Interpretable multiscale Machine Learning-Based Parameterizations of Convection

Helge Heuer[1], Mierk Schwabe[1], Pierre Gentine[2], Marco A. Giorgetta[3], Veronika Eyring[1,4]

[1] German Aerospace Center (DLR), Institute of Atmospheric Physics, Oberpfaffenhofen, Germany; [2] Columbia University, Center for Learning the Earth with Artificial Intelligence and Physics (LEAP), New York, USA; [3] Max Planck Institute for Meteorology, Hamburg, Germany; [4] University of Bremen, Institute of Environmental Physics (IUP), Bremen, Germany

Contact: helge.heuer@dlr.de

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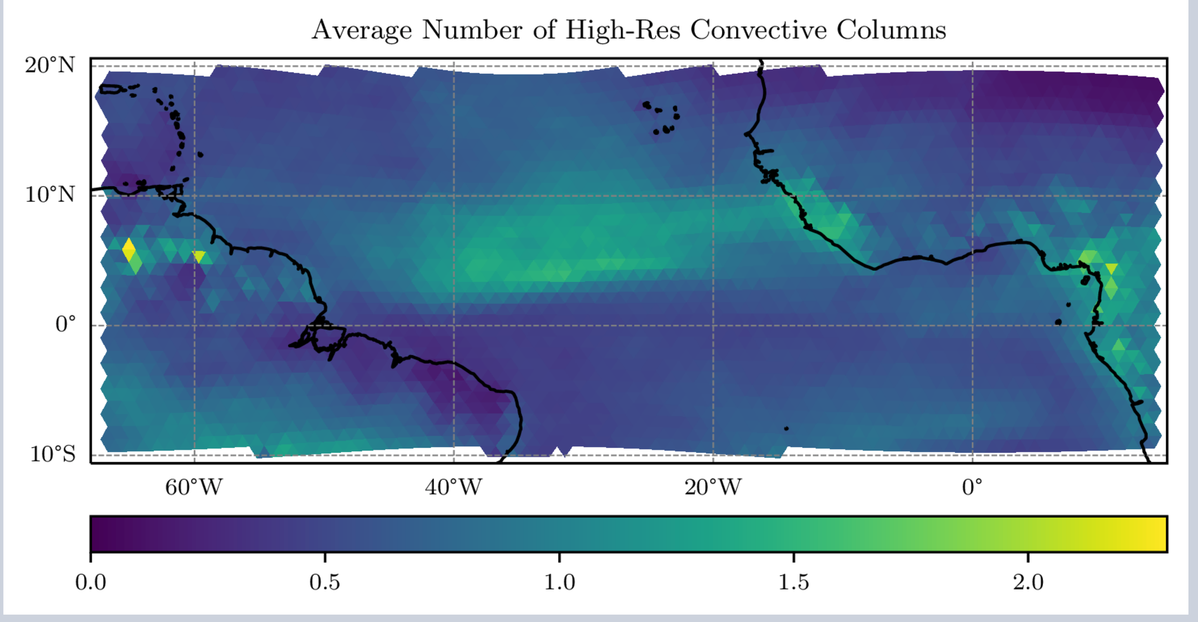


Figure 1: The high-resolution dataset ($\Delta x \approx 2.5$ km) is coming from the tropical Atlantic (NARVAL campaign[2]). Only radiation, cloud microphysics, and turbulence where parameterized.

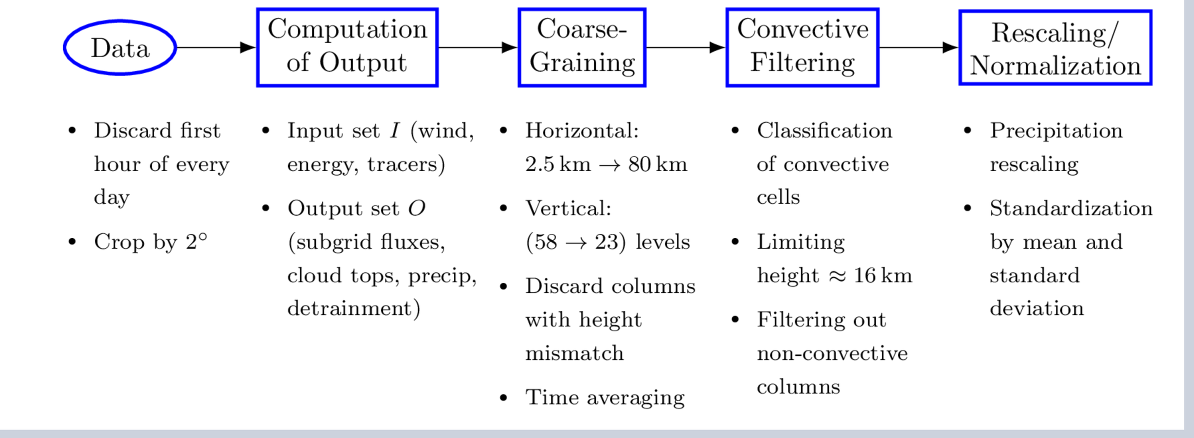


Figure 2: Summary of preprocessing steps. Starting from the original data, we computed the output fields, applied coarse-graining operators, filtered the data, and rescaled the resulting dataset.

We calculate the subgrid fluxes without using the Boussinesq approximation from the processed data.

$$F_u^{sg} = \overline{\rho w u} - \bar{\rho}\tilde{w}\tilde{u} = \bar{\rho}\,\overline{w'u'} + \bar{w}\,\overline{\rho' u'} + \bar{u}\,\overline{\rho' w'} + \overline{\rho' w' u'}$$

This flux is then converted to tendencies by taking the vertical divergence.

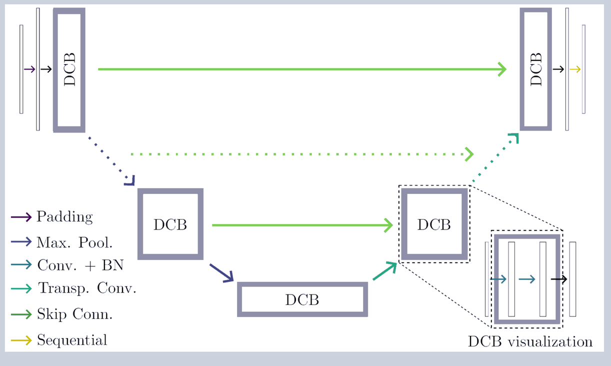


Figure 3: The used U-Net architecture is visualized schematically.

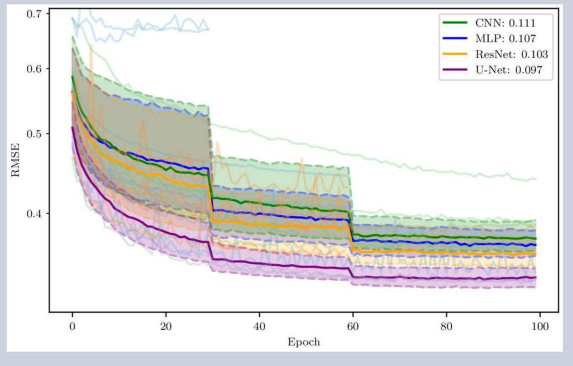


Figure 4: The median and quartiles of the validation error for four different NN architectures is shown.

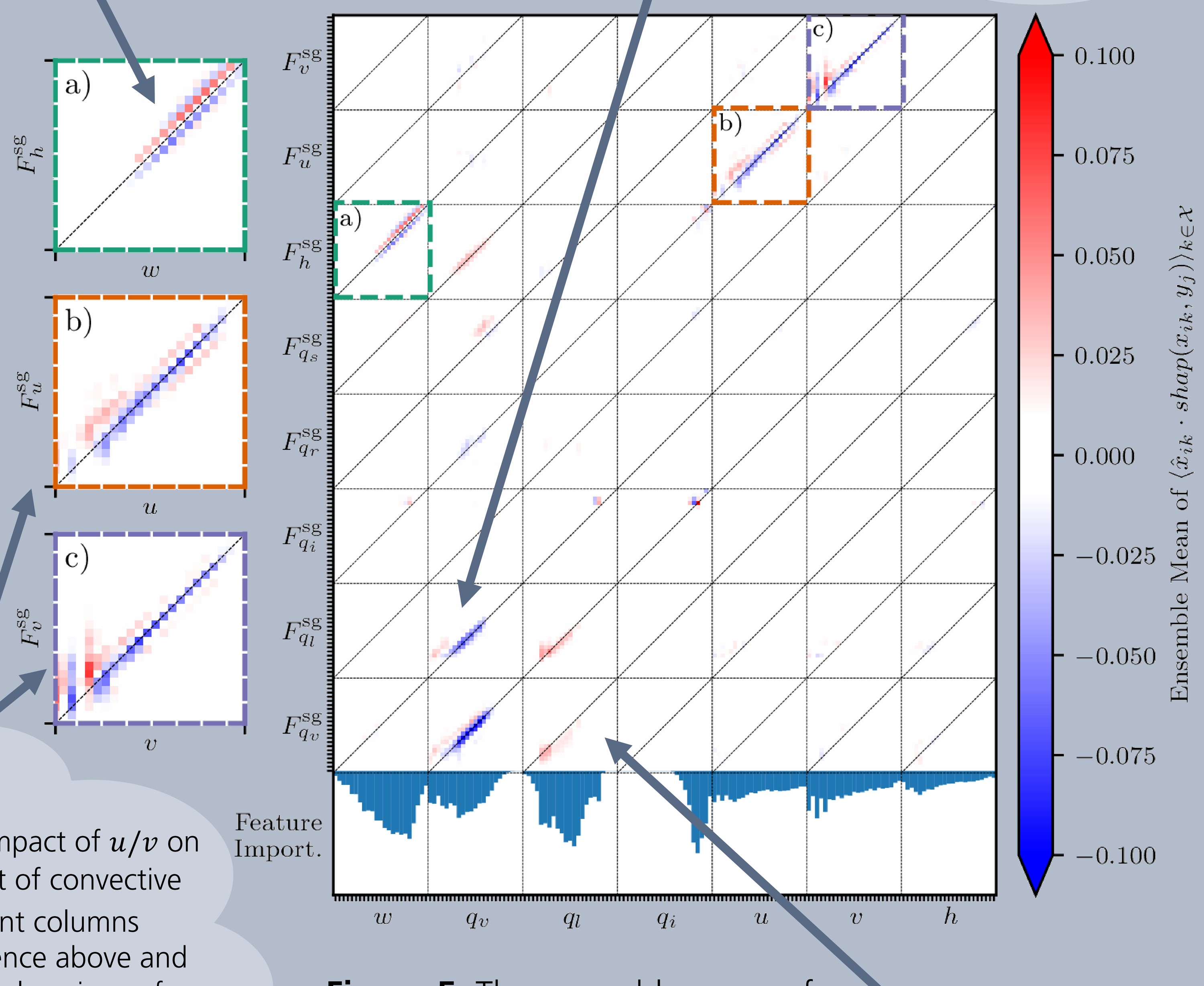
We built a physically explainable multiscale machine-learning convection parameterization[1]

github.com/ automatic1111/ stable-diffusion-webui

- Model predictions can be explained by using the SHapley Additive exPlanations (SHAP) framework[3] and taking weighted averages.[1,4]

positive super- and negative sub-diagonal → high vertical velocities increase subgrid flux above, reduction below
- Impact of large scale ascent and mesoscale convergence on convection

Negative impact of q_v → local drying effect (entrainment of water vapor into the plume[6])
- Slight positive influence for lower levels on higher levels → decreased density as water evaporates and decreased lapse rate for buoyant air parcels (as they are closer to saturation)



Negative local impact of u/v on $F_{u/v}^{sg}$ → transport of convective plume to adjacent columns
- Positive influence above and below diagonal → signs of forced convection and impact of shear on mesoscale convective systems[5]
- In lower levels some consistent (over different data sets X) non-local patterns

Figure 5: The ensemble mean of weighted SHAP values for the ablated U-Net is visualized. Aggregated feature importance is shown in lowermost row.

Positive influence of q_l on F_{ql}^{sg} and F_{qv}^{sg} → increased buoyancy in a cell because of latent heat release due to condensation

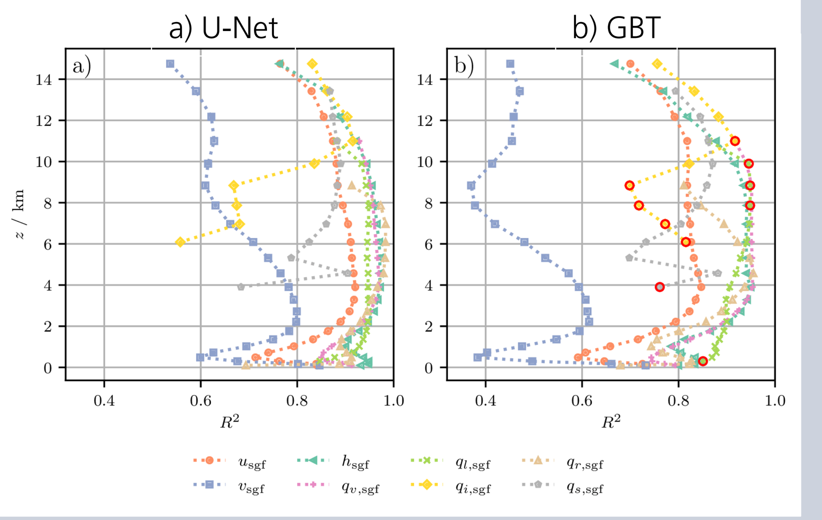


Figure 6: Height dependent performance comparison between a) U-Net and b) gradient boosted trees (GBT) model.

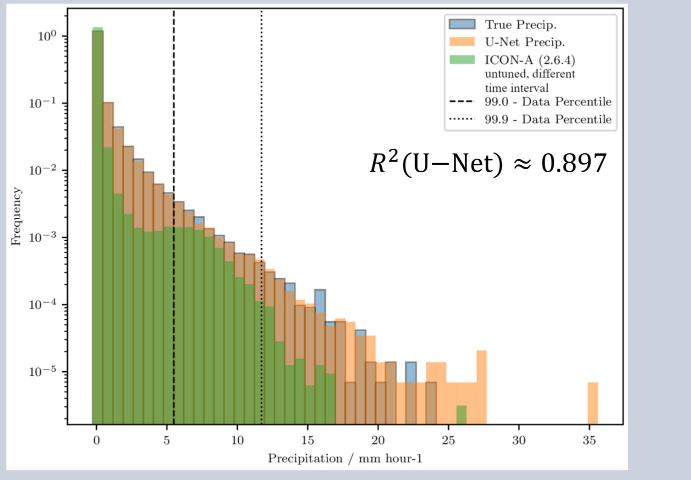


Figure 7: Precipitation distribution comparison btw. NARVAL data, U-Net and data from an untuned ICON simulation over a different time period (years 1980 & 1989).

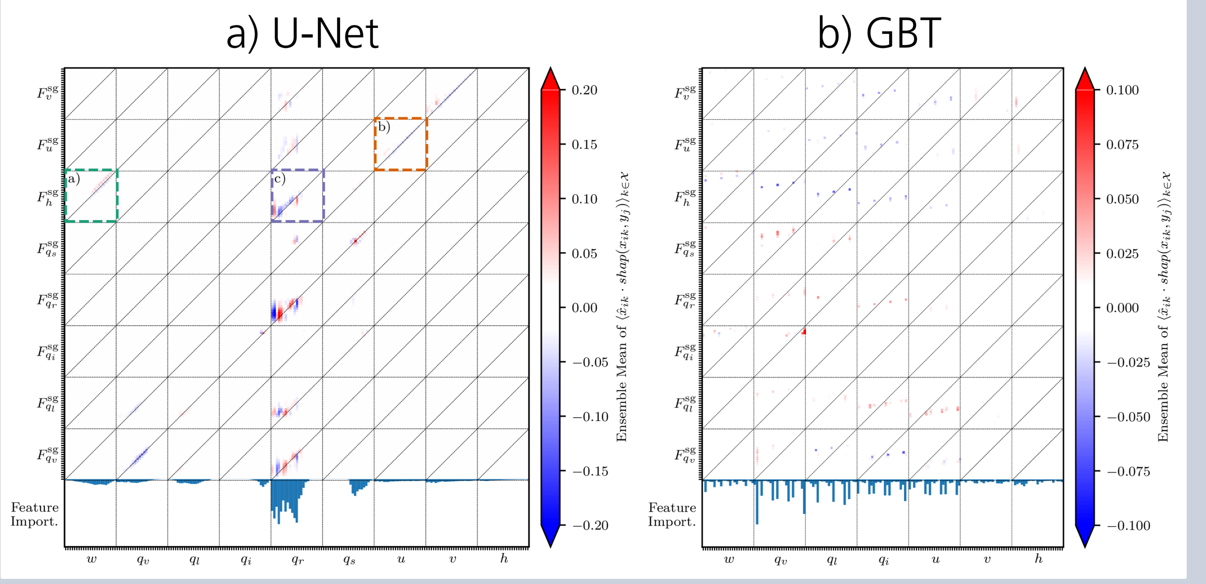


Figure 8: The ensemble mean of weighted SHAP values for a) the full U-Net and b) the GBT model is shown. For a) the full U-Net a focus on precipitating tracers is found to be non-causal. For b) the GBT the found patterns are non-local and non-regular / "noise-like".

Outlook

- Online coupling
- Transition to global training dataset

arXiv Preprint

References

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