Contribution ID: **59** Type: **Oral presentation**

# Assessing Machine Learning Approaches for Physical Parameterizations in Atmospheric General Circulation Models

*Wednesday, 7 October 2020 14:30 (30 minutes)*

Atmospheric General Circulation Models (GCMs) contain computationally-demanding physical parameterization schemes, which approximate the unresolved subgrid-scale physics processes. This work explores whether a selection of machine learning (ML) techniques can serve as computationally-efficient emulators of physical parameterizations in GCMs, and what the pros and cons of the different approaches are. We test the ML emulators in a simplified model hierarchy with NCAR's Community Atmosphere Model version 6 (CAM6), which is part of NCAR's Community Earth System Model. Dry and idealized-moist CAM6 model configurations are used, which employ simplified physical forcing mechanisms for radiation, boundary layer mixing, surface fluxes, and precipitation (in the moist setup). Several machine learning techniques are developed, trained, and tested offline using CAM6 output data. These include linear regression, random and boosted forests, and multiple deep learning architectures. We show that these methods can reproduce the physical forcing mechanisms. We also show that the growing complexity of the physical forcing in our model hierarchy puts increased demands on the ML algorithms and their training & tuning. We compare the different machine learning techniques and discuss their strengths and weaknesses.

## Thematic area

1. Machine Learning for Model Identification and Development - Including Model identification, Fast Emulation of Parameterisations, Data driven Parameterisations

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**Session Classification:** Session 5 (cont.): ML for Model Identification and development

**Track Classification:** ECMWF-ESA Workshop on Machine Learning for Earth System Observation and Prediction