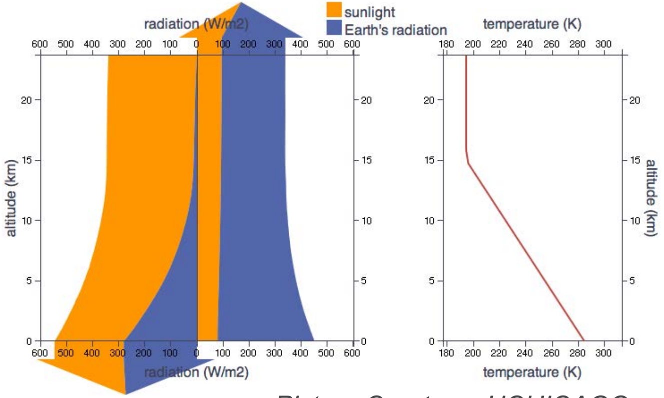
2023 ARM/ASR JOINT USER FACILITY AND PI MEETING

PHYSICS-CONSTRAINED MACHINE LEARNING EMULATOR FOR RAPID RADIATION TRANSFER MODEL (RRTMG)



Picture Courtesy: UCHICAGO

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Remote

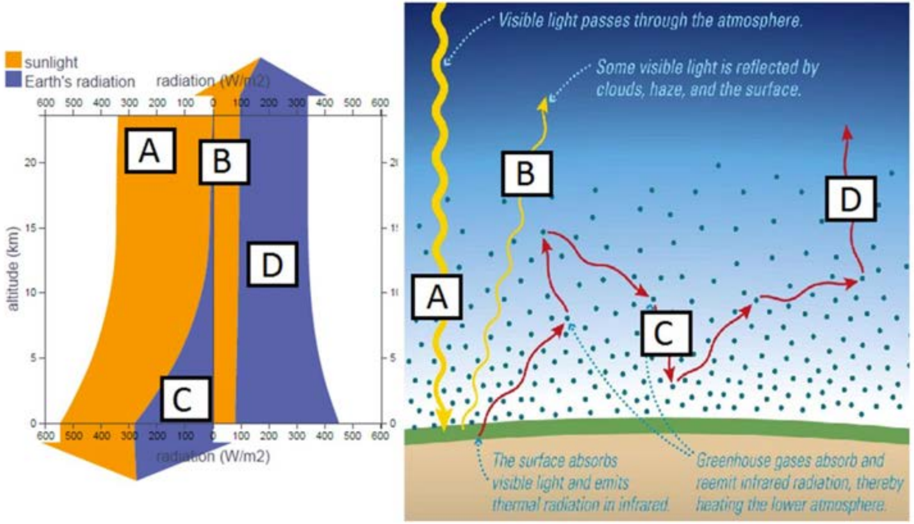
BRIEF OVERVIEW OF THE PRESENTATION

- Overview of RRTMG process model
- Why Emulate RRTMG?
- Description of the Dataset used
- Domain Aware CNN Framework
- Custom Loss Function Based on Clouds and Sun Angle
- Results
  Shortwave Radiation Emulator
  Longwave Radiation Emulator
- Conclusions and Future Work

RAPID RADIATIVE TRANSFER MODEL (RRTMG)

Brief Overview of the Radiative Transfer

- RRTMG is designed to calculate the radiative transfer of solar and thermal (infrared) radiation through the Earth's atmosphere.
- The primary purpose of RRTMG is to estimate how atmospheric gases, aerosols, and clouds interact with incoming solar radiation and outgoing terrestrial radiation, affecting the energy balance of the Earth's climate system.
- RRTMG utilizes a set of mathematical equations and algorithms to simulate the absorption, emission, and scattering of radiation by various atmospheric constituents (e.g., CO_2, H_2O, CH_4, O_3, Aerosols, and clouds).



Picture Courtesy: UChicago

WHY EMULATE RRTMG?

Computational Cost and Efficiency

- Radiative transfer in general is quite complex due to the spectral nature of gaseous absorption, as well as changes in the refractive index and shape of particles acting to scatter and absorb radiation.
- The most accurate radiative transfer models are line-by-line models, which explicitly simulate gaseous absorption in each band, but they are very expensive to run.
- RRTMG emulates these line-by-line models and thus is relatively faster but still too slow for numerical weather prediction (e.g., WRF, HRRR) and Earth system models (e.g., E3SM) and is too slow to call at every model time step.
- Therefore while other parameterizations are called at every time step, RRTMG is called less often, thus making model predictions less accurate.

DATASET USED TO EMULATE RRTMG

DATASET

WRF v3.8.1 with RRTMG

- We used 12-km WRF runs initialized using NCEP Reanalysis dataset over the Continental United States (CONUS) at 37 vertical levels (Surface to 116 hPa).
- Training is performed over a single column located over 35.15°N and -95°W and the emulator was tested on data from 36.15°N, -94°W.

Total 302 Inputs

Inputs at Vertical Levels

Temperature
Pressure
Mixing Ratios of
a) Water Vapor
(b) Ice
(c) Cloud Water
Cloud Fraction
CO_2 and O_3

Surface Inputs

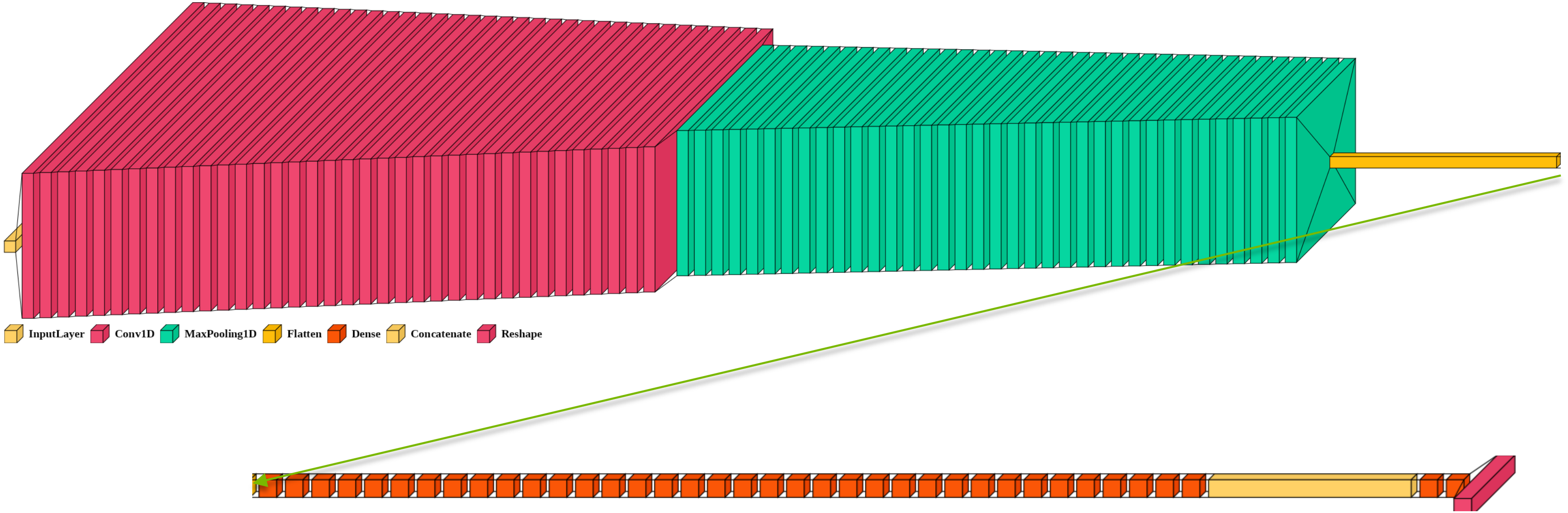
Surface Albedo
Elevation
Surface Temperature
Surface Emissivity
Surface Pressure
Cosine of Solar Zenith Angle

Heating Rates at each Vertical Level Outputs

Longwave (LW)
Shortwave (SW)

DOMAIN AWARE CONVOLUTIONAL NEURAL NETWORK

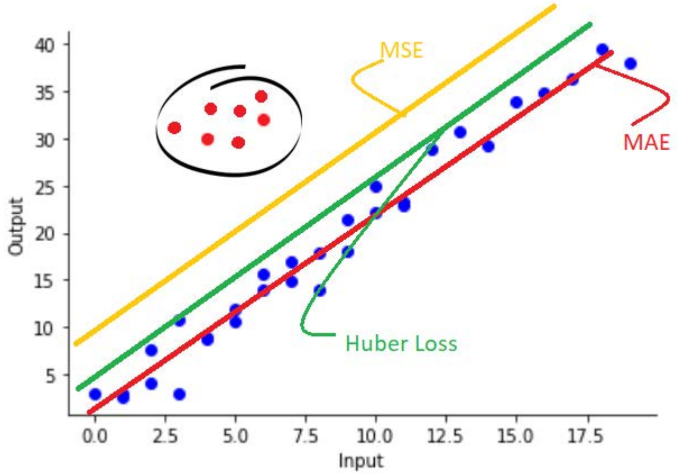
Domain-Aware: Each Vertical Level is dependent on Preceding Level (Wang et al., 2019)



Total Learnable Parameters: ~1.48 Million

CUSTOM LOSS FUNCTION

Huber Loss Weighted by Solar Zenith Angle and Cloud Properties



Courtesy: DataMonje

SW Radiation

SZA + Clouds

For SW:
1) Check if its day or night and apply SZA mask to loss
2) Penalize cloudy layers more

LW Radiation

Clouds

For LW:
Penalize cloudy layers more

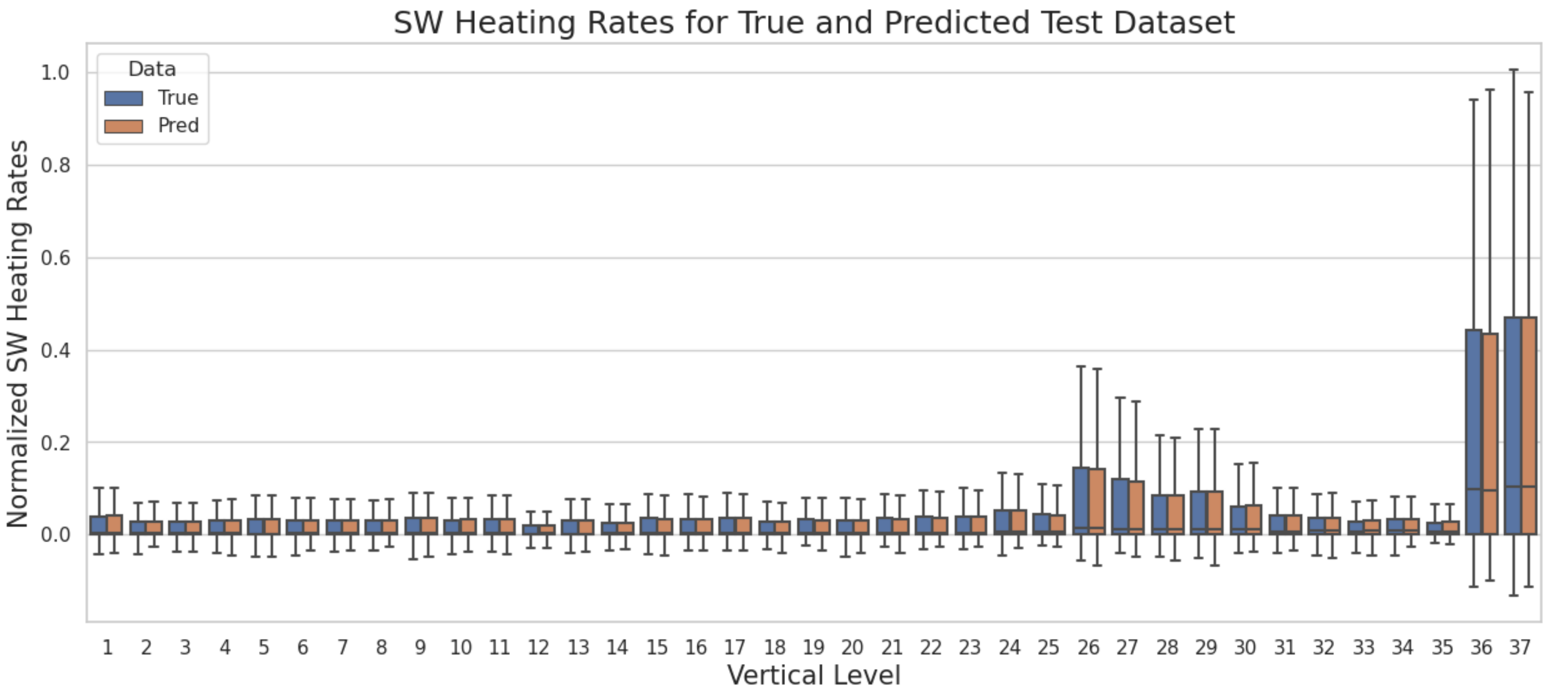
RESULTS

SW RADIATION

LW RADIATION

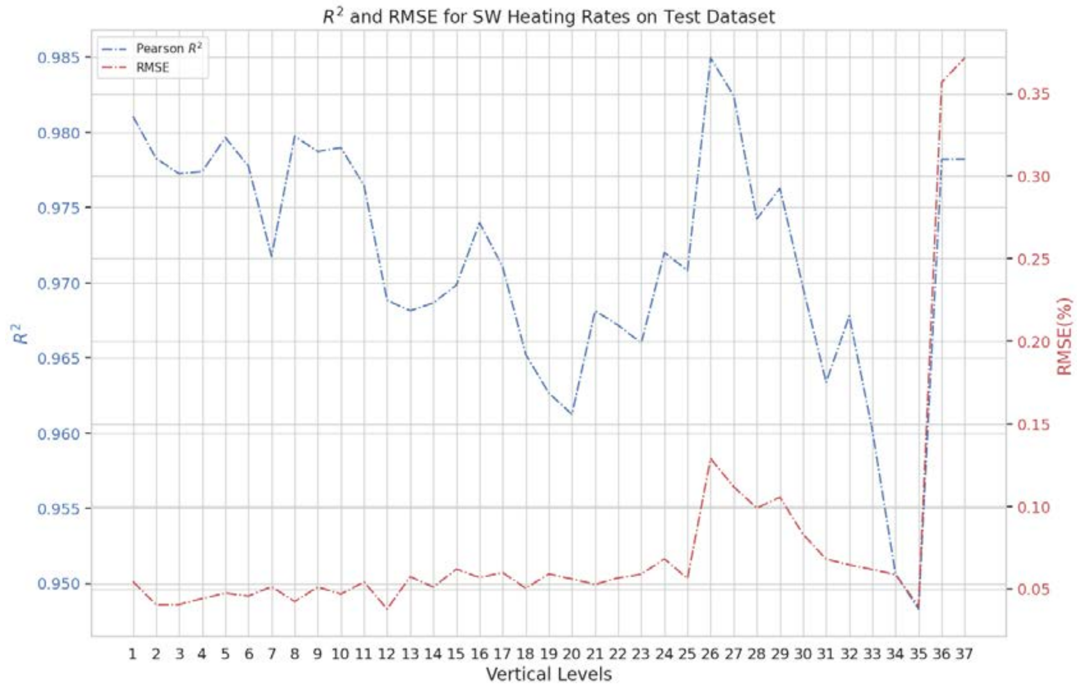
SW RADIATION EMULATOR ON TEST LOCATION

Training Mean R^2: 0.985 (mean) Percentage RMSE: 0.12%



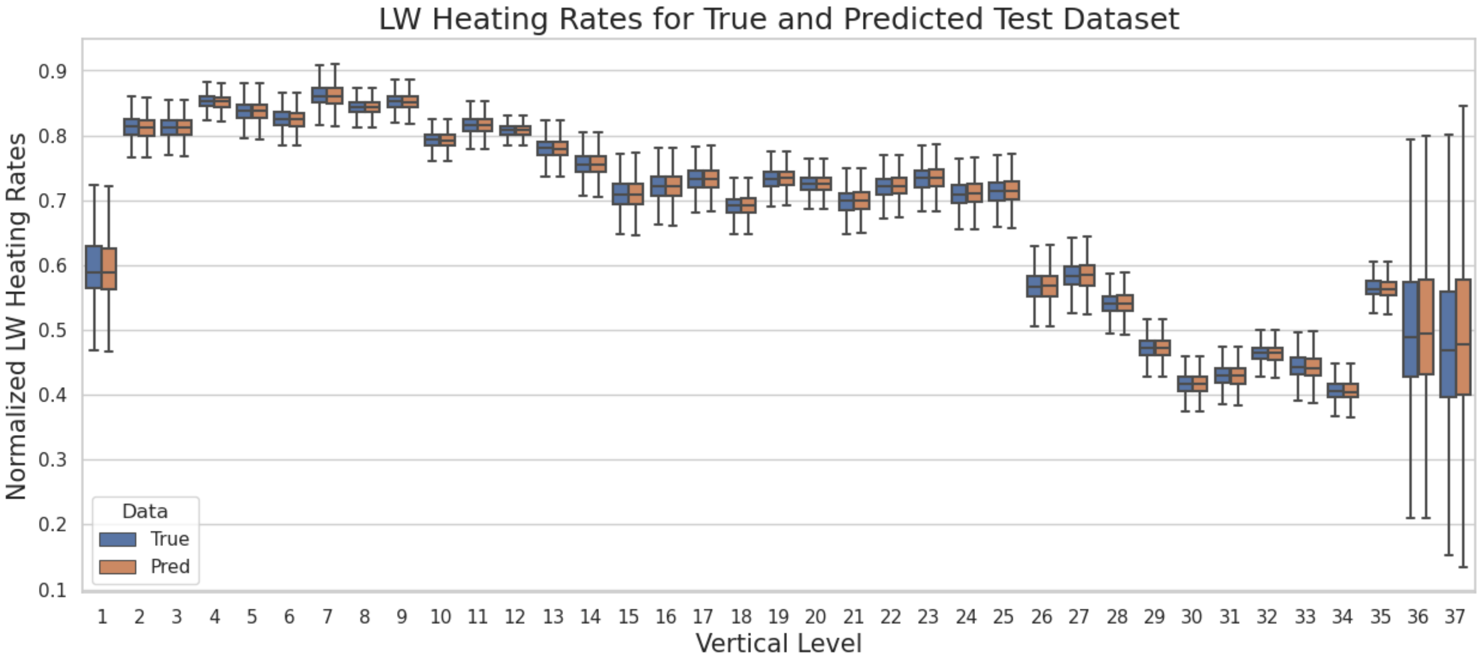
SW RADIATION EMULATOR ON TEST LOCATION

Training Mean R^2: 0.985 (mean) Percentage RMSE: 0.12%



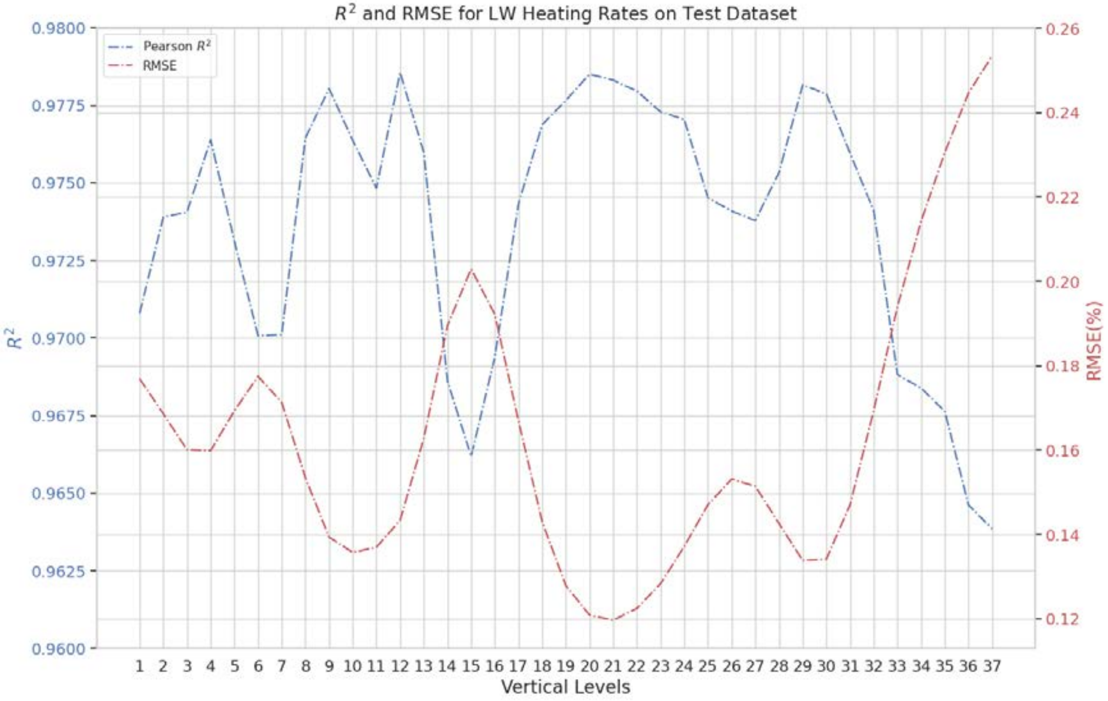
LW RADIATION EMULATOR ON TEST LOCATION

Training Mean R^2: 0.971 (mean) Percentage RMSE: 0.22%



LW RADIATION EMULATOR ON TEST LOCATION

Training Mean R^2: 0.981 (mean) Percentage RMSE: 0.22%



CONCLUSIONS

Key Takeaway Points

- We tested a range of ML algorithms to emulate SW and LW radiation and traditional loss functions did not perform well.
- Domain-aware 1D CNN lets us learn the relationship between each vertical level thus leading to higher accuracy in predictions.
- Custom Huber loss function based on clouds and solar zenith angle helped us learn the impact of clouds on both SW and LW radiation better.
- The CNN emulator is approximately 56 times faster than traditional RRTM on CPUs (same architecture).
- Physics-constrained deep learning outperformed traditional deep learning and decision-tree-based approaches.

FUTURE WORK

We are working with TEMPOQUEST to couple this emulator with WRF.

THANK YOU FOR YOUR ATTENTION!

For any Questions:
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