Using Neural Network to Emulate the Radiative Transfer

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Motivation

1. Radiative transfer is one of the most computationally expensive components in the atmosphere model.
2. Current models parameterize it and trade off accuracy for speed by grouping wavebands and using precalculated huge lookup tables (for example: RRTM).
3. Even so, we cannot afford to call radiative transfer on every time step, and it still takes about half of total cost of a typical atmosphere model.
4. Previous work has show promising results by training a neural network to emulate the radiative transfer(ref. 1-4).

So, we believe machine learning, specifically artificial neural network, can help us to automatically optimize the accuracy-speed tradeoff in radiative transfer parameterization.

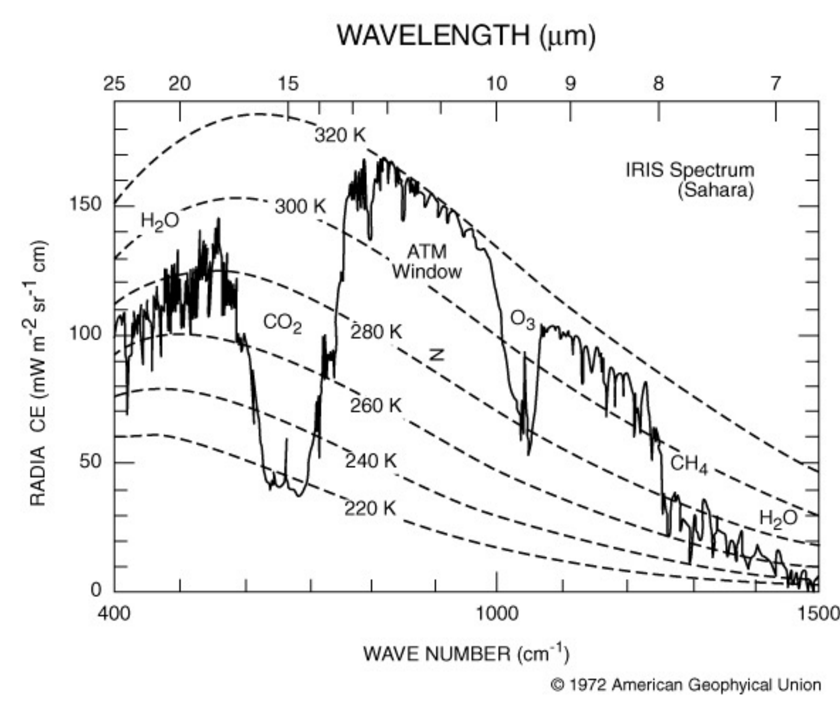


Fig. 1. A typical outgoing longwave radiation observation at top of the atmosphere. Different gases active at different wavelength and climate models have to solve it explicitly to account their climate impact.

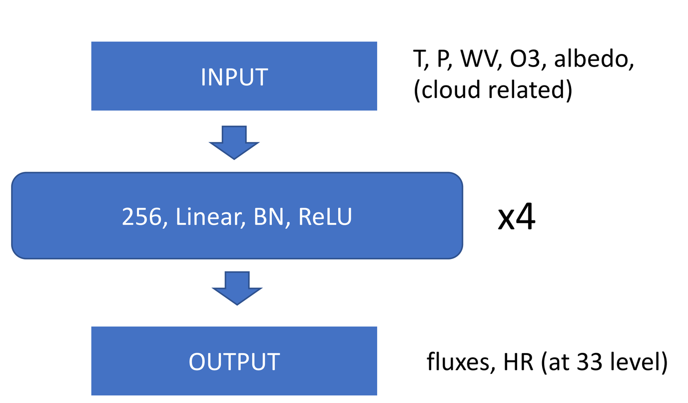
Data and Method

Data:

- One year run of the GFDL-AM4 model (radiative transfer module: RRTMGP). We use 24 days (1st and 7th of 12 month) to train/validate the neural network (NN). Each day has 8 globally snapshots (on model grid: cubic sphere, ~10.6 million columns in total).
- The performance of NN shown here is test on the different 5 days of 12 month (15th, 18th, 21st, 24th and 27th, ~25 million columns in total).

Neural Network:

- Target to emulate the radiative transfer of the whole column (4 independent NNs for different sky condition: LW/SW clear/all sky, no aerosol in this work).
- Fully connected with four hidden layers (256 nodes, ReLU).
- Batch normalization layer is applied before activation function to reduce training time.
- The optimization algorithm is Adam with L2 regularization.



Input:

1. LW clear sky (102): surface pressure, temperature (level), surface temperature, specific humidity (level), Ozone (level)
2. SW clear sky (108): + cosine_zenith, visible/infrared direct/diffused albedo, rsdt

3/4 LW/SW cloud sky (432/438): + stratiform/shallow droplet number, liquid content, ice content, cloud fraction

Output:

1. LW (36): rlds, rlus, rlut, heating rate ($\frac{dT}{dt}$, level)
2. SW (36): rsut,rsds, rsus, heating rate ($\frac{dT}{dt}$, level)

Loss function:

- Data loss:

$$loss_{data} = MSE(Y^{pred}, Y^{truth})$$

- Energy conservation:

$$F_{net}^{atm} = \int \frac{c_p}{g}\frac{dT}{dt}dP$$

$$loss_{energy} = MSE(F_{net}^{atm}, \int \frac{c_p}{g}\frac{dT}{dt}dP)$$

- Total loss = $loss_{data} + \alpha\ loss_{energy}$

Others:

◉PyTorch ◉ NVIDIA A100

Results

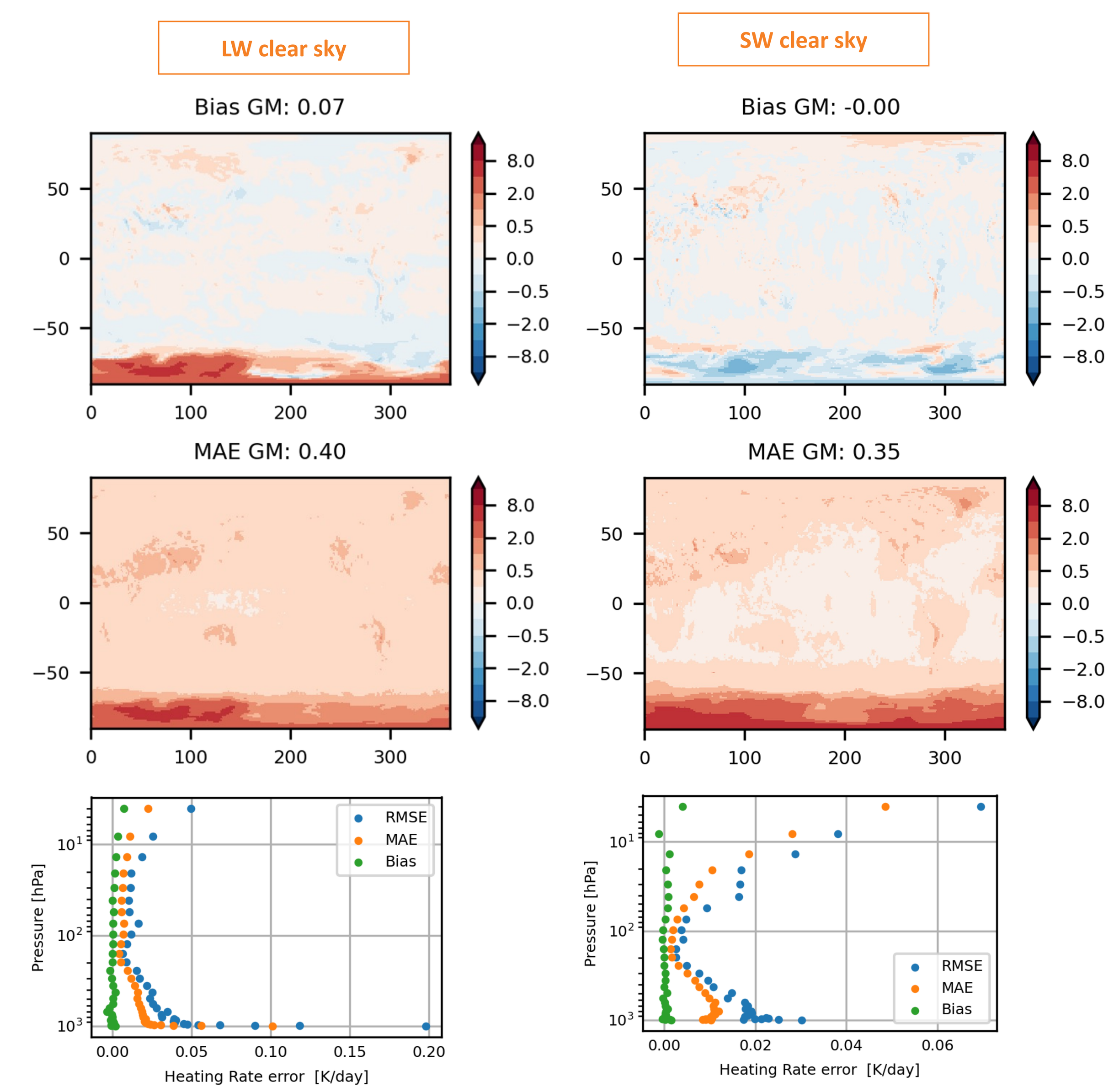


Fig. 2. Performance of the NN for LW/SW in clear-sky condition. Top/mid row shows the bias/MAE [W/m^2] of the outgoing longwave radiation (rlut) and upward shortwave (rsut) at the TOA. Bottom arow shows the heating rate error on 33 hybrid pressure levels.

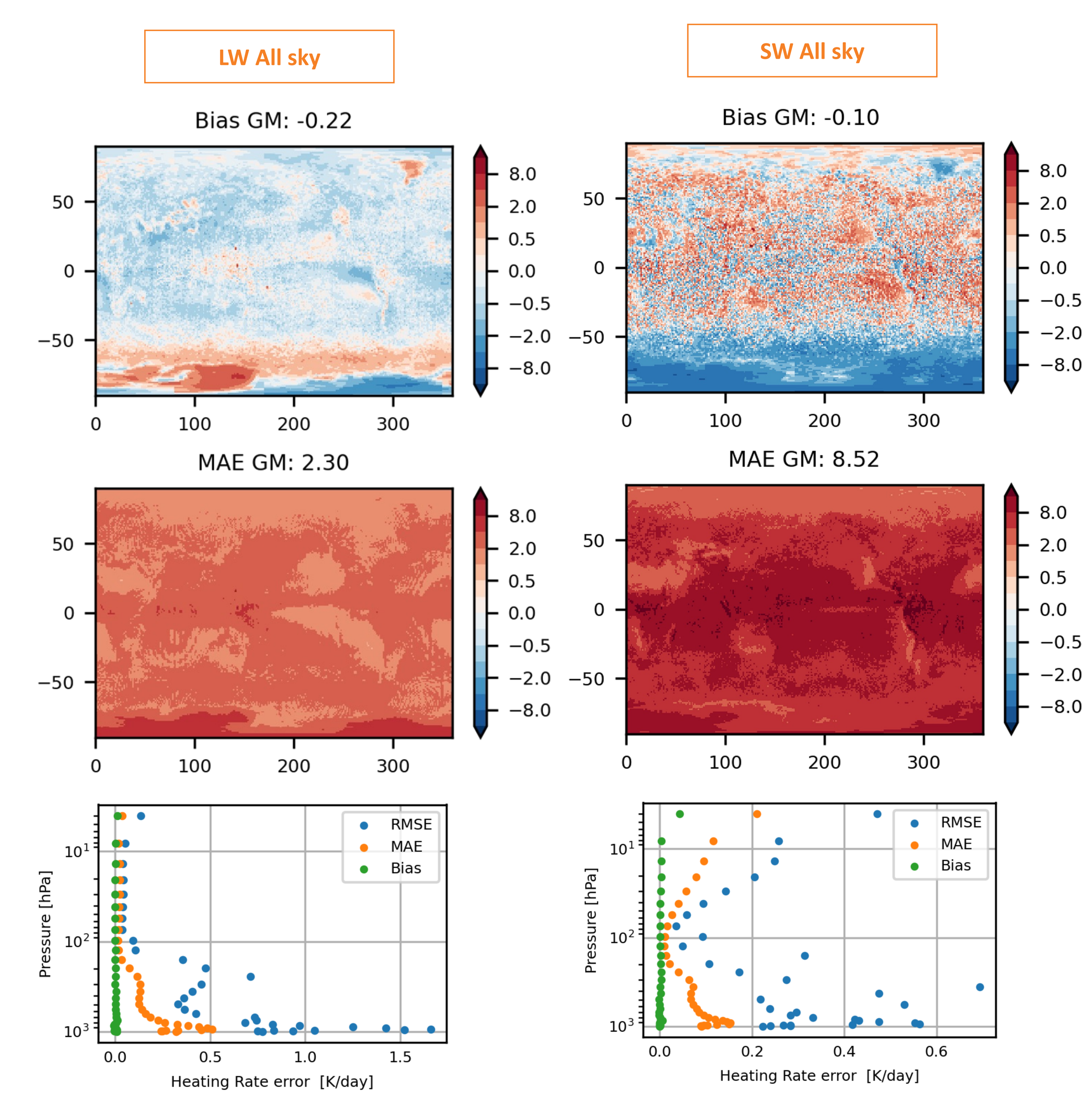


Fig. 3. Same as in Fig. 2 but for all-sky condition.

Clear sky:

1. LW (1st column): Biases/MAE are small overall and Antarctica region seems to be a major source of error. The large error in heating rates near surface is mainly due to large variation in data itself (hence a harder target to learn).
2. SW (3rd column): The performance is similar to LW, but relatively large error on land may be due to varying surface albedo. Heating rate error in stratosphere is larger than troposphere.

Overall, the error of NN emulator for clear sky radiative transfer is small and reliable (flux < 0.5 W/m^2, HR < 0.05K/day). Further improvements can be done, like balancing the training data in ocean/land/ice region or even create different emulators.

All sky:

Because stochastic cloud overlap scheme is adopted in AM4 (and also in many other GCMs) to account for partial cloud cover (ref. 5&6), larger MAE here is expected. It is difficult to separate the error of NN and noise in current results. But bias still works as good indicator. Our results suggest that NNs are able to deal with randomness in training data.

1. LW (2nd column): Large biases in Antarctica is about the same as clear sky. Additional biases appears in Pacific cloud tongue and Southern Ocean. Heating rate error in upper troposphere and top of the boundary layer also stands out.
2. SW (4th column): The noisy pattern in bias reflect the randomness (noise) in training dataset. The bias in Southern Ocean and Antarctica can be attributed to clouds.

Limitations and Further work:

1. The speed of the NN emulator is to be tested. We will implement the NN into the AM4 and perform the online test. Naively, larger NN will have higher accuracy but slower speed.
2. Including aerosols. The number of aerosol related variables is large and whether to use the current fully connected NN or something else like in Lagerquist et al (2021).
3. Including greenhouse gases like CO2, CH4.

References:

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