Project: **1179**
Project title: **ML-based parameterizations and analysis for the ICON model (ICON-ML)**
Principle investigator: **Prof. Dr. Veronika Eyring**
Report period: **2024-05-01 to 2025-04-30**

## Oveview

parameterizations of subgrid-scale effects in climate models lead to biases and uncertainties in future projections, which could be improved with machine learning (ML)-based methods. This report summarizes the progress made within project 1179 in the last 12 months on (i) developing new ML approaches for parameterizations of small-scale atmospheric processes in ICON, (ii) tuning and evaluating ICON and ICON-ML, and (iii) developing ESMValTool for the evaluation of ICON-ML.
In general, one major step was taken last year to ensure the transition from ICON-A to ICON-XPP (official release `icon-2024.10`). Future works will be centered around ICON-XPP as the base model, and we plan to remain up-to-date with respect to ICON-XPP's official releases.

## Report for Task (i) Development of ML-based parameterizations for ICON

In project 1179 we are developing an extended version of the atmosphere component of the ICON-XPP model (ICON-XPP-MLe) in which several physical parameterizations are replaced with ML-based models. This model version is expected to reduce certain longstanding systematic errors and to provide more robust climate projections. In this section, we summarize the progress for different ML-based parameterizations.

**parameterization of cloud cover**: A novel, physically consistent, data-driven cloud cover parameterization was implemented into ICON-XPP. The parameterization, a diagnostic equation derived from storm-resolving simulations via symbolic regression, retains the interpretability and efficiency of traditional parameterizations while improving fidelity. A new automated tuning procedure was then introduced to recalibrate the new climate model with Earth observations (see Task (ii)). We were able to show that the tuned hybrid model significantly reduces long-standing biases in cloud cover and radiative budgets, particularly over certain critical regions.
**parameterization of cloud microphysics**: We improved our ML-based microphysics parameterization without aerosols and ran several online tests. Our ML approach combines a classifier that identifies grid cells where cloud microphysics is active, and a regression model to predict seven different microphysical tendencies. The model was designed to ensure mass positivity and water mass conservation. Using explainability methods, we explored correlations between input and output features to assess the physical consistency of all microphysical processes. This parameterization provides the foundation to advance the representation of cloud microphysical processes in climate models with ML (Sarauer et al., 2025).
**parameterization of convection**: A tunable, physically informed ML parameterization for convection was developed for ICON-XPP-MLe. Fundamental physical principles were incorporated in the model to enforce strict conservation of key predicted variables. The model is still under development to improve its online stability and performance. In addition, we developed an alternative technique employing variational autoencoders (VAE) to capture the internal uncertainty associated with convective processes in the training dataset. The use of a VAE was shown to yield good offline performance while providing a means to represent the stochastic nature of convection.

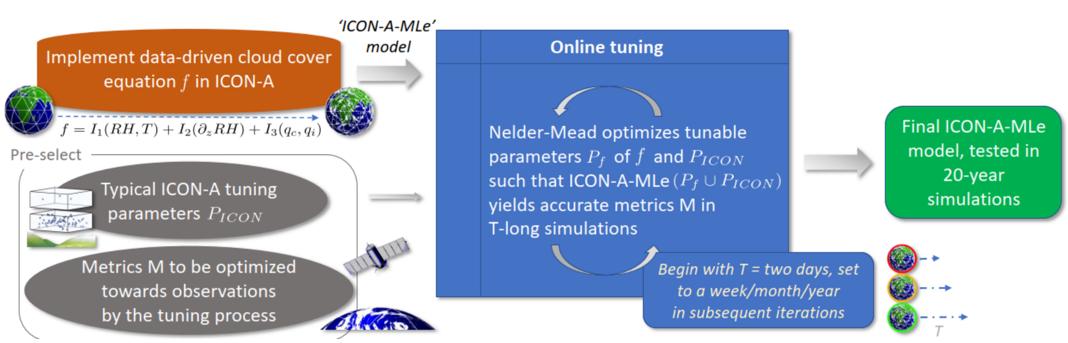


Figure 1: Automatic tuning pipeline of ICON-XPP-MLe.

Compared to a traditional scheme, this parameterization improves the prediction of tropical extreme precipitation with respect to observations when coupled to an ESM (Behrens et al., 2025).
**parameterization of radiation**: Provided that traditional radiation transfer models require intensive computational resources (up to 85% of the total ESM runtime), we developed an ML-based emulator of the radiation scheme and implemented it in ICON-XPP. The emulator, trained on coarse-resolution data (80 km), was able to predict unbiased heating rates while providing a substantial speed-up compared to the traditional scheme (Hafner et al., 2024). Considering that climate models often neglect fractional cloudiness within each grid cell, our current work focuses on designing a new ML-based parameterization that not only provides a fast emulation of radiation but also improves the representation of cloud-radiative feedbacks.
**parameterization of turbulence**: The vertical diffusion parameterization implemented in ICON-XPP is a complex scheme requiring the estimation of key turbulence-related variables like the convective boundary layer height (BLH). In an attempt to improve the representation of turbulent mixing in ICON-XPP, we improved the parameterization of the BLH by designing a simple feed-forward neural network model. Training the model on simulations highly-resolved in the vertical (250 levels) yielded substantially improved BLH predictions when coupled to ICON. Work is underway to parameterize the full subgrid turbulent fluxes by training deep neural networks using large-eddy simulations operating at 150 m horizontal grid spacing.

## Report for Task (ii) Tuning and evaluating ICON and ICON-MLe

Here, we worked on automated objective methods for 'tuning' climate models by finding values of 'free' parameters yielding model outputs in line with historical observations. One such automated procedure was developed for ICON (Bonnet et al., 2024) and extensively tested over the last allocation period. The methodology involves running large ensembles of simulations with perturbed parameters, training Gaussian Process models to predict key climate metrics as functions of the chosen parameters, and using history matching to restrict the plausible parameter space to regions producing realistic climates.
An alternative method (Figure 1) developed specifically for the tuning of our data-driven cloud cover equation (see Task (i)) was also designed. This approach relies on the Python module Scipy (in particular, the Nelder-Mead algorithm) to find parameter values that minimize the distance between ICON model outputs and predefined climate metrics whose target values are set from observations and reanalysis. The overall computational cost of the procedure was kept low by progressively increasing the simulation duration for optimization from 1 day to 1 year. Whereas this work was carried out with an older version of ICON, the same method is currently used to tune our new baseline ICON-XPP model.
We also conducted different tuning experiments focusing exclusively on ICON's land model JSBACH (Reick et al., 2021). An ensemble based sensitivity analysis was carried out to investigate the dependency of land and atmospheric climate metrics to 30 JSBACH parameters. This study allowed us to restrict the number of JSBACH parameters relevant for tuning to 10. We currently investigate the application of the two tuning methods mentioned previously (originally designed for atmospheric parameters only) to the JSBACH land model implemented in ICON-XPP.

## Report for Task (iii) Development of ESMValTool for the evaluation of ICON-MLe

During the reporting period, ESMValTool (see Schlund et al., 2023) has been extended to be able to read and process native ICON-XPP outputs. To further facilitate the evaluation of output from ICON-XPP and its ML–enhanced version (ICON-XPP-MLe), a thin wrapper around ESMValTool called ICONEval has been developed which automatically runs a set of predefined evaluation recipes on the model output. At the moment, this focuses on the atmospheric domain and includes comparisons of relevant variables to observations and other state-of-the-art ESMs from the Couple Model Intercomparison Project Phase 6 (CMIP6).

## References


Behrens, G. et al. (2025). *Journal of Advances in Modeling Earth Systems* accepted.

Bonnet, P. et al. (2024). *Tuning a Climate Model with Machine-learning based Emulators and History Matching.* DOI: 10.5194/egusphere-2024-2508.

Hafner, K. et al. (2024). *Interpretable Machine Learning-based Radiation Emulation for ICON.* DOI: 10.22541/essoar.173169996.65100750/v1.

Reick, C. H. et al. (2021). DOI: 10.17617/2.3279802.

Sarauer, E. et al. (2025). *Environmental Data Science* submitted.

Schlund, M. et al. (2023). *Geoscientific Model Development* 16.1, pp. 315–333. DOI: 10.5194/gmd-16-315-2023. URL: https://gmd.copernicus.org/articles/16/315/2023/.