Deep learning parameterization of small-scale vertical velocity variability for atmospheric models

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Small-scale fluctuations in vertical wind velocity, unresolved by climate and weather forecast models play a particularly important role in determining vapor and tracer fluxes, turbulence and cloud formation. Fluctuations in vertical wind velocity are challenging to represent since they depend on orography, large scale circulation features, convection and wind shear. Parameterizations developed using data retrieved at specific locations typically lack generalization and may introduce error when applied on a wide range of different conditions. Retrievals of vertical wind velocity are also difficult and subject to large uncertainty. This work develops a new data-driven, neural network representation of subgrid scale variability in vertical wind velocity. Using a novel deep learning technique, the new parameterization merges data from high-resolution global cloud resolving model simulations with high frequency Radar and Lidar retrievals. Our method aims to reproduce observed statistics rather than fitting individual measurements. Hence it is resilient to experimental uncertainty and robust to generalization. The neural network parameterization can be driven by weather forecast and reanalysis products to make real time estimations. It is shown that the new parameterization generalizes well outside of the training data and reproduces much better the statistics of vertical wind velocity than purely data-driven models.