Neural Representation of the Stratospheric Ozone Chemistry

Helge Mohn*
Climate Sciences | Atmospheric Physics
Alfred Wegener Institute
14473 Potsdam, Germany
helge.mohn@awi.de

Daniel Kreyling
Climate Sciences | Atmospheric Physics
Alfred Wegener Institute
14473 Potsdam, Germany

Ingo Wohltmann
Climate Sciences | Atmospheric Physics
Alfred Wegener Institute
14473 Potsdam, Germany

Ralph Lehmann
Climate Sciences | Atmospheric Physics
Alfred Wegener Institute
14473 Potsdam, Germany

Peter Maass
Center for Industrial Mathematics
University of Bremen
28359 Bremen, Germany

Markus Rex
Climate Sciences | Atmospheric Physics
Alfred Wegener Institute
14473 Potsdam, Germany

Abstract

In climate modeling, the stratospheric ozone layer is typically only considered in a highly simplified form due to computational constraints. For climate projections, it would be of advantage to include the mutual interactions between stratospheric ozone, temperature, and atmospheric dynamics to accurately represent radiative forcing. The overarching goal of our research is to replace the ozone chemistry in climate models with a machine-learned neural representation of the stratospheric ozone chemistry that allows for a particularly fast, but accurate and stable simulation.

We created a benchmark data set from pairs of input and output variables that we stored from simulations of a chemistry and transport model. We analyzed several variants of multilayer perceptrons suitable for physical problems to learn a neural representation of a function that predicts 24-hour ozone tendencies based on input variables. We performed a comprehensive hyperparameter optimization of the multilayer perceptron using Bayesian search and Hyperband early stopping. We validated our model by implementing it in a chemistry and transport model and comparing computation time, accuracy, and stability with the full chemistry module.

We found that our model had a computation time that was a factor of 700 faster than the full chemistry module. The accuracy of our model compares favorably to the full chemistry module within a two-year simulation run, also outperforms a previous polynomial approach for fast ozone chemistry, and reproduces seasonality well in both hemispheres.

In conclusion, the neural representation of stratospheric ozone chemistry in simulation resulted in an ozone layer that showed a high accuracy, significant speed-up, and stability in a long-term simulation.

*Center for Industrial Mathematics, University of Bremen, 28359 Bremen, Germany

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