

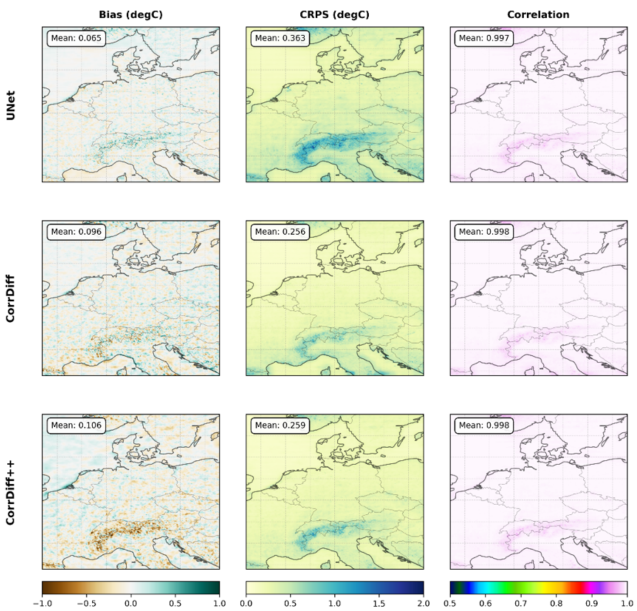

Figure 2:

Task (iii) Development of the ESMValTool for the evaluation of ICON-XPP-MLe
Finally, task (iii) has successfully supported the development of ICON-XPP-MLe during the 2025-2026 allocation period by providing an efficient and automatic evaluation framework, ESMValTool [10]. In particular, a series of diagnostics designed to 1) facilitate model calibration and 2) test the physical consistency of the hybrid model were implemented and systematically used to evaluate the different iterations of ICON-XPP-MLe.

References

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