Physics-informed Machine Learning-based Cloud Microphysics parameterization for Earth System Models

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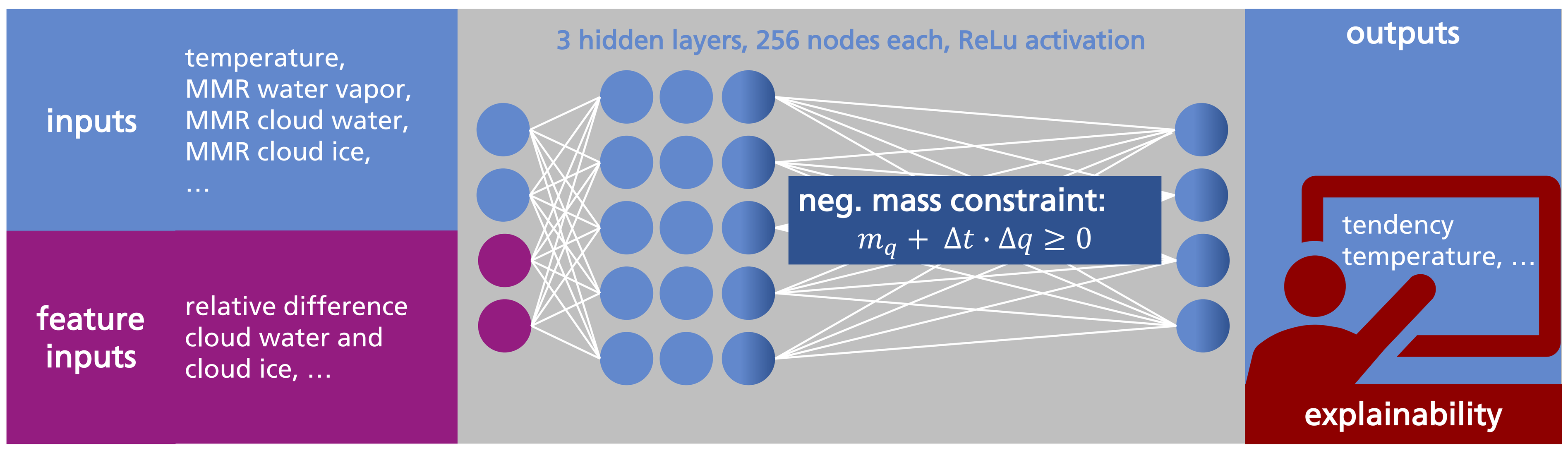
Motivation

- ML models trained on high-resolution climate simulations or observations, coupling with coarse climate models **reduces biases in Earth system models (ESMs)** [1,2]
- Novel approach to **enhance subgrid-scale cloud microphysics** in ESMs for the Icosahedral Non-hydrostatic modeling framework (ICON)
- Cloud microphysics parameterization **only been emulated at the same resolution** as simulation data [3,4]
- Integrating higher resolution dynamics into the lower resolution ESM, particularly beneficial for cloud convection studies
- Developing an ML-based parameterization based on more complex graupel scheme (in comparison to current ESMs)

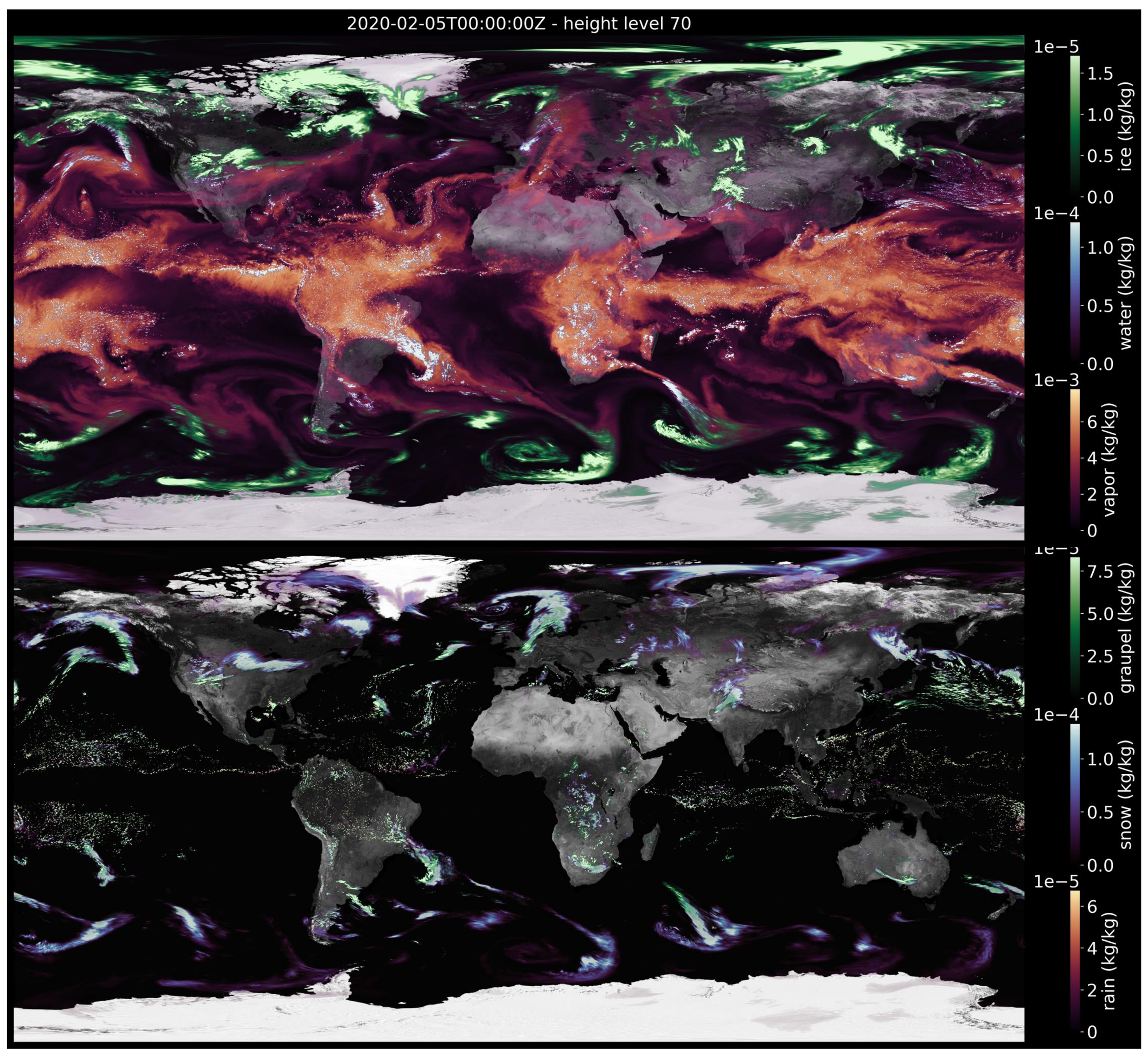
Goal: Improve Earth System Models by replacing traditional parameterization schemes with Machine learning based parameterizations

Machine learning methodology



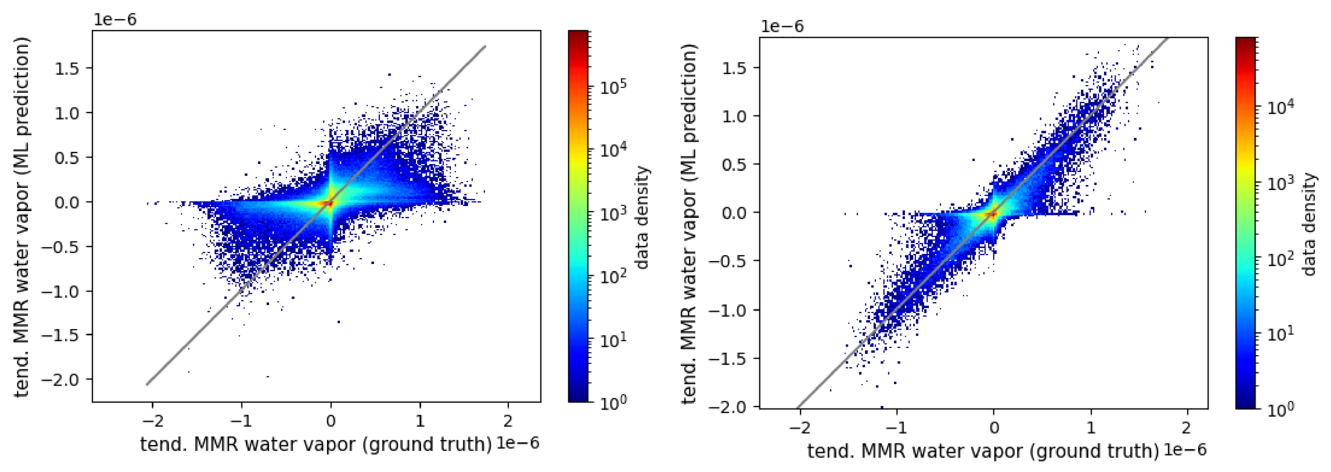
High-resolution climate data

- Using **ICON Sapphire** [5,6] with prescribed sea ice and sea surface temperature and 5 km resolution
- **Run the simulation** for 30 days from 20 January 2020, microphysics model time step set to 40 seconds, store data every three hours
- **Coarse-graining**, adopting the same methodology as [7] mapping the data to a coarser ICON grid with a horizontal resolution of 80 km



Results

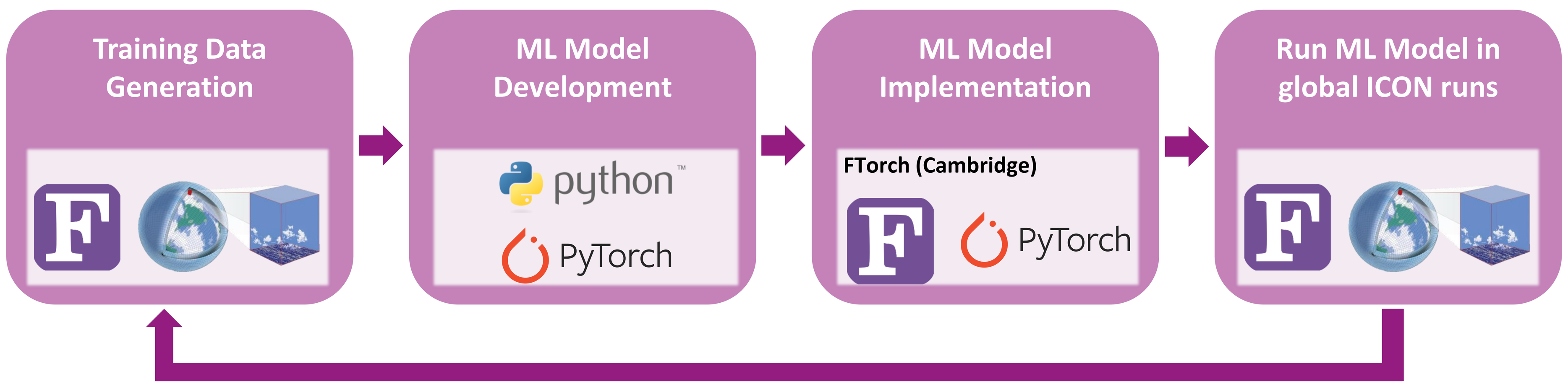
- **Physics constraining** does not affect overall performance but leads to improved and stable simulations when coupled to climate models
- **Explainability techniques** such as Shapley value calculation reveal strong correlations between microphysical tendencies and air pressure, temperature, and vertical velocity
- **Feature engineered variables** describing relative differences between tracers lead to better prediction than mass mixing ratios, cf. figures and table



Output variable	R-squared (base)	R-squared (full)
Tendency Temperature [T/s]	0.370	0.726
Tendency water vapor [kg/kg/s]	0.367	0.731
Tendency cloud liquid water [kg/kg/s]	0.412	0.777
Tendency cloud ice [kg/kg/s]	0.337	0.687
Tendency rain [kg/kg/s]	0.188	0.492
Tendency snow [kg/kg/s]	0.126	0.388
Tendency graupel [kg/kg/s]	0.226	0.493

Outlook

- Improve model performance by generating a **more balanced dataset** through multiple shorter simulations
- Implement and evaluate ML-based microphysics parameterization in a global climate model (**online coupling**) for full benefits.
- Develop **cloud microphysics and convection parameterization** to reduce uncertainties in climate simulations



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