Data-Driven Cloud Cover Parameterizations for the ICON model

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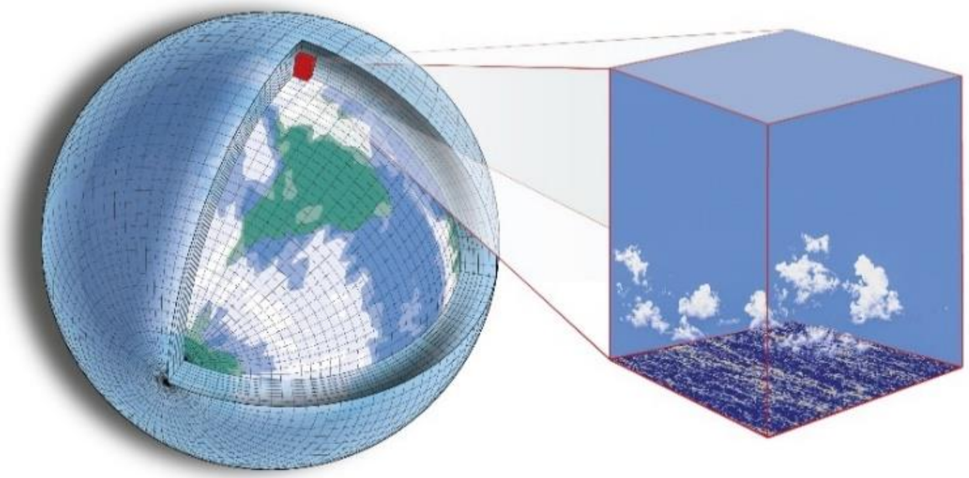
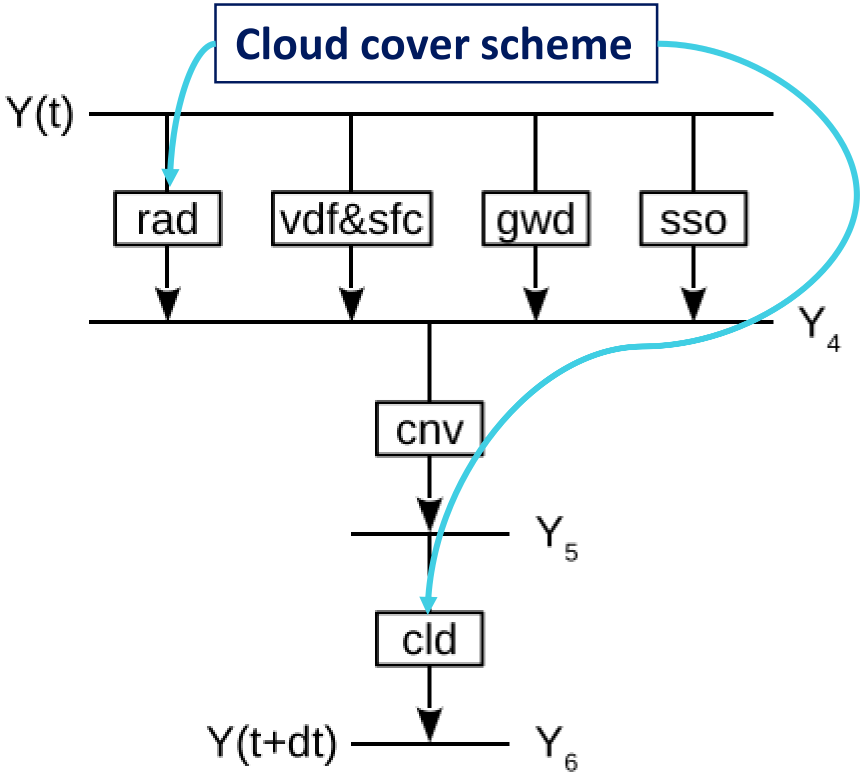
$$C = f(RH, p) \Rightarrow C = P_3(RH, T) + (c_1 \partial_z RH + c_2)(\partial_z RH)^2 - \frac{1}{c_3 q_c + c_4 q_i + \varepsilon}$$

PASC23, Davos
28 June, 2023

Clouds need to be parameterized in climate models

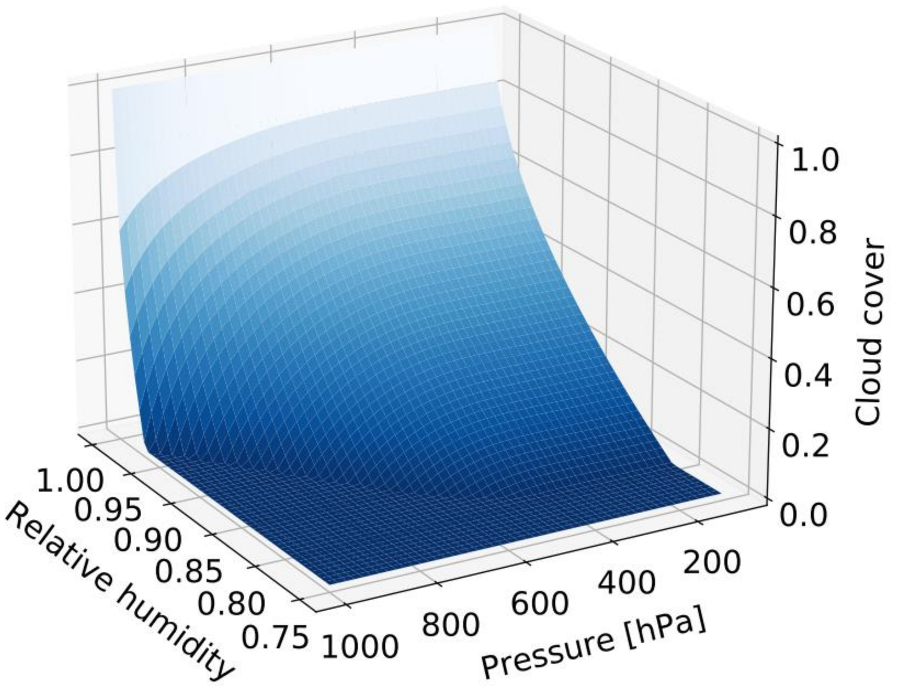


Most clouds are subgrid-scale phenomena

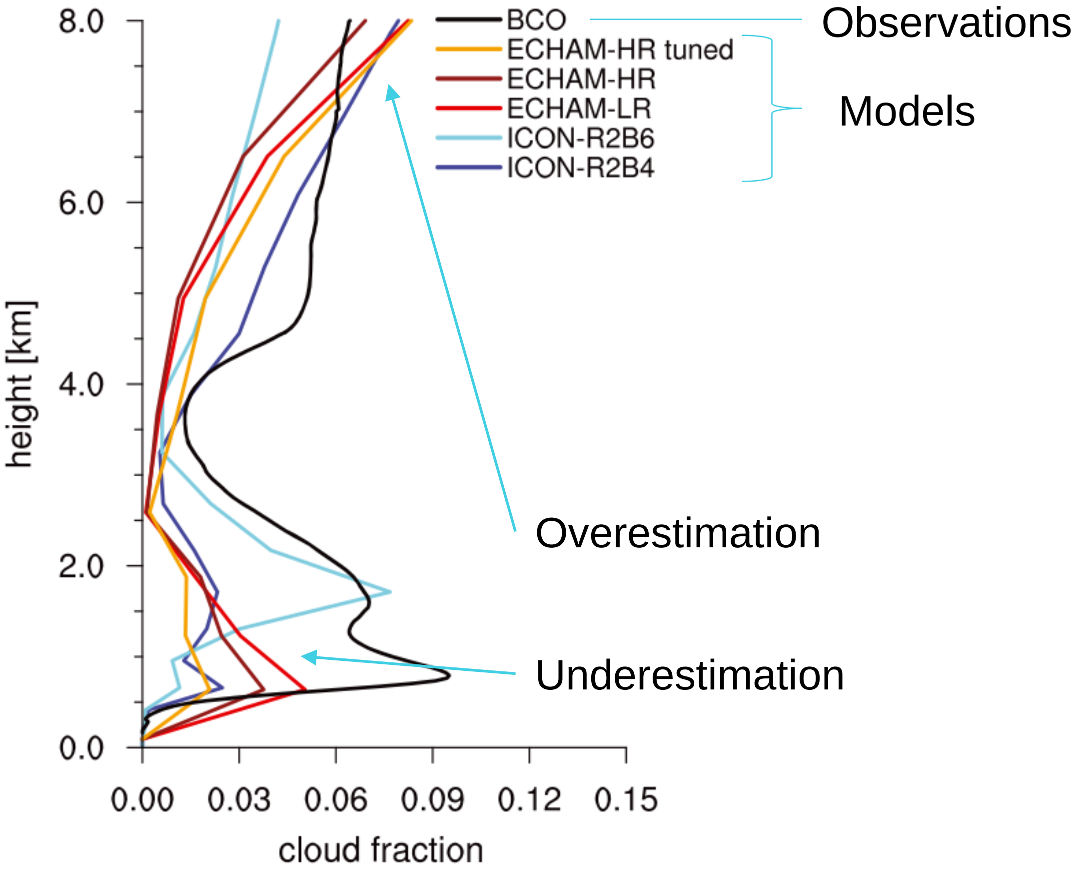


Parameterizations in ICON
Adapted from Giorgetta, et al. (2018)

ICON’s current cloud cover scheme misrepresents observations



Sundqvist scheme at $p_s = 1000hPa$

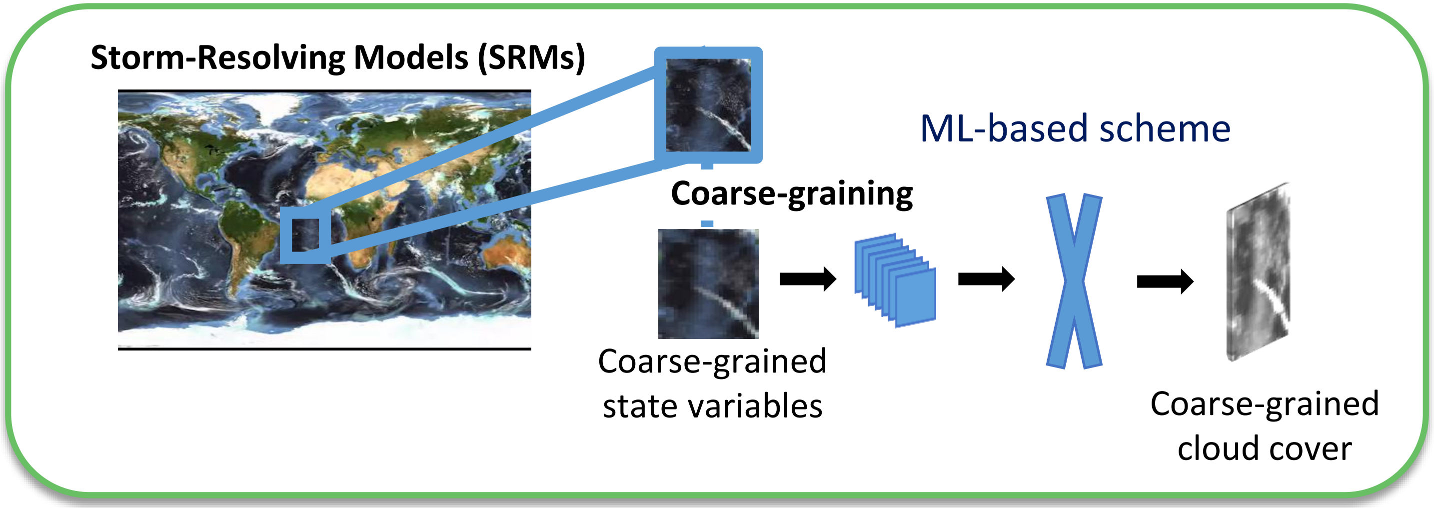


Annually averaged cloud cover profile over Barbados
Crueger, et al. (2018)

We train schemes on coarse-grained global high-resolution data

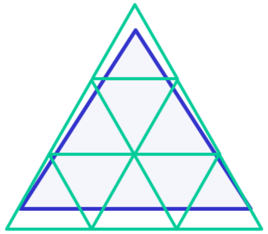
Our approach:

- Temperature
- Humidity
- Pressure
- Water vapor
- Cloud water
- Cloud ice



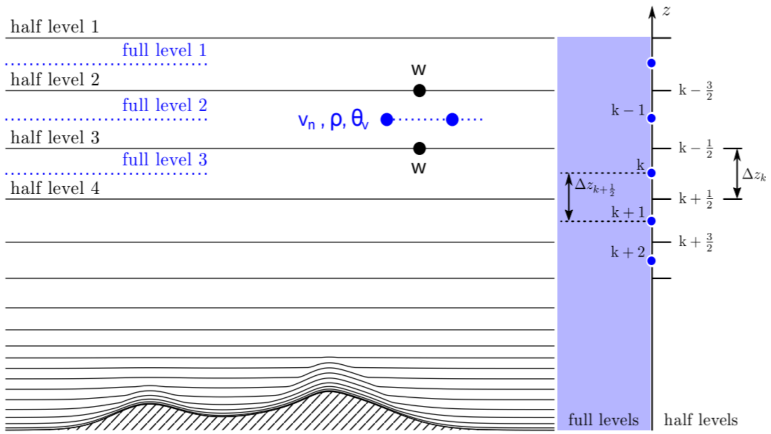
Coarse-graining on ICON's irregular grid is challenging

ICON's horizontal fields



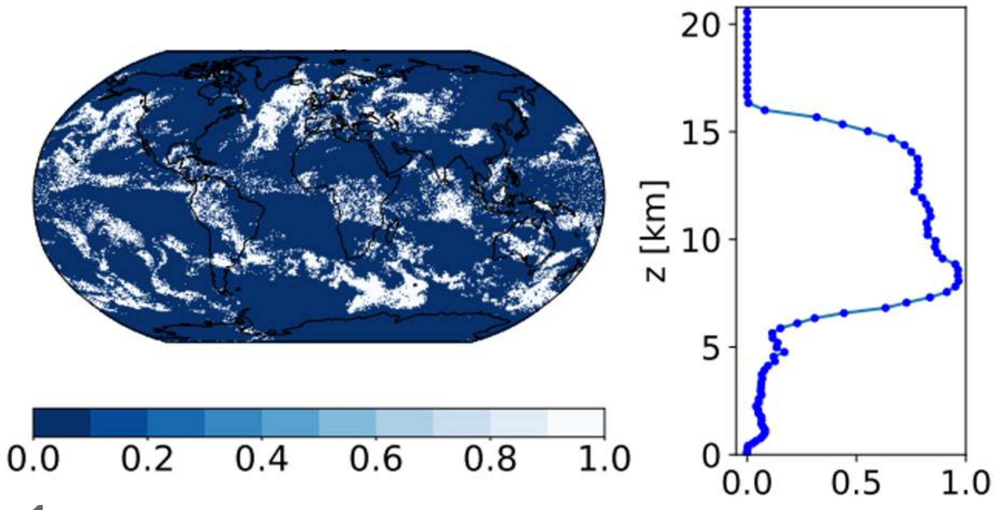
Blue cell: Coarse-scale ICON grid cell
Green cells: Fine-scale ICON-SRM grid cells

ICON's vertical layers

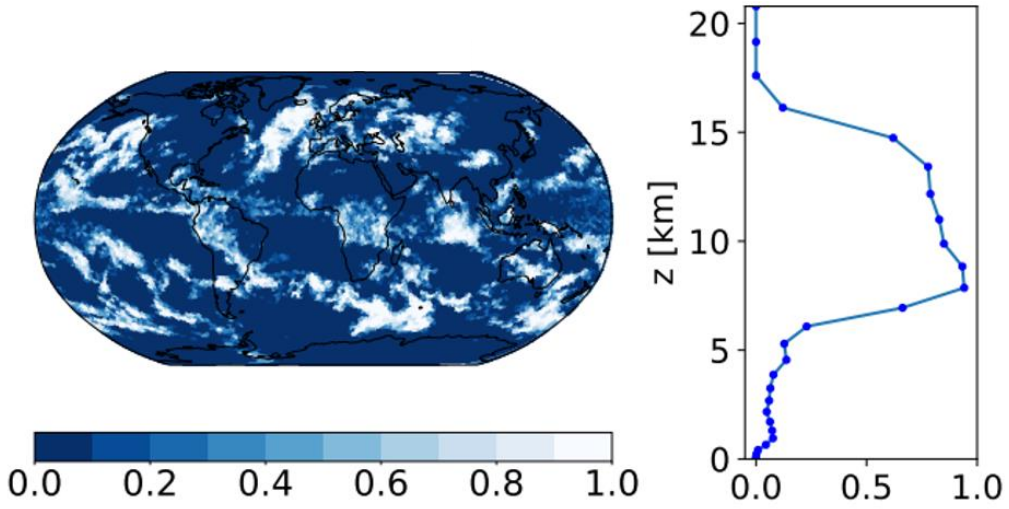


Terrain-following hybrid sigma height grid

Example of cloud cover:



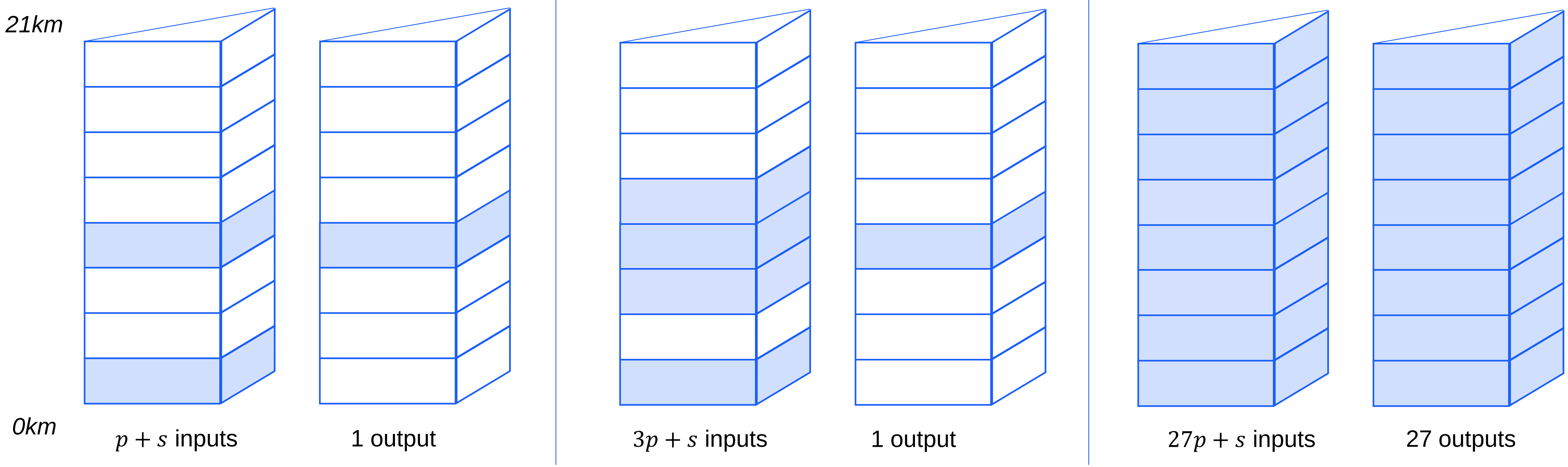
Coarse-graining



Grundner et al. (2022)

Three neural network types as ML-based cloud cover schemes

Grid cell based | **Neighborhood based** | **Column based**



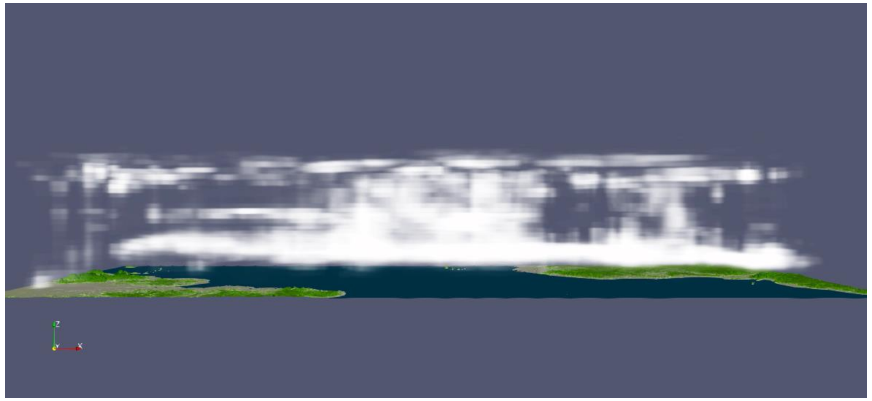
local → **non-local**

Input features are a subset of:
Temperature; pressure; air density; zonal, meridional wind; specific humidity; cloud ice; cloud water; geometric height; fraction of lakes, land, sea ice; Coriolis parameter
Output feature: Cloud Cover

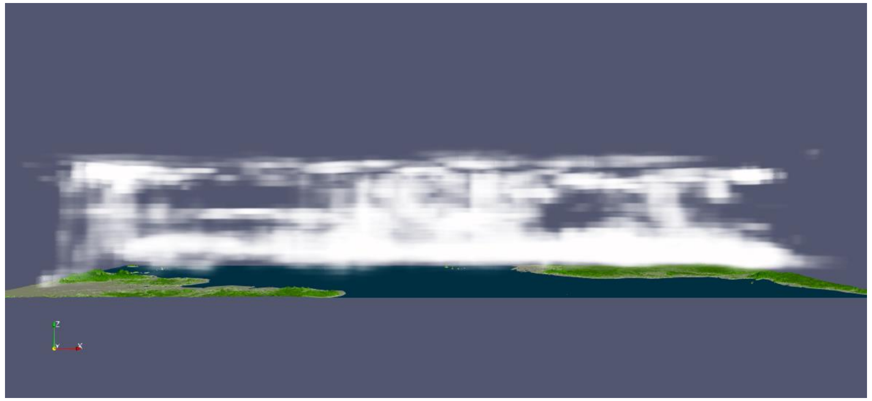
Grundner et al. (2022)

These neural networks can accurately reproduce cloud cover!

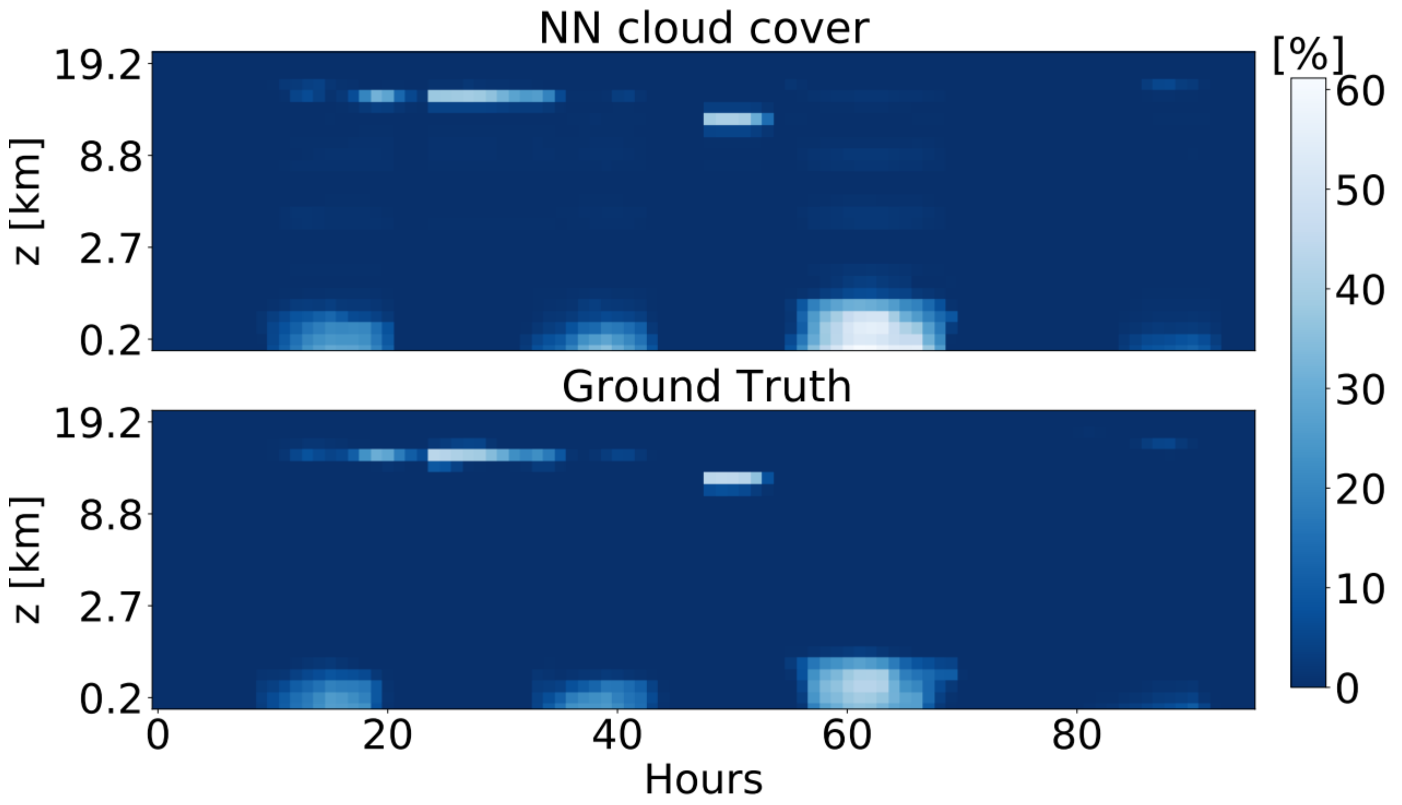
ML estimate
(Some columns over land excluded from training)



Reference
(Coarse-grained)

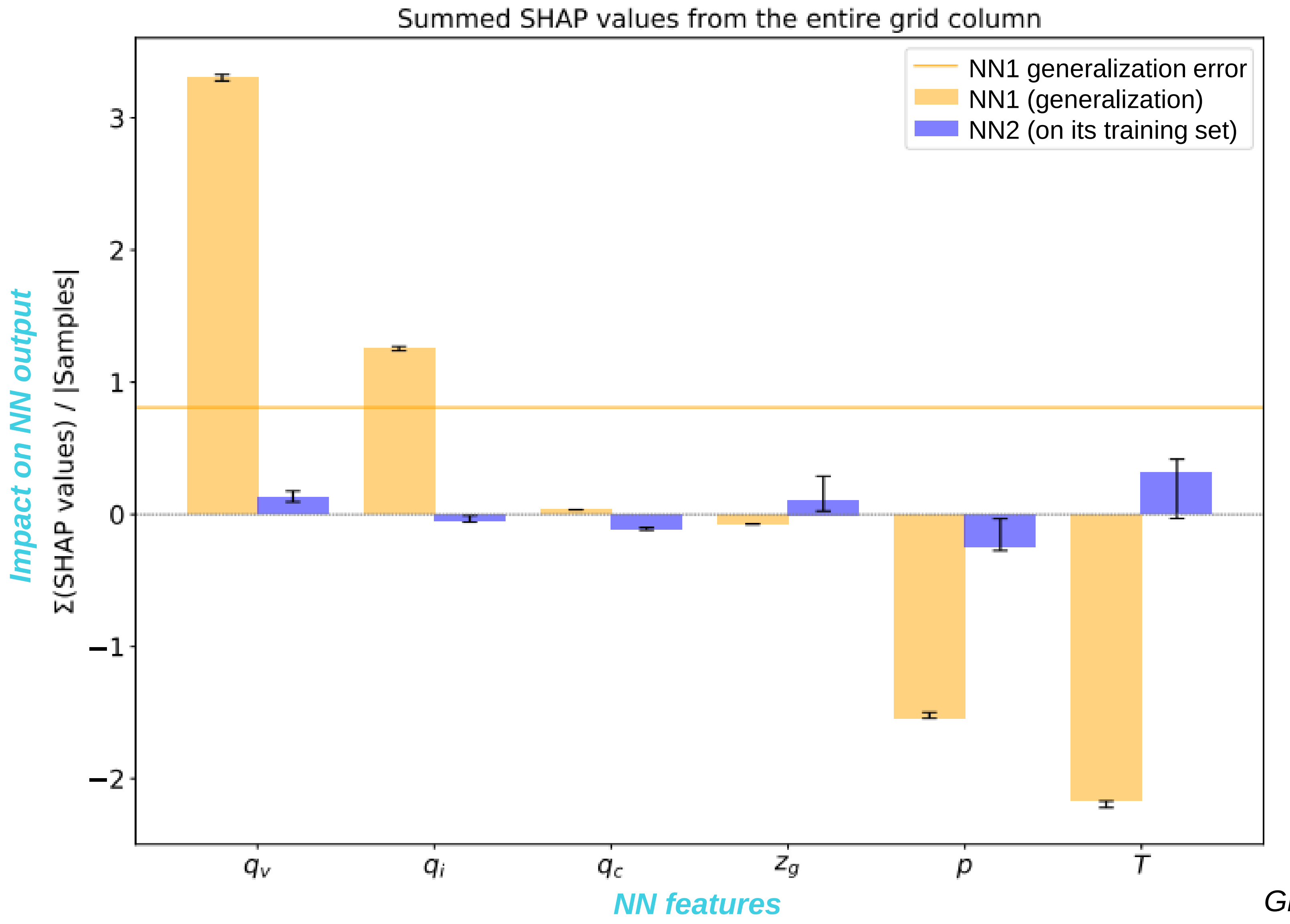


Hovmoeller plot



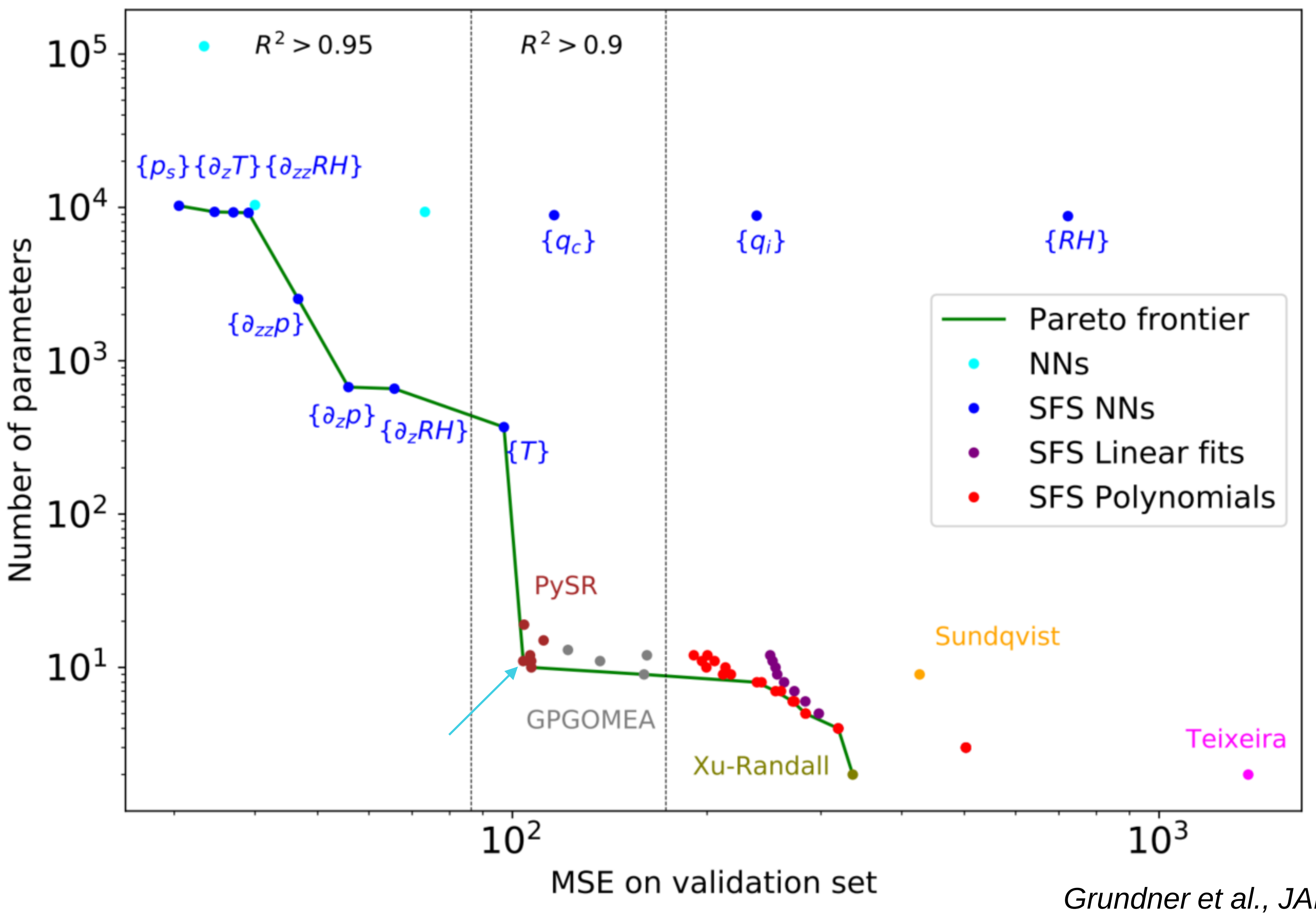
Grundner et al. (2022)

With XAI we can explain our neural network predictions



Grundner et al. (2022)

But what if our schemes were explainable by construction?



Grundner et al., JAMES, 2023, subm.

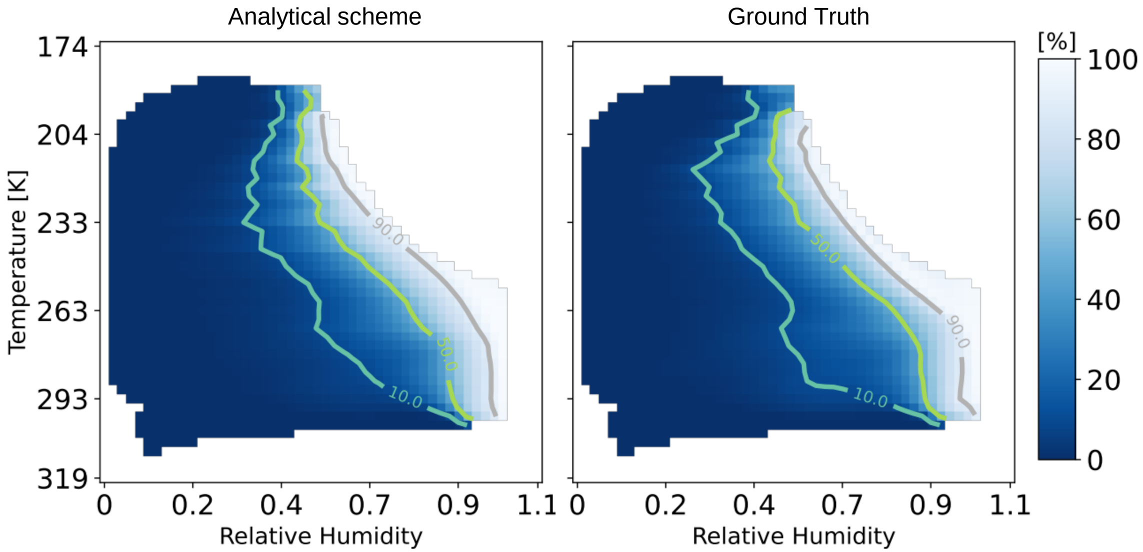
Our best data-driven analytical scheme performs competitively...

$$f(RH, T, \partial_z \mathrm{RH}, q_c, q_i) = I_1(RH, T) + I_2(\partial_z \mathrm{RH}) + I_3(q_c, q_i),$$

$$I_1(RH, T) \stackrel{\text{def}}{=} a_1 RH^2 + (a_2 \mathrm{RH} - a_3) T^2 - a_4 \mathrm{RH} T + a_5 \mathrm{RH} + a_6 T - a_7$$

$$I_2(\partial_z \mathrm{RH}) \stackrel{\text{def}}{=} (a_8 \partial_z \mathrm{RH} + a_9)(\partial_z \mathrm{RH})^2$$

$$I_3(q_c, q_i) \stackrel{\text{def}}{=} -1/(a_{10} q_c + a_{11} q_i + \epsilon).$$



Grundner et al., JAMES, 2023, subm.

…is interpretable and fulfills physical constraints by construction

$$f(RH, T, \partial_z \mathrm{RH}, q_c, q_i) = I_1(RH, T) + I_2(\partial_z \mathrm{RH}) + I_3(q_c, q_i),$$

$$I_1(RH, T) \stackrel{\mathrm{def}}{=} a_1 RH^2 + (a_2 \mathrm{RH} - a_3)T^2 - a_4 \mathrm{RH} T + a_5 \mathrm{RH} + a_6 T - a_7$$

$$I_2(\partial_z \mathrm{RH}) \stackrel{\mathrm{def}}{=} (a_8 \partial_z \mathrm{RH} + a_9)(\partial_z \mathrm{RH})^2$$

$$I_3(q_c, q_i) \stackrel{\mathrm{def}}{=} -1/(a_{10} q_c + a_{11} q_i + \epsilon).$$

Physical Constraints

PC$_1$: $\mathcal{C}(X) \in [0, 100]\%$

PC$_2$: $(q_c, q_i) = 0 \Rightarrow \mathcal{C}(X) = 0$

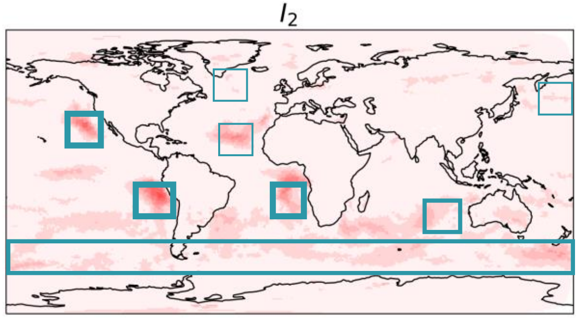
PC$_3$: $\partial \mathcal{C}(X)/\partial \mathrm{RH} \geq 0$

PC$_4$: $\partial \mathcal{C}(X)/\partial q_c \geq 0$

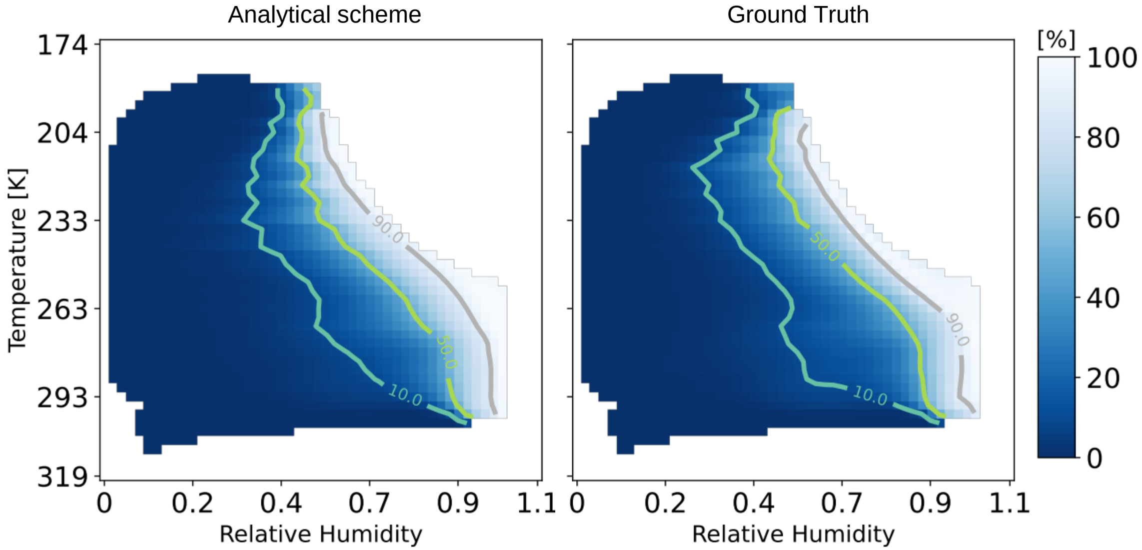
PC$_5$: $\partial \mathcal{C}(X)/\partial q_i \geq 0$

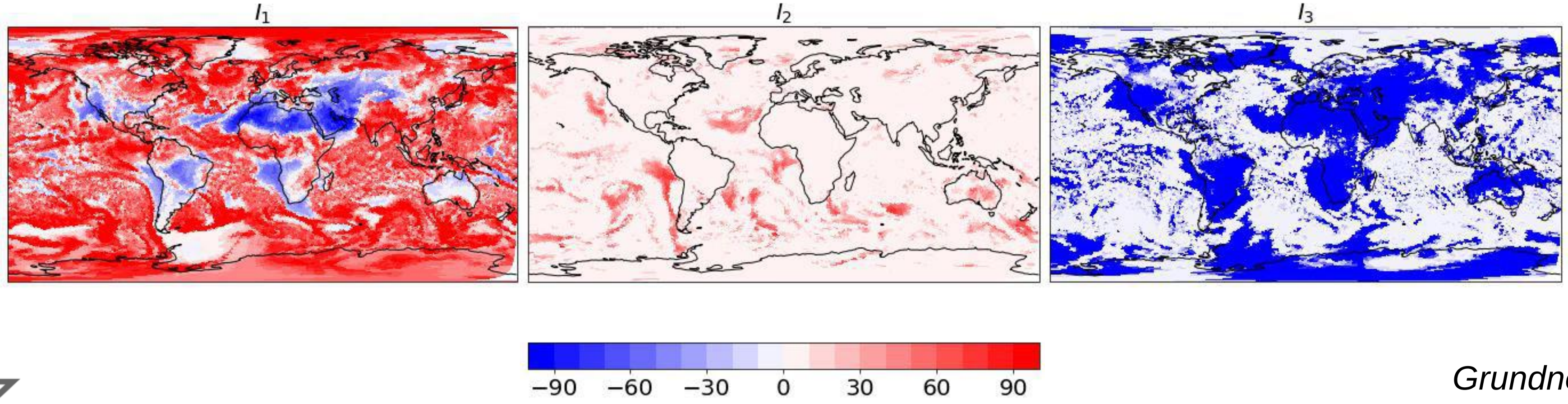
PC$_6$: $\partial \mathcal{C}(X)/\partial T \leq 0$

PC$_7$: $\mathcal{C}(X)$ is a smooth function



Boxes from Muhlbauer et al., 2014





Grundner et al., JAMES, 2023, subm.

Summary of the ‘offline’ section

- While deep learning methods are powerful and explainable post-hoc, they are less interpretable
- We can retain interpretability by learning nonlinear equations directly from the data, using symbolic regression methods
- We discover a new data-driven, analytical cloud cover scheme which is characterized by an excellent trade-off between performance and simplicity
- One of its three terms predominantly captures marine stratocumuli
- Physical constraints can be easily verified or enforced in the cloud cover equation

We use FKB to couple our neural networks to ICON

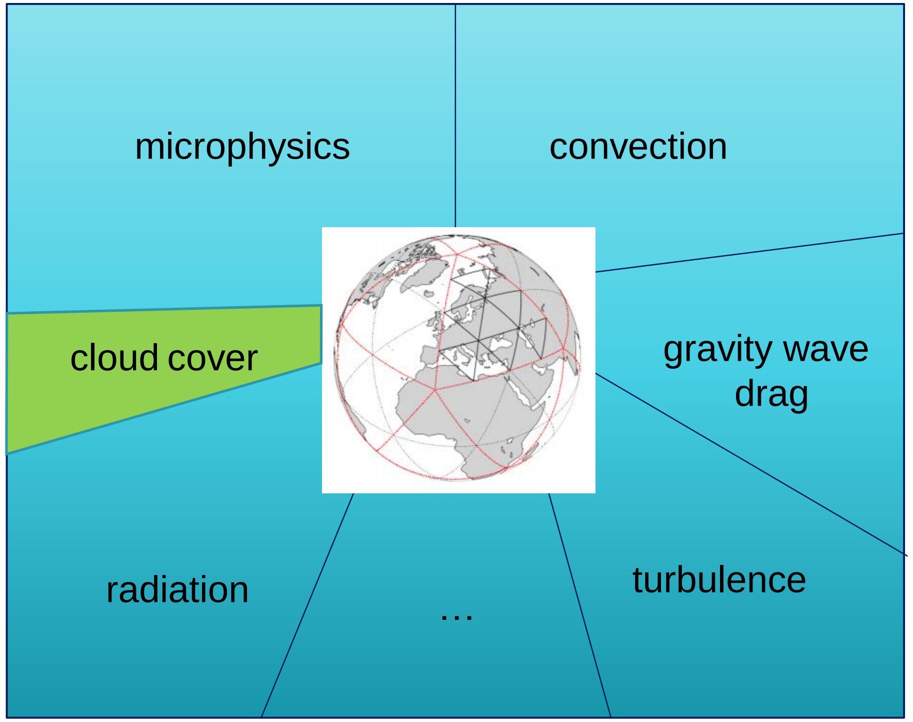
Keras: Model training

FKB – Python

> **Conversion** of the NN (h5 → txt)

FKB - Fortran NN library

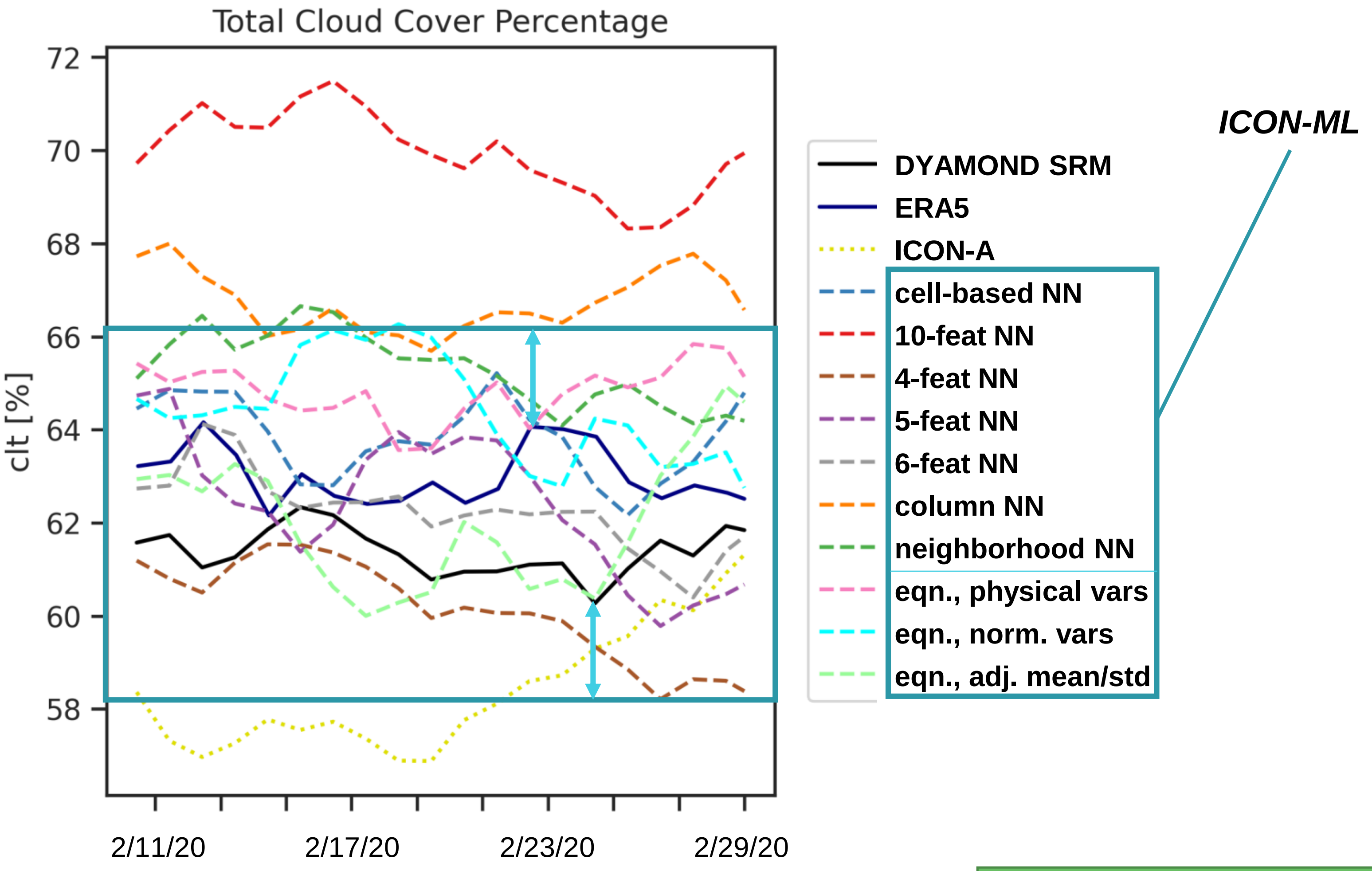
> **Loads** & processes converted **NNs at the start of ICON**



ICON climate model

Ott et al. (2020)
GitHub

Coupled ‘online’ ICON-ML simulations yield reasonable results!

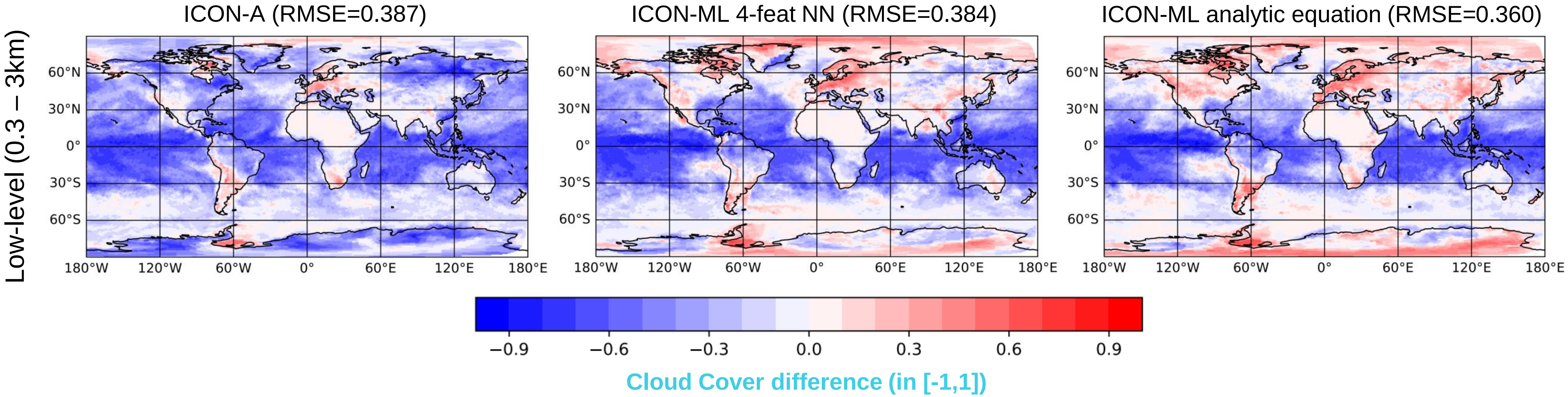


Short simulation for the same timespan as the high-res data
> Reference to compare to & NNs know climatic conditions
→ Most ICON-ML simulations are closer to the high-res data

Grundner et al., in prep.

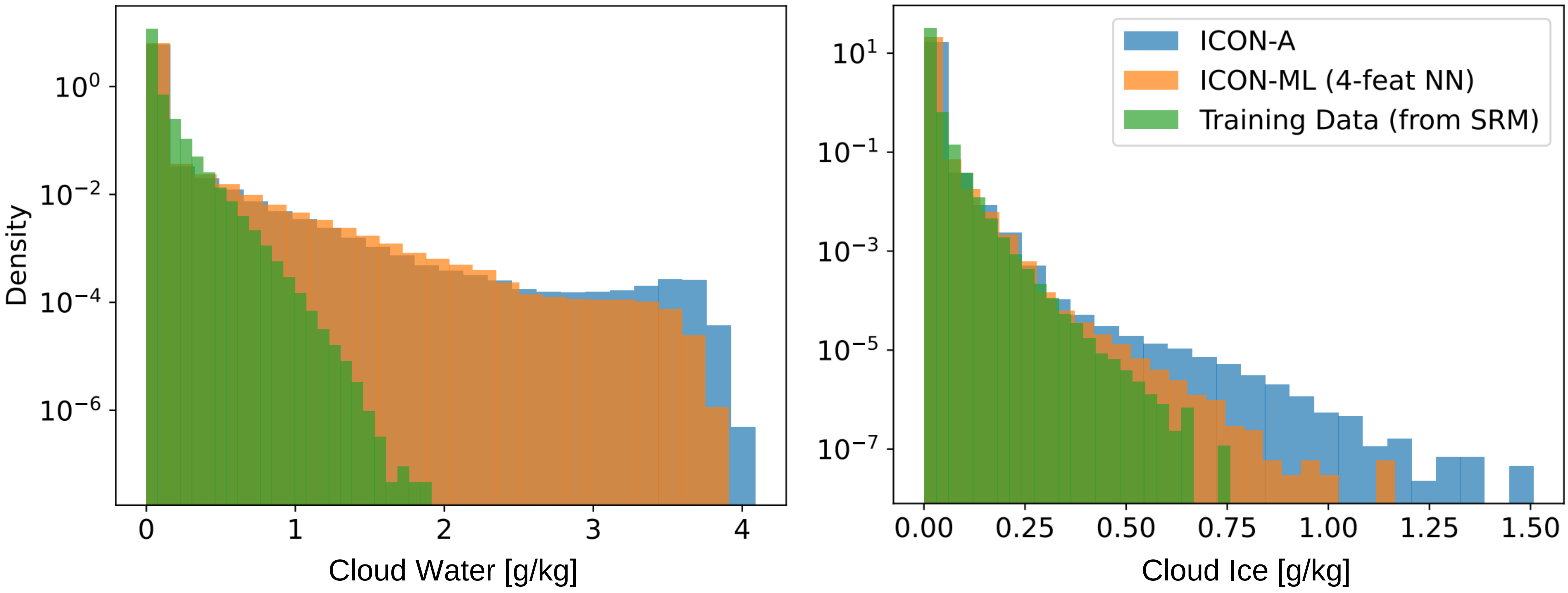
ICON-ML improves upon low-level total cloud cover

mean(clt_ICON) – mean(clt_SRM)



Grundner et al., in prep.

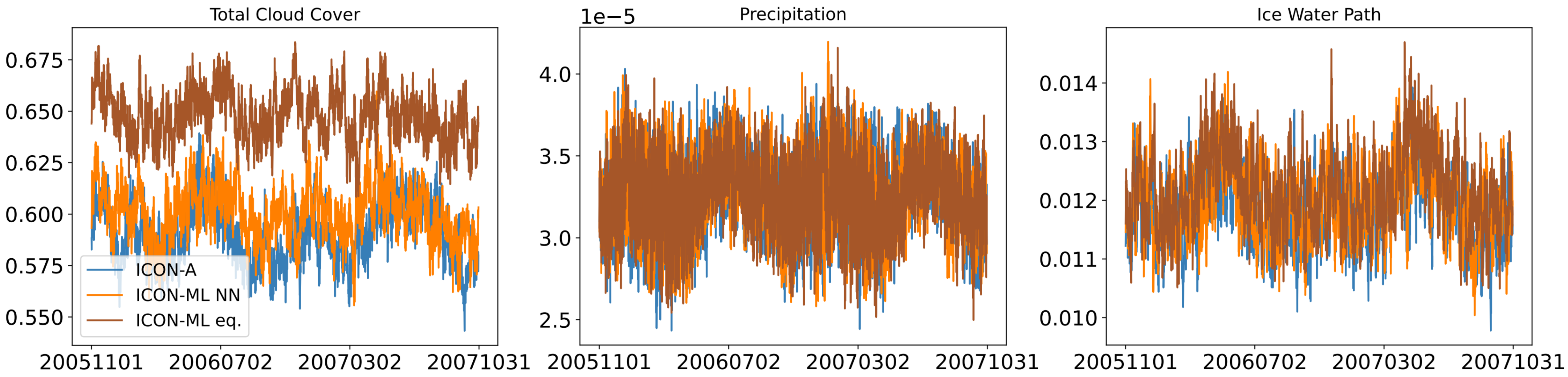
Good results even though NNs in ICON are out-of-distribution



Grundner et al., in prep.

→ **The ML-based schemes in ICON-A face out-of-distribution cloud water/ice**

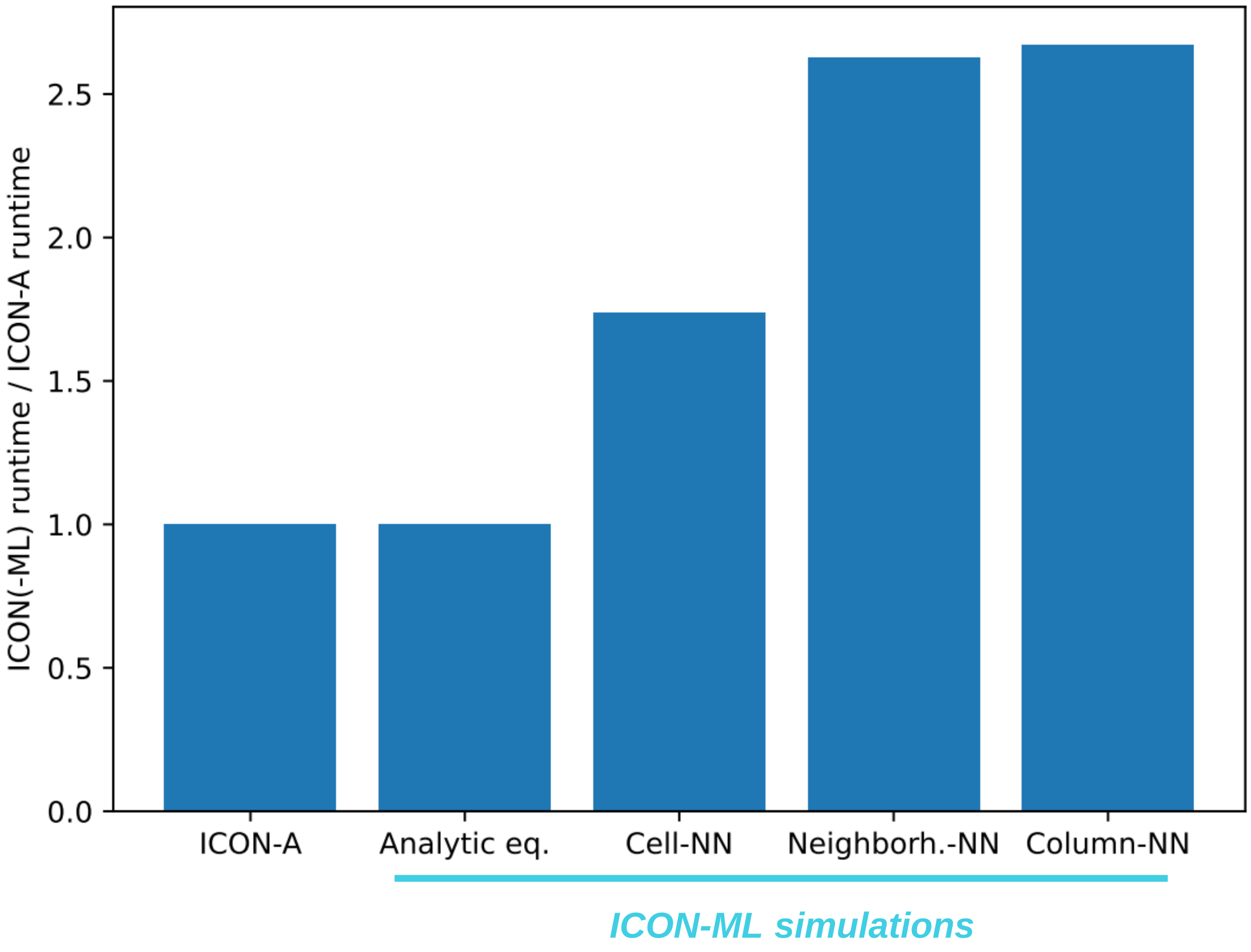
2-year long simulation shows stability of ICON-ML



Grundner et al., in prep.

→ **No model drifts in longer simulations**

Challenge: ICON-NN runtime increased by a factor of 1.7



Grundner et al., in prep.

Summary of the ‘online’ section

Summary

- Successful coupling of ML based schemes to ICON-A using the FKB
- The resulting ICON-ML model is stable
- Performance (measured through mismatch to high-res) already competitive to ICON-A

Potential for further improvements

- Working on additional ML based parameterizations (e.g., convection)
- Meanwhile: ICON-ML results can be improved further by transfer learning cloud cover NNs to ICON-A output (and its inherent biases)
- High-resolution data used for evaluation only covers a relatively small time span. Comparison to observations instead?
- Increase in computational runtime when replacing the simple cloud cover scheme by NNs (need efficient Python-Fortran bridges)

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