Physics-Informed Deep Learning to Infer Radiative Fluxes

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1 Introduction

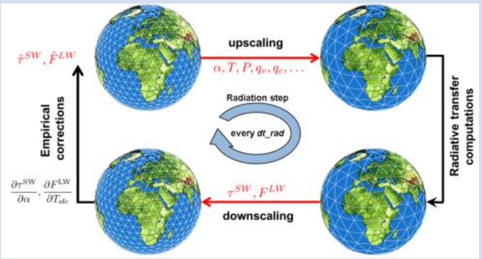
Because of the computational demands, many weather centers use a **reduced spatial grid (fig. 1)** and reduced temporal frequency for radiative transfer calculations in their forecast models.

In this project, we contribute to the discussion on **how to incorporate physical constraints into an ML-based radiative parameterization**, whether to predict radiative flux or its convergence (i.e. heating rates), and how different **neural network (NN)** designs (MLP, **Unet (fig. 2)**) and input features normalization affect prediction performance.

A **random forest (RF)** is used as a baseline method, with ECMWF model **ecRad**, the operational radiation in the **ICON** climate model, used for training. The RF is not affected by the **top-of-atmosphere (TOA)** bias found in all NNs tested. At lower atmospheric levels, the RF is able to compete with the NNs, but its memory requirements become prohibitive.

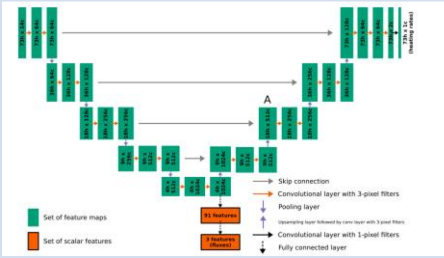
For a fixed memory size, most NNs outperform the RF except at TOA. Introducing physical constraints into ML design **by penalizing the NNs via heating rates** seems promising.

Computational grid for the radiation in ICON (fig. 1)



F. Prill, D. Reinert, D.Rieger, G. Zängl, Working with the ICON Model, 2020

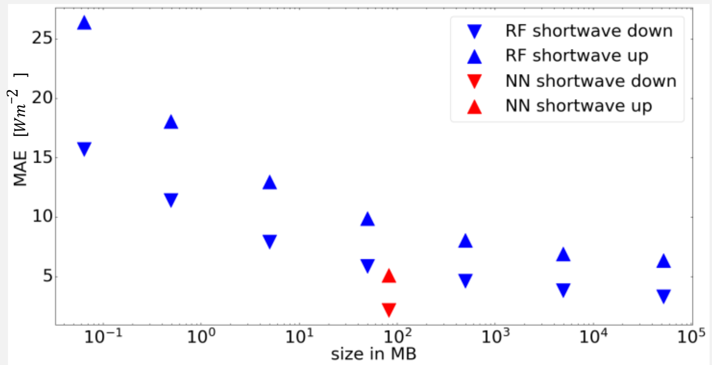
UNet architecture (fig. 2)



R. Lagerquist, D. Turner, I. Evert-Uphoff, J. Stewart, V. Hagerty, (2021)

2 Random Forest size limitations

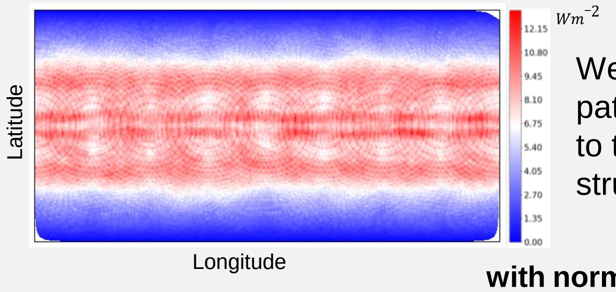
Mean Absolute Error (MAE) of the RF against its size in MB:



→ The RF can compete with NNs but its size in MB becomes prohibitive

3 Random Forest normalization

Shortwave prediction without normalization:



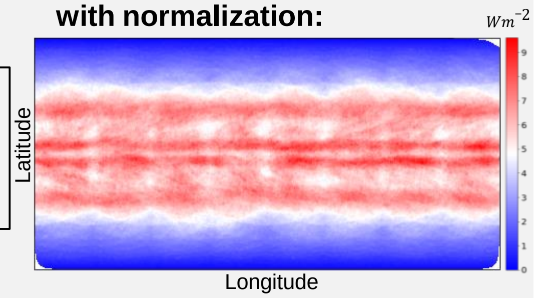
We observe discrete patterns in the error due to the piecewise constant structure of the RF.

with normalization:

→ **Output normalization:**

We divide the shortwave fluxes by $\boldsymbol{cos(\theta)}$.

θ: solar zenith angle



4 Physics-informed loss functions

Physics informed loss function:

$$\mathrm{Loss}_2 = \frac{1}{N_{columns}} \sum_{n=1}^{N_{columns}} \left\| flux_{NN,n} - flux_{ecRad,n} \right\|^2 + \lambda \cdot penalty$$

Physics informed penalty:

1) Total column energy absorbed penalty:

$$\frac{1}{N_{columns}} \sum_{n=1}^{N_{columns}} \left\| \left(Netflux_{top} - Netflux_{surface}\right)_{NN,n} - \left(Netflux_{top} - Netflux_{surface}\right)_{ecRad,n} \right\|^2$$

2) Heating rates penalty:

$$\frac{1}{N_{columns}} \sum_{n=1}^{N_{columns}} \left\| \overrightarrow{HR}_{NN,n} - \overrightarrow{HR}_{ecRad,n} \right\|^2$$

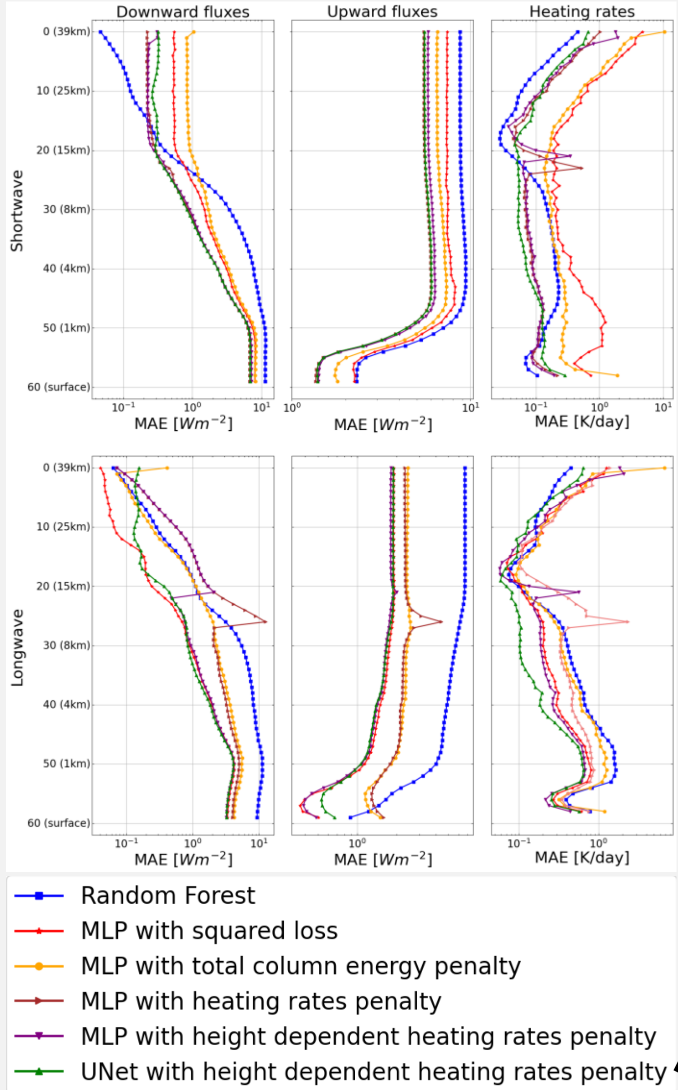
3) Height dependent heating rates penalty:

$$\frac{1}{N_{columns}} \sum_{n=1}^{N_{columns}} \sum_{h=59}^{0} \alpha_h \left(HR_{NN,n,h} - HR_{ecRad,n,h}\right)^2$$

α_h = average height in km at atmospheric level h

5 Results and outlook

MAE in the fluxes and heating rates:



__Observation__:

1) For the total column energy absorbed penalty, the MLP learns to modify the top and bottom fluxes predictions to satisfy the additional penalty. This causes large heating rates MAE at the TOA and surface.

2) We observe a large MAE at the tropopause for the MLP with HR penalty and .

3) The random forest outperforms all NNs at the ToA for the heating rates predictions.

4) The model we recommend is the UNet with height dependent heating rates penalty. It has neither an error kink at the tropopause nor a large jump in the error at the TOA. It is extremely accurate at all heights for both the fluxes and heating rates prediction.

Best model

Next step:
Online performance

References

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