PHYSICS-INFORMED DOMAIN-AWARE ATMOSPHERIC RADIATIVE TRANSFER EMULATOR FOR ALL SKY CONDITIONS

Objective: Guide a Deep Learning Framework with Cloud Radiative Forcing Physics

Piyush Garg, Emil Constantinescu, Bethany Lusch, Troy Arcomano, Jiali Wang, Rao Kotamarthi

Argonne National Laboratory, Lemont, IL

Contact: pgarg@anl.gov

INTRODUCTION AND MOTIVATION

- Radiative transfer modeling is a complex and computationally expensive process that is used to predict how radiation interacts with the atmosphere and Earth's surface.
- Shortwave (SW) radiation is mostly incoming solar radiation (ƛ ≤ 4μ) while longwave (LW) spectrum is primarily terrestrial infrared radiation (ƛ ≥ 4μ). Both these spectrums work in tandem with each other to create the energy balance in the Earth's atmosphere.
- These radiation interactions are represented by widely-developed radiative transfer models (RTMs) as a process-scale model in the numerical weather prediction and climate models (Mlawer et al., 1997).

These RTMs are computationally expensive to run at every model time step and thus **machine learning-based radiation emulators** can help reduce the computational cost and improve the accuracy of weather and climate models.

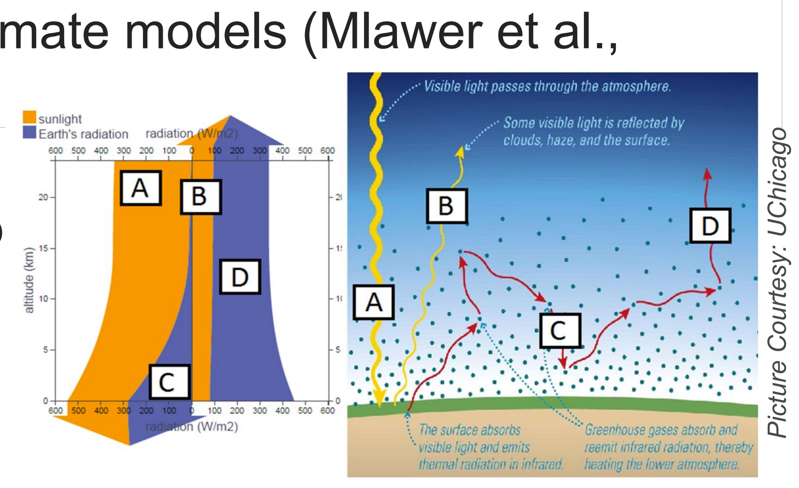


Figure 1: Radiative Transfer in the Atmosphere

DATASET USED

- The data used in this study is from 28 years of output from the regional climate model using **Weather Research and Forecasting (WRF) version 3.3.1**, driven by the National Centers for Environmental Prediction (NCEP-R2) from **1982 to 2009**.
- The model covers the entire troposphere with 38 vertical levels from surface to ~16 km (110 hPa).
- This version uses Rapid Radiation Transfer Model for GCMs (RRTMG; Pincus et al., 2003).

INPUTS & OUTPUTS

Inputs

- Surface: Albedo, solar zenith angle, elevation, air temperature, atmospheric pressure
- Vertical: Ozone, water vapor, ice, cloud water, rain concentration, cloud fraction

Outputs

- ***LW***: Outgoing longwave radiation (OLR), Up and Down fluxes at TOA and surface, heating rates
- ***SW***: Up and Down fluxes at TOA and surface, heating rates

PHYSICS-INFORMED DOMAIN-AWARE NETWORK

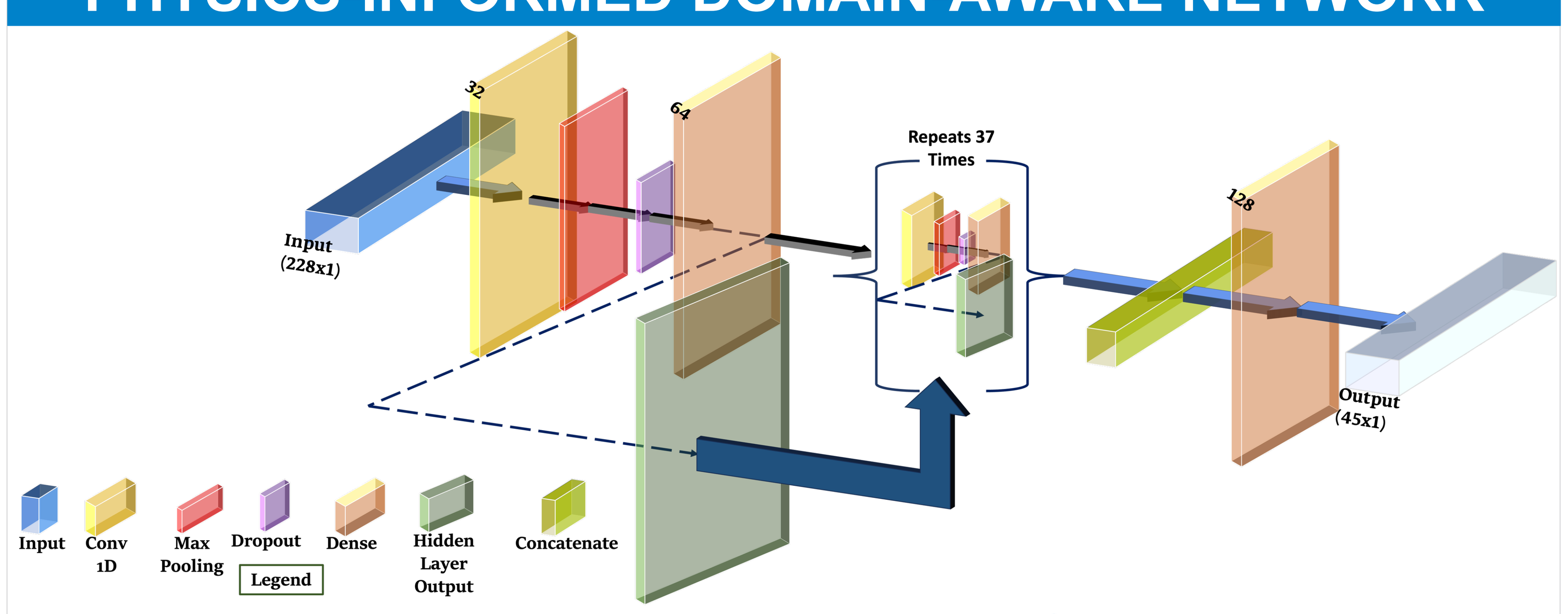


Figure 2: Deep Learning Framework Schematic

- Figure 2 depicts our **PIDA-CNN** architecture where we have 38 hidden layer blocks containing a 1D Convolutional layer (32 filters) followed by a Max Pooling and dropout layer, which connects to a dense layer of 64 neurons (similar to Wang et al., 2019).
- The output of this block is passed as an additional input to the next neural network block and it repeats 37 times.
- The outputs of these blocks are then concatenated into one layer which then connects to a dense layer of 128 neurons.
- The final output is SW/LW heating rates at 38 vertical levels and upward and downward fluxes at the top of the atmosphere and surface.

SZA: Solar Zenith Angle

- The following equations describe the custom loss functions for SW and LW outputs where $\mathcal{L}_\delta(y,\hat{y})$ is the traditional Huber loss function with additional penalties for SZA, CRF, and an L_1 regularization term.

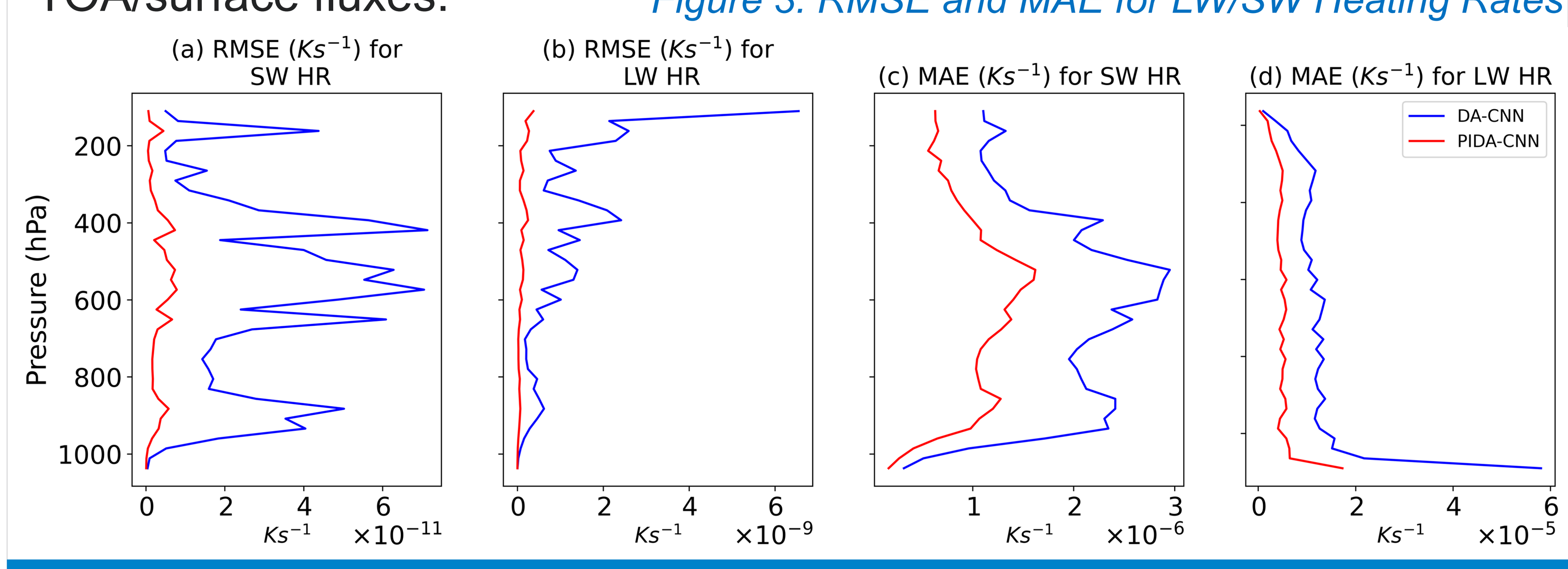
$$\mathcal{L}_{SW}(y,\hat{y},\beth_{sza},\beth_{CRF}) = \mathcal{L}_\delta(y,\hat{y}) + \mathcal{L}_\delta(y,\hat{y}) * \beth_{sza} + \mathcal{L}_\delta(y,\hat{y}) * \beth_{CRF} + L_1$$
$$\mathcal{L}_{LW}(y,\hat{y},\beth_{CRF}) = \mathcal{L}_\delta(y,\hat{y}) + \mathcal{L}_\delta(y,\hat{y}) * \beth_{CRF} + L_1$$

- We compare our results with a baseline CNN **(DA-CNN)** without a custom loss function.

HEATING RATES PERFORMANCE

PIDA-CNN outperforms the traditional DA-CNN for heating rates and TOA/surface fluxes.

Figure 3: RMSE and MAE for LW/SW Heating Rates



TOA/SURFACE FLUXES

SW flux prediction is better than LW flux prediction.

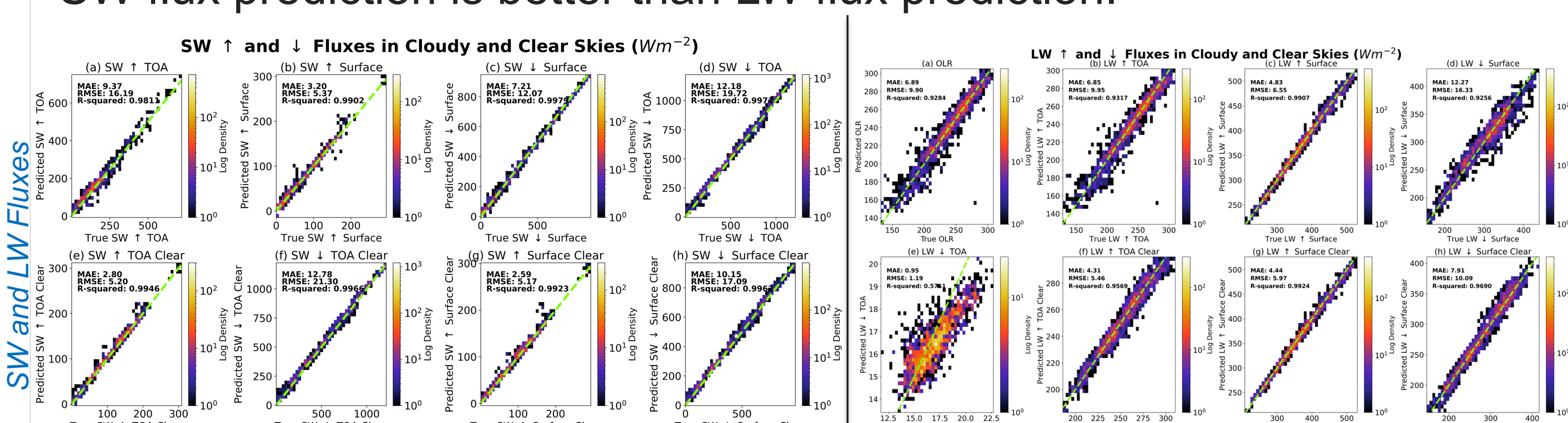
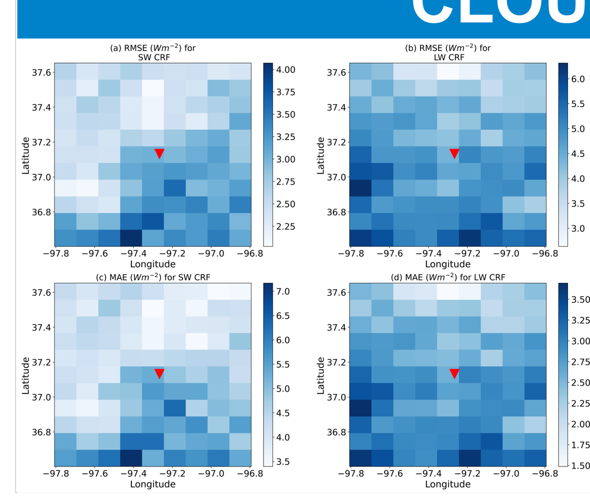


Figure 4 and 5: True and Predicted SW and LW Fluxes

CLOUD RADIATIVE FORCING



$$CRF_{LW/SW} = F_{cld}^{LW/SW} - F_{clr}^{LW/SW}$$

Figure 6 shows RMSE and MAE for SW/LW CRF on the training location and the surrounding grid.

Overall, PIDA-CNN performs well in predicting both SW and LW CRF.

Figure 6: RMSE and MAE for LW/SW CRF

CONCLUSIONS

- In this study, we develop an atmospheric radiative transfer emulator for all sky conditions (cloudy) using a CNN architecture where we physically constrain the SW and LW vertical heating rates and fluxes using solar position and cloud radiative forcing.
- We also enforce the vertical dependence of atmospheric layers using a "Domain-Aware" approach.
- Our PIDA-CNN emulator obtains low RMSE/MAE and high correlation in predicting both SW and LW fluxes, heating rates, and CRF.

NEXT STEPS

- The emulator is ~100 times faster than traditional RRTMG on GPUs.
- This speed-up would allow us to couple the emulator with a traditional dynamical core of WRF/SCREAM.
- In our next steps, we aim to couple the PIDA-CNN emulator with the WRF/E3SM dynamical core to run radiative transfer parameterization at every model time step.
- With this exercise, we hope to improve the accuracy of weather and climate predictions.

REFERENCES

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