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# Interpretable multiscale Machine Learning-Based Parameterizations of Convection for ICON

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In order to improve climate projections, machine learning (ML)-based parameterizations have been developed for Earth System Models (ESMs) with the goal to better represent subgrid-scale processes or to accelerate computations by emulating existent parameterizations. These data-driven models have shown success in approximating subgrid-scale processes based on high-resolution storm-resolving simulations. However, most studies have used a particular machine learning method such as simple Multilayer Perceptrons (MLPs) or Random Forest (RFs) to parameterize the subgrid tendencies or fluxes originating from the compound effect of various small-scale processes (e.g., turbulence, radiation, convection, gravity waves). Here, we use a filtering technique to explicitly separate convection from these processes in data produced by the Icosahedral Non-hydrostatic modelling framework (ICON) in a realistic setting. We use a method improved by incorporating density fluctuations for computing the subgrid fluxes and compare a variety of different machine learning algorithms on their ability to predict the subgrid fluxes. We further examine the predictions of the best performing non-deep learning model (Gradient Boosted Tree regression) and the U-Net. We discover that the U-Net can learn non-causal relations between convective precipitation and convective subgrid fluxes and develop an ablated model excluding precipitating tracer species. We connect the learned relations of the U-Net to physical processes in contrast to non-deep learning-based algorithms. Our results suggest that architectures such as a U-Net are particularly well suited to parameterize multiscale problems like convection, paying attention to the plausibility of the learned relations, thus providing a significant advance upon existing ML subgrid representation in ESMs.