Towards an aerosol-aware ML-based cloud microphysics parameterization in ICON

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Motivation

- Cloud microphysics remains a major uncertainty in ESMs, while key processes occur at sub-grid scales
- Aerosols influence cloud droplet number concentration (cdnc) and thus precipitation and radiative effects, yet are absent from most ML microphysics frameworks

Goal: Extend our physics-informed ML microphysics parameterization [0] in ICON to be aerosol-aware via HAM-lite [1]

Possibilities for a data-driven microphysics parameterization

Learn from LES and superdroplet models

- Resolve key microphysical processes in detail [2,3]
- Provide rich, physically grounded training data

→ *Computationally expensive and limited in domain, challenging for generalization in global runs*

Physics-informed ML trained on km-scale ICON simulations

- Learn from convection-permitting, global ICON simulations at 5 km resolution
- Use complex graupel microphysics for training [4]
- Capture subgrid-scale dynamics at target ESM resolution (80 km)

→ *Balances physical fidelity and computational feasibility for next-gen hybrid ESMs* [5]

Emulate existing parameterizations in GCMs

- ML can replicate traditional schemes efficiently [6,7,8]
- Improves computational speed and scalability

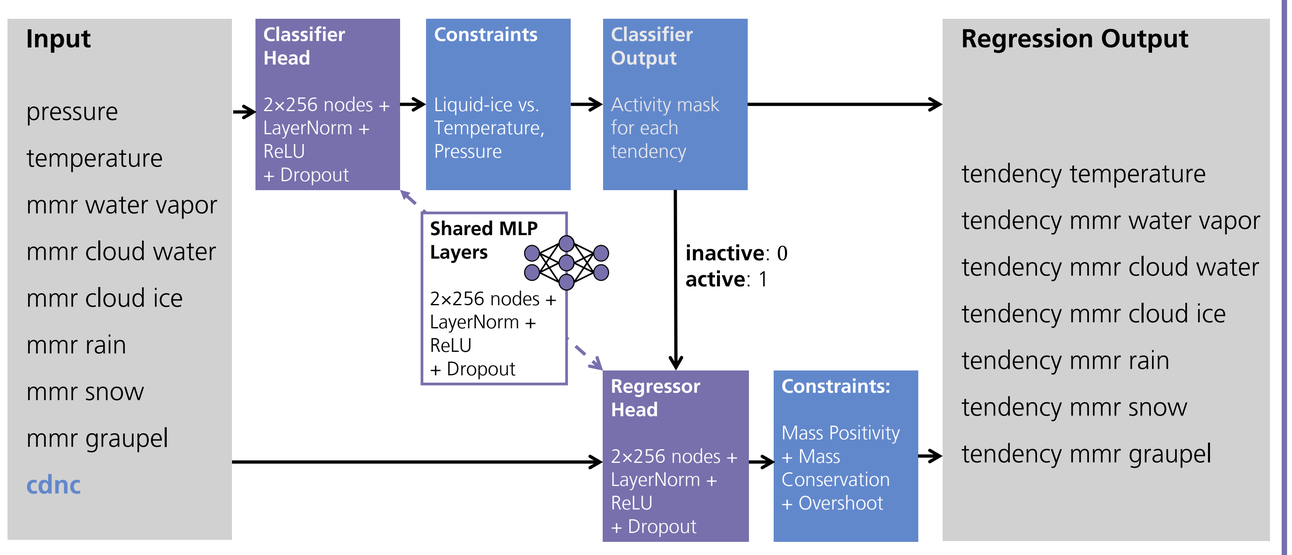
→ *Often replicates existing biases and lacks physical improvement*

scale

50 m — 5 km — 80 km

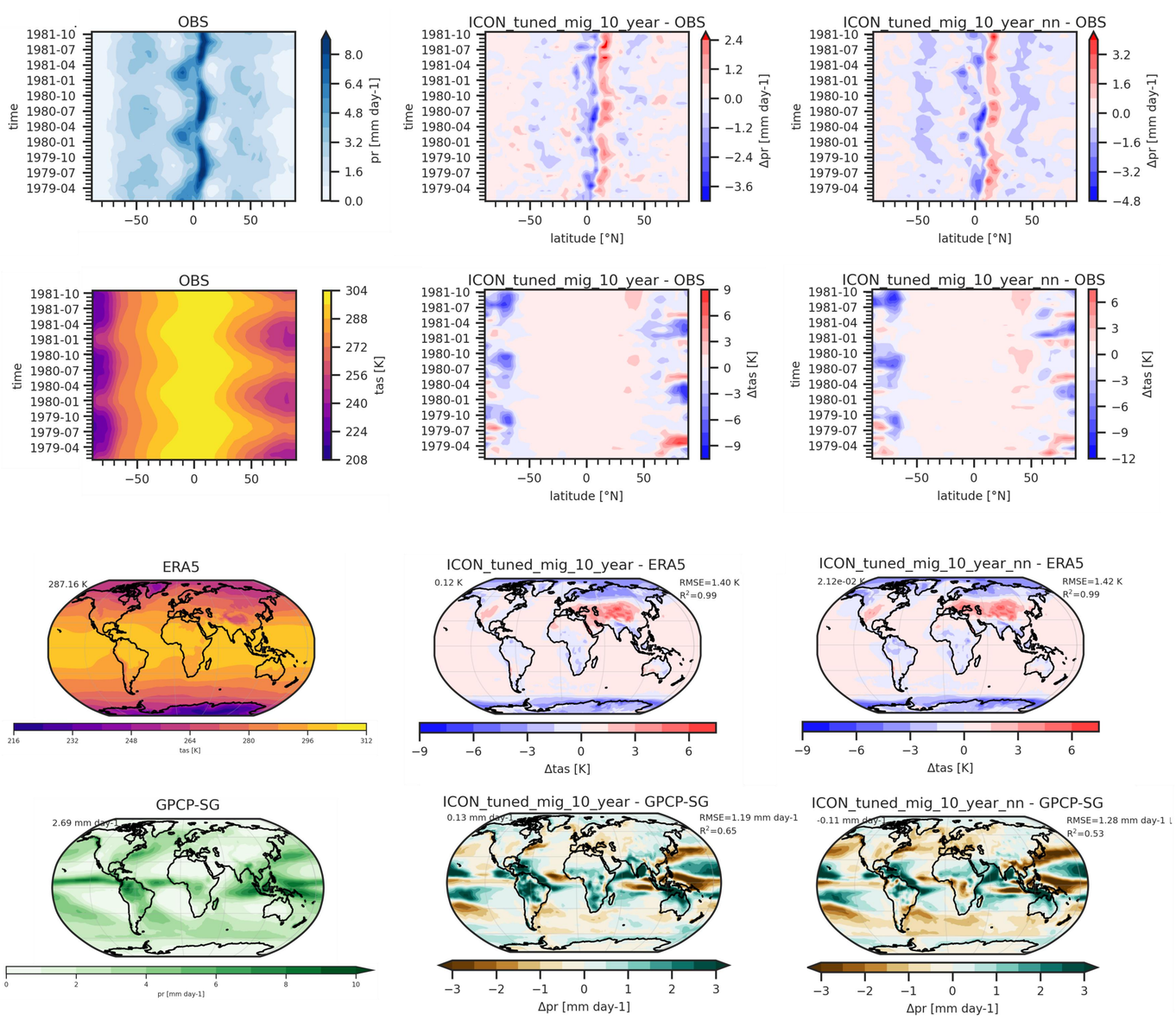
Model Setup & Training Data

- ICON Sapphire at 5 km resolution, 12 days of January 2020 used for training
- Coarse-grained to 80 km following [9]
- ML parameterization: classifier (identifies active grid cells) + regressor (predicts tendencies) with physical constraints (mass positivity, overshoot prevention)
- Aerosol climatologies prescribed from HAM-lite simulations as intermediate step toward interactive aerosols



Online Coupling Results

- Stable decade-long simulations achieved
- Physical constraints (mass positivity + overshoot prevention) are necessary for stability; strong offline performance alone is insufficient
- Climate metrics comparable to classical graupel baseline (temperature, precipitation, water vapor)



Aerosol-aware Extension & Next Steps

- Aerosols influence cloud droplet number concentration (cdnc) and thus precipitation and radiative effects, yet aerosol effects are absent from most ML microphysics frameworks
- Incorporating HAM-lite aerosol module [1] to prescribe aerosol climatologies as an intermediate step toward fully interactive aerosol-cloud coupling
- cdnc added as additional input predictor to the ML model, enabling the parameterization to respond to aerosol-mediated changes
- Expand training data to include multiple seasons and diverse atmospheric regimes

References

[0] Sarauer et al. (2025). A physics-informed machine learning parameterization for cloud microphysics in ICON. Environmental Data Science, 4, e40.

[1] Weiss et al. (2025). ICON-HAM-lite 1.0: simulating the Earth system with interactive aerosols at kilometer scales. Geoscientific Model Development, 18(12), 3877–3894.

[2] Seifert et al. (2024). An ML-based P3-like multimodal two-moment ice microphysics in the ICON model. Journal of Advances in Modeling Earth Systems, 16(8), e2023MS004206.

[3] Sharma et al. (2025). SuperdropNet: A stable and accurate machine learning proxy for droplet-based cloud microphysics. Journal of Advances in Modeling Earth Systems, 17(6), e2024MS004279.

[4] Baldauf et al. (2011). Operational convective-scale numerical weather prediction with the COSMO model: Description and sensitivities. Monthly Weather Review, 139(12), 3887–3905.

[5] Eyring et al. (2024). Pushing the frontiers in climate modelling and analysis with machine learning. Nature Climate Change, 14, 1–13.

[6] Perkins et al. (2024). Emulation of cloud microphysics in a climate model. Journal of Advances in Modeling Earth Systems, 16(4), e2023MS003851.

[7] Gettelman et al. (2021). Machine learning the warm rain process. Journal of Advances in Modeling Earth Systems, 13(2), e2020MS002268.

[8] Han et al. (2020). A moist physics parameterization based on deep learning. Journal of Advances in Modeling Earth Systems, 12, e2020MS002076.

[9] Grundner et al. (2022). Deep learning based cloud cover parameterization for ICON. Journal of Advances in Modeling Earth Systems, 14(12), e2021MS002959.

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