EGU24-10087, updated on 27 Mar 2025
https://doi.org/10.5194/egusphere-egu24-10087
EGU General Assembly 2024

Contribution of latent variables to emulate the physics of the IPSL model

Ségolène Crossouard[1], Masa Kageyama[1], Mathieu Vrac[1], Thomas Dubos[2], Soulivanh Thao[1], and Yann Meurdesoif[1]
[1]Laboratoire des Sciences du Climat et de l'Environnement (LSCE/IPSL), CEA/CNRS/UVSQ, Gif-sur-Yvette, France
[2]Laboratoire de Météorologie Dynamique (LMD/ISPL), Ecole Polytechnique, Palaiseau, France

Atmospheric general circulation models include two main distinct components: the dynamical one solves the Navier-Stokes equations to provide a mathematical representation of atmospheric movements while the physical one includes parameterizations representing small-scale phenomena such as turbulence and convection (Balaji et al., 2022). However, computational demands of the parameterizations limit the numerical efficiency of the models. The burgeoning field of machine learning techniques opens new horizons by producing accurate, robust and fast emulators of parts of a climate model. In particular, they can reliably reproduce physical processes, thus providing an efficient alternative to traditional process representation. Indeed, some pioneering studies (Gentine et al., 2018; Rasp et al., 2018) have shown that these emulators can replace one or more parameterizations that are computationally expensive and so, have the potential to enhance numerical efficiency.

Our research work aligns with these perspectives, since it involves exploiting the potential of developing an emulator of the physical parameterizations of the IPSL climate model, and more specifically of the ICOLMDZOR atmospheric model (for DYNAMICO, the dynamic solver using an icosahedral grid - LMDZ, the atmospheric component - ORCHIDEE, the surface component). The emulator could improve performance, as currently almost half of the total computing time is given to the physical part of the model.

We have developed two initial offline emulators of the physical parameterizations of our standard model, in an idealized aquaplanet configuration, to reproduce profiles of tendencies of the key variables - zonal wind, meridional wind, temperature, humidity and water tracers - for each atmospheric column. The results of these emulators, based on a dense neural network or a convolutional neural network, have begun to show their potential for use, since we easily obtain good performances in terms of the mean of the predicted tendencies. Nevertheless, their variability is not well captured, and the variance is underestimated, posing challenges for our application. A study of physical processes has revealed that turbulence was at the root of the problem. Knowing how turbulence is parameterized in the model, we show that incorporating physical knowledge through latent variables as predictors into the learning process, leading to a significant improvement of the variability.

Future plans involve an online physics emulator, coupled with the atmospheric model to provide a better assessment of the learning process (Yuval et al., 2021).