Developing a unified parameterization of diabatic heating for regional climate modeling simulations

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Introduction

• Atmospheric processes such as turbulence fluxes, short- and longwave radiative fluxes, and convective and stratiform cloud precipitation are conventionally parameterized separately as one-dimensional problems.

• Such a separation is not realistic as these processes are three-dimensional in nature and interact with each other.

• Parameterizations represent a large source of model errors and sensitivities at a large computational cost.

• Many of the inputs of the different parameterizations are the same.

Objective

The major goal is to create a unified transfer function called <u>Universal Look-Up Table</u> (ULUT) for the diabatic heating and moistening/drying that would be able to reproduce the meteorological fields with the same accuracy as in the original model configuration but at a fraction of the cost.

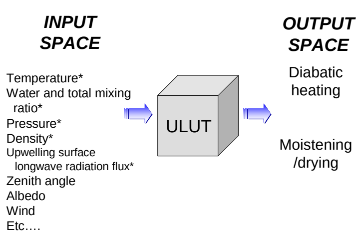


*Fig. 1. Schematic illustration of the Universal Look-up Table implementation within a regional climate model. Input space for the longwave heating rates are marked with **

Experimental Design

• We run the Regional Atmospheric Modeling System (RAMS) for selected months in 2006 using the standard one-dimensional parameterizations for diabatic heating.

• Simulation domain is centered at (33°N, 100°W) and has 160x120 grid points of 35 x 35 km grid-cell size. There are 30 levels in the atmosphere, with the first vertical level at 100 m and gradually stretching to 1 km, with a ratio of 1.2.

• The 30-hour test cases use the North American Regional Reanalysis for initial and lateral boundary conditions.

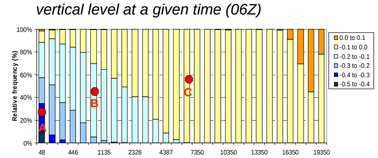
• The diabatic heating rates for each of the parameterizations are stored together with the input variables.

Preliminary results

1.What are the output and input space distributions (example for longwave radiation parameterization)?

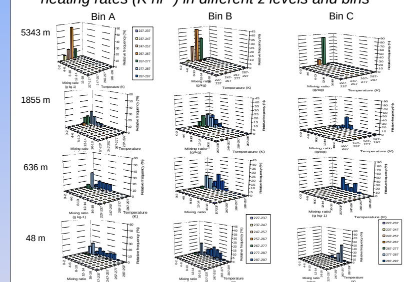
• For the ***output space*** heating rates are binned to a rate of 0.1K per hour. The example for the upper levels really shows that parameterization overkill is usually used since such limited values are needed. Even for a finer resolution, 0.05Khr^{-1}, the number of intervals is one or two more.

Fig 2. Relative frequency of longwave heating rates (K hr^{-1}) for a each model vertical level at a given time (06Z)



• As an example of the ***input space***, for some of the bins, pairs of [Temperature (z), water vapor mixing ratio (z)] are binned for different levels (A, B, C in previous figure)

Fig 3. Bivariate histograms of temperature (K) and water vapor mixing ratio (g kg^{-1}) for the longwave heating rates (K hr^{-1}) in different z levels and bins



Associated profiles of the input space are also distributed in a small number of bins, specially for higher levels (at point C)

2. Ongoing work: proof of concept with the longwave radiative flux parameterization.

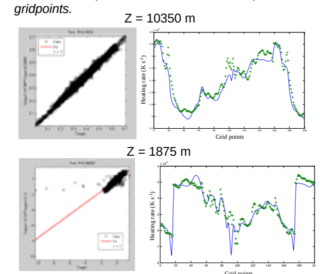
• We are currently using feed-forward, backpropagation neural networks (NN) with two layers of fully interconnected nodes (sigmoidal transfer function on the hidden layer and linear transfer function on the output layer). The hidden layer has 35 neurons.

• We chose to generate a NN for each vertical level. The input space is shown in Fig. 1 with *****, while the output is the vertical profile of longwave flux heating rates. All datasets are rescaled to have zero mean and unity standard deviation.

• The neural networks are trained by using a fast training algorithm based on Levenberg-Marquart optimization. For each level, these networks are trained and tested using sets of grid points chosen at random (11,200 points are using for training, and 3,700 for testing the network predictions). Network performance during training and testing is measured by mean squared error.

• Preliminary results are encouraging – see Fig 4.

*Fig. 4. (**Left**) Scatterplot of NN estimated vs. RAMS output of longwave radiation parameterization of heating rates (LWHR) for all gridpoints. (**Right**) NN estimated and RAMS output LWHR for a smaller sample of gridpoints.*



•Next steps include incorporating trained networks within RAMS to compare prediction accuracy. Also, we need to expand the training sets to account for possible conditions not seen on the initial training sets, and optimize the structure of the neural network.

• Later on, the rest of the parameterizations within RAMS will be added and also with the typical options for a regional climate modeling simulation.

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