Uncertainty Quantification of Machine Learning Subgrid-Scale Parameterizations for Gravity Waves

DATAWAVE

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Introduction

There has been a dramatic rise machine learning (ML) subgrid-scale parameterizations which aim for faster prediction and/or higher accuracy. We aim to quantify the uncertainties associated with an ML-based parameterization for gravity waves.

Gravity waves

Atmospheric gravity waves (GWs) drive middle atmosphere circulation as they transport momentum vertically away from their sources (e.g., convection, frontogenesis and orography). GW lengthscales range from tens to thousands of km, but typical climate model resolutions are around 100 km, meaning a large portion GWs are not resolved explicitly. Instead, subgrid-scale GW drag must be captured via parameterizations.

GW parameterization (AD99)

We use the convective GW parameterization to estimate gravity wave drag (GWD) based on Alexander and Dunkerton, 1999 (AD99):

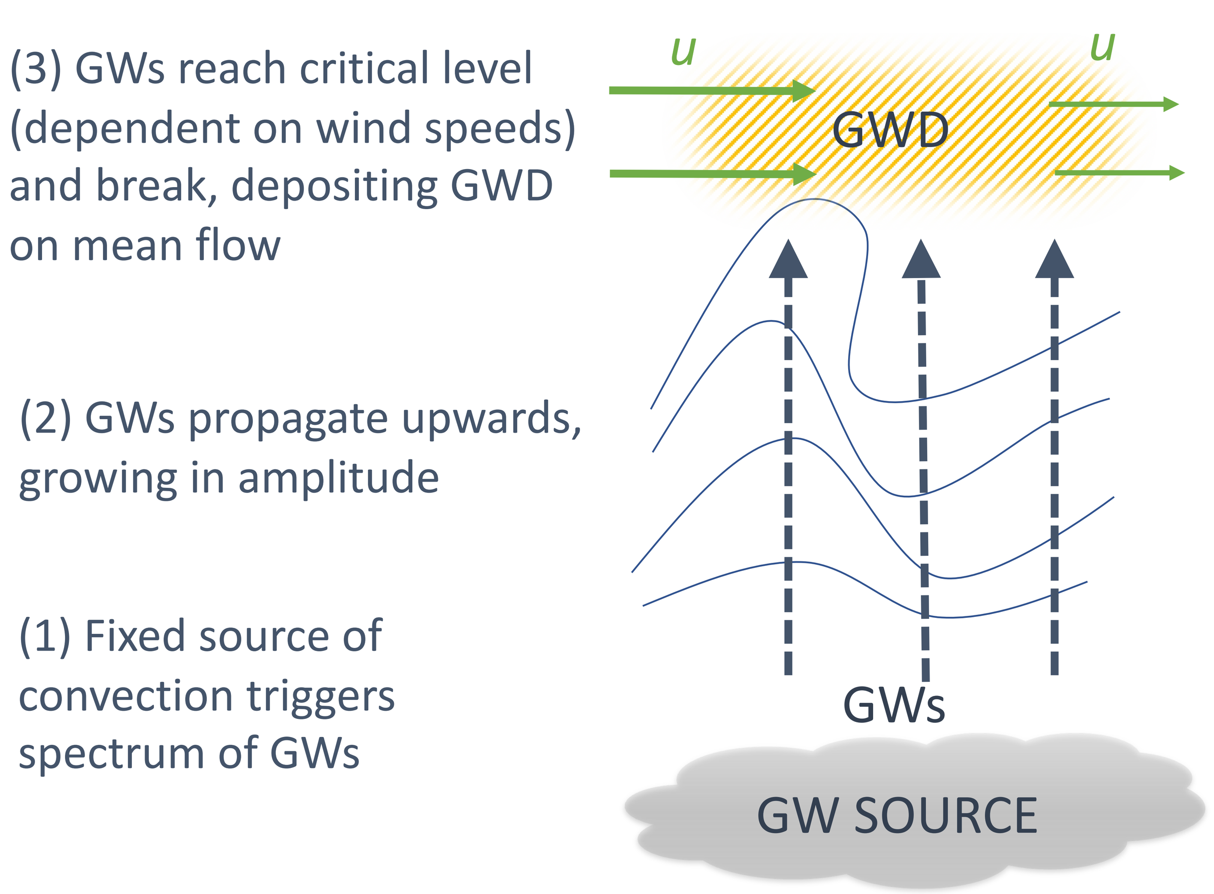

Fig. 1: AD99 schematic

We use AD99 coupled to an intermediate complexity climate model, MiMA, to train a neural network following Espinosa et al., 2022.

A neural network emulator of AD99

Espinosa et al. (2022) train a neural network (NN) that emulates GWD from AD99, using data from climate model, MiMA.

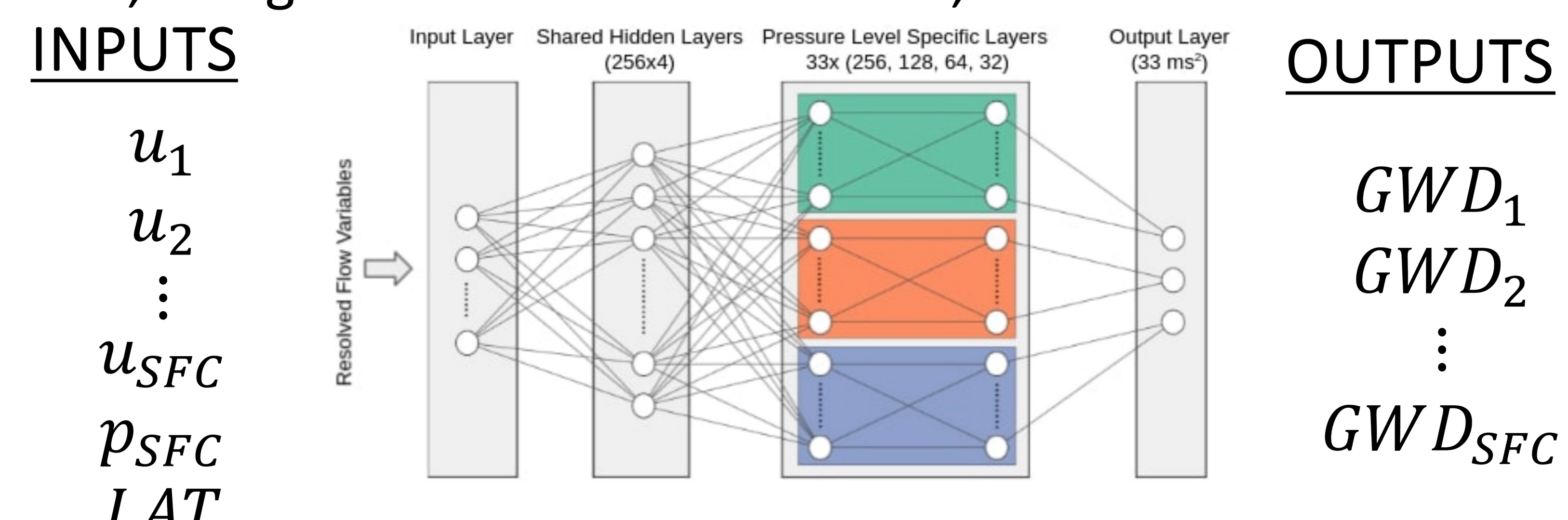

Fig. 2: NN emulator of AD99

Estimating Parametric Uncertainties

Train 50-member ensemble of NNs, each with the same architecture but different random initialization → distribution of parameters.

Offline Uncertainties

Fig. 3 shows the NN ensemble mean (red) and standard deviation (orange shading) compared against the ground truth (black) at a single gridpoint and timestep. We call these *offline uncertainties,* i.e., not coupled to the climate model.

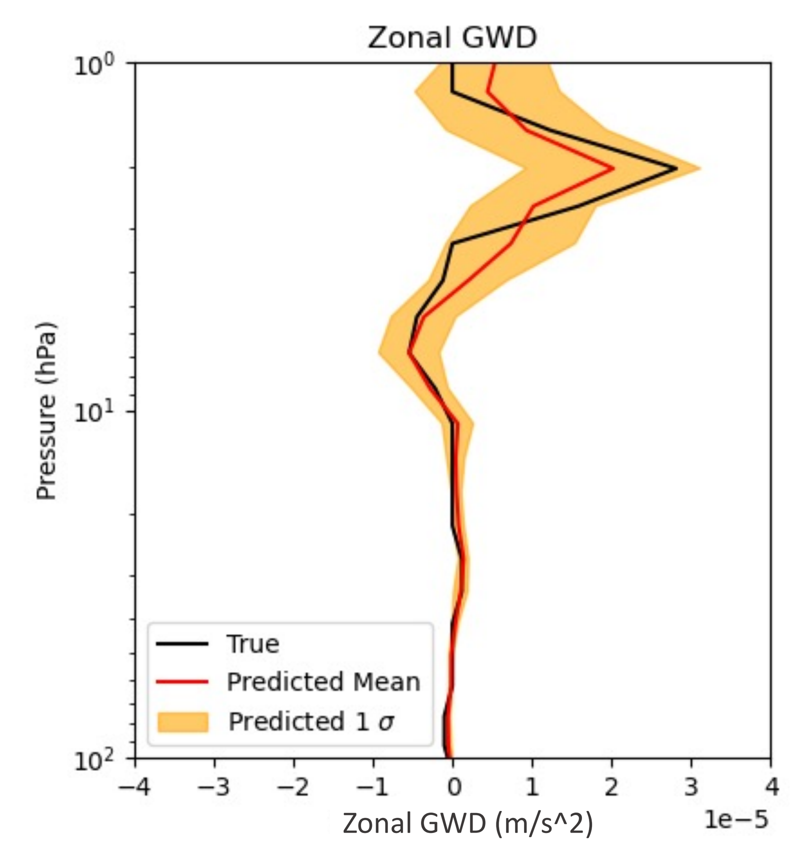

Fig. 3: Profiles of AD99 vs. NN GWD offline

Increased online uncertainties

We estimate *online uncertainties* (uncertainty in GWD within the climate model) by running an ensemble of MiMA simulations, each coupled to a separately trained NN described above. Comparing distributions of gravity wave drag, we find greater uncertainties increase due to error propagation and diverging simulations, which leads to filtering of winds.

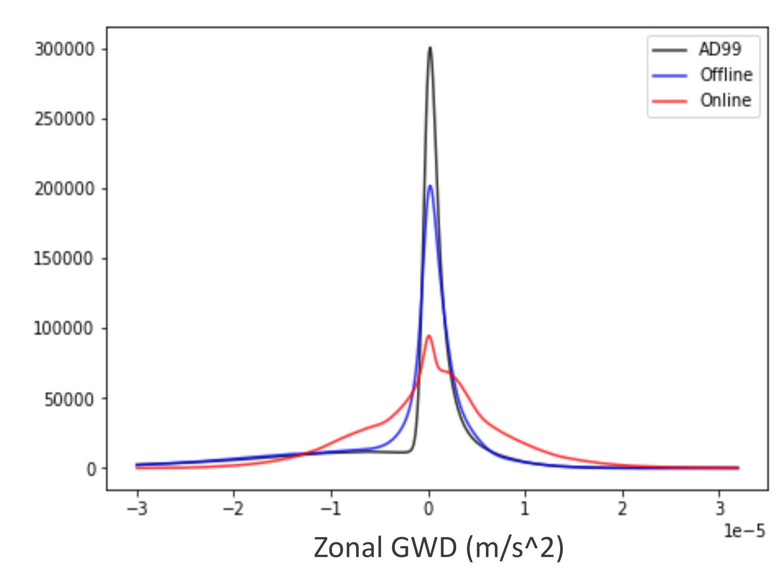

Fig. 4: Distributions of gravity wave drag in tropics at 10 hPa

Uncertainties in the QBO

GWs drive stratospheric phenomena such as the Quasi-Biennial Oscillation (QBO), the downwards propagating zonal winds in the equatorial stratosphere. Parameterizations are required for a spontaneous QBO in climate models. Fig. 5 shows the QBO in MiMA when coupled to (a) AD99 and (b-d) three of the NNs.

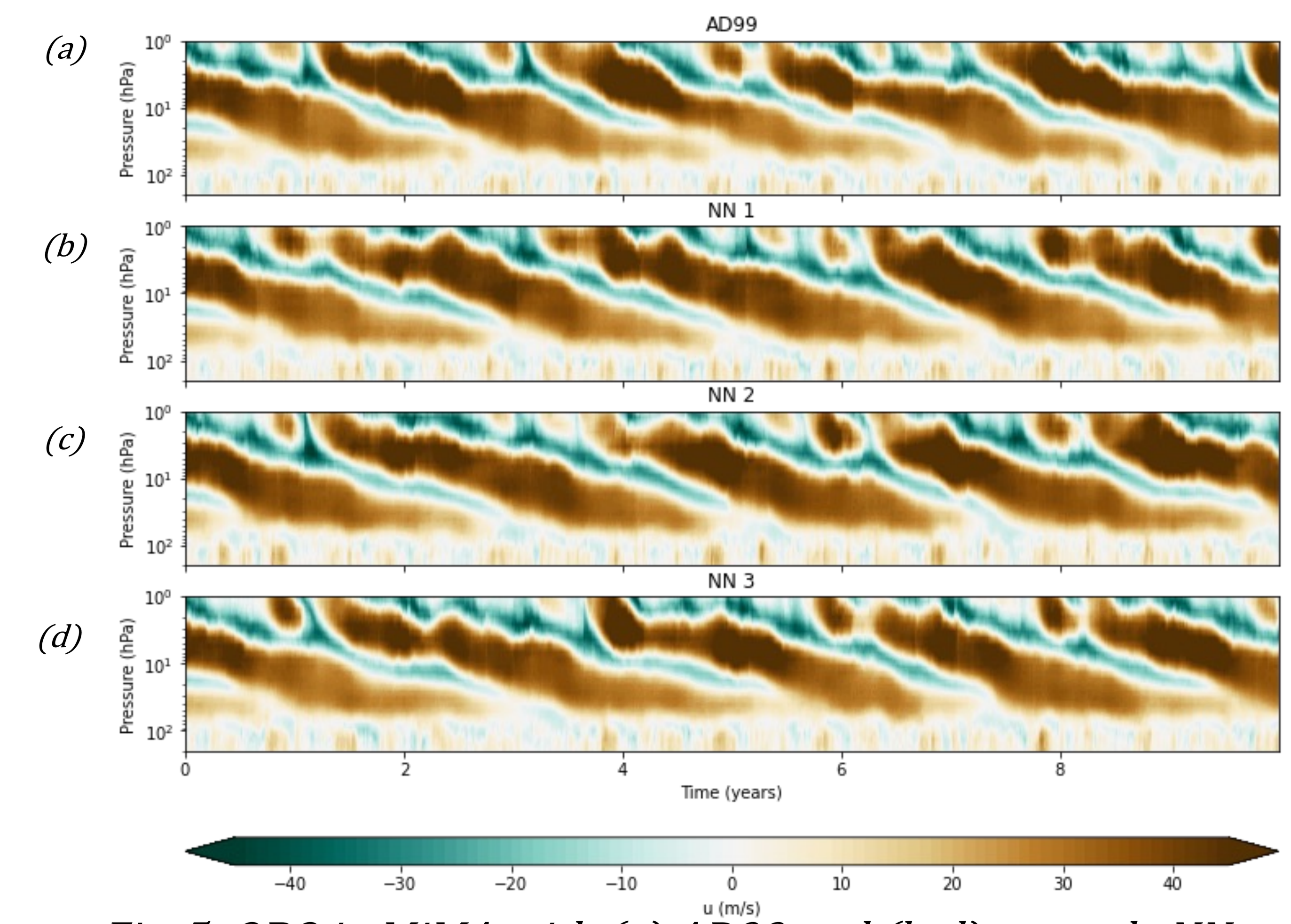

Fig. 5: QBO in MiMA with (a) AD99 and (b-d) example NNs

Fig. 6 shows the increased variability in QBO periods at 10 hPa for NNs compared to AD99.

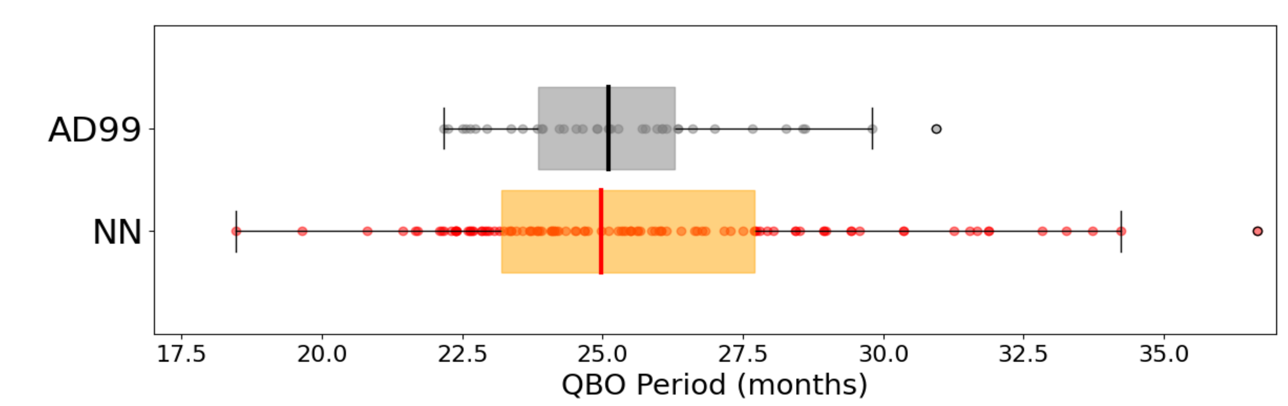

Fig. 6: QBO period at 10 hPa in MiMA for AD99 and NNs

Conclusions

Replacing an existing gravity wave parameterization with a machine learning alternative increases the uncertainty in QBO period. Next, we should consider the breakdown of uncertainty by source: structural uncertainty, training data uncertainty, generalization uncertainty. This also provides a basis for online training/calibration of NNs.

Refs.: Alexander and Dunkerton (1999), *JAS*, 56, 24 pp. 4167-4182; Espinosa et al. (2022) *GRL*, 49, 8, e2022GL098174. Contact me: lauraman@stanford.edu