A Framework for Embedding ML Physics into Climate Models
Or
Can We Use Machine Learning to Improve Conventional Models?

David Fuchs, Abhnil Prasad, Steven Sherwood, Kirill Trapeznikov, Jim Gimlett

UNSW Climate Change Research Centre

climate extremes ARC centre of excellence

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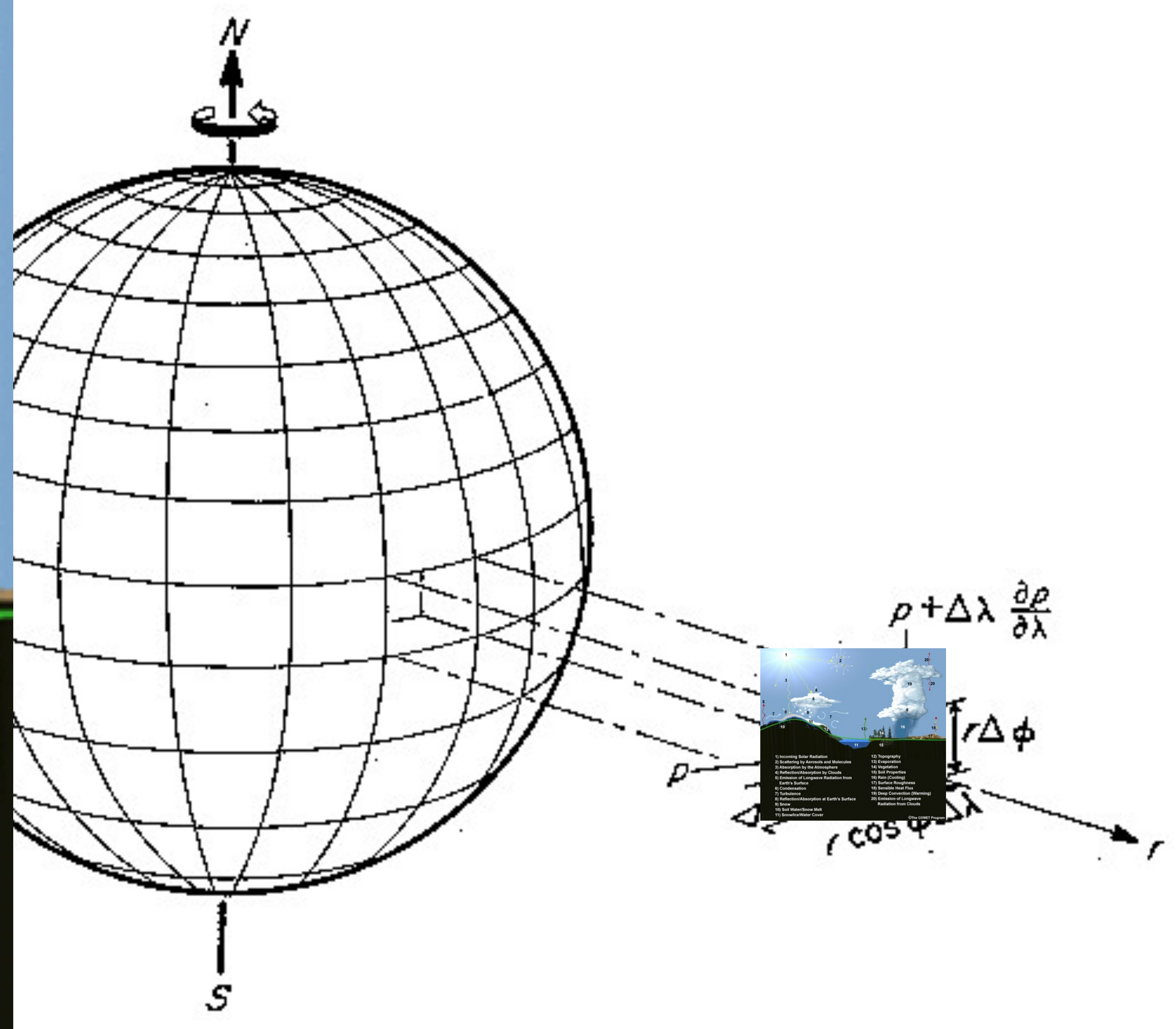
Parameterized “physics” a weak point of global models



Model output

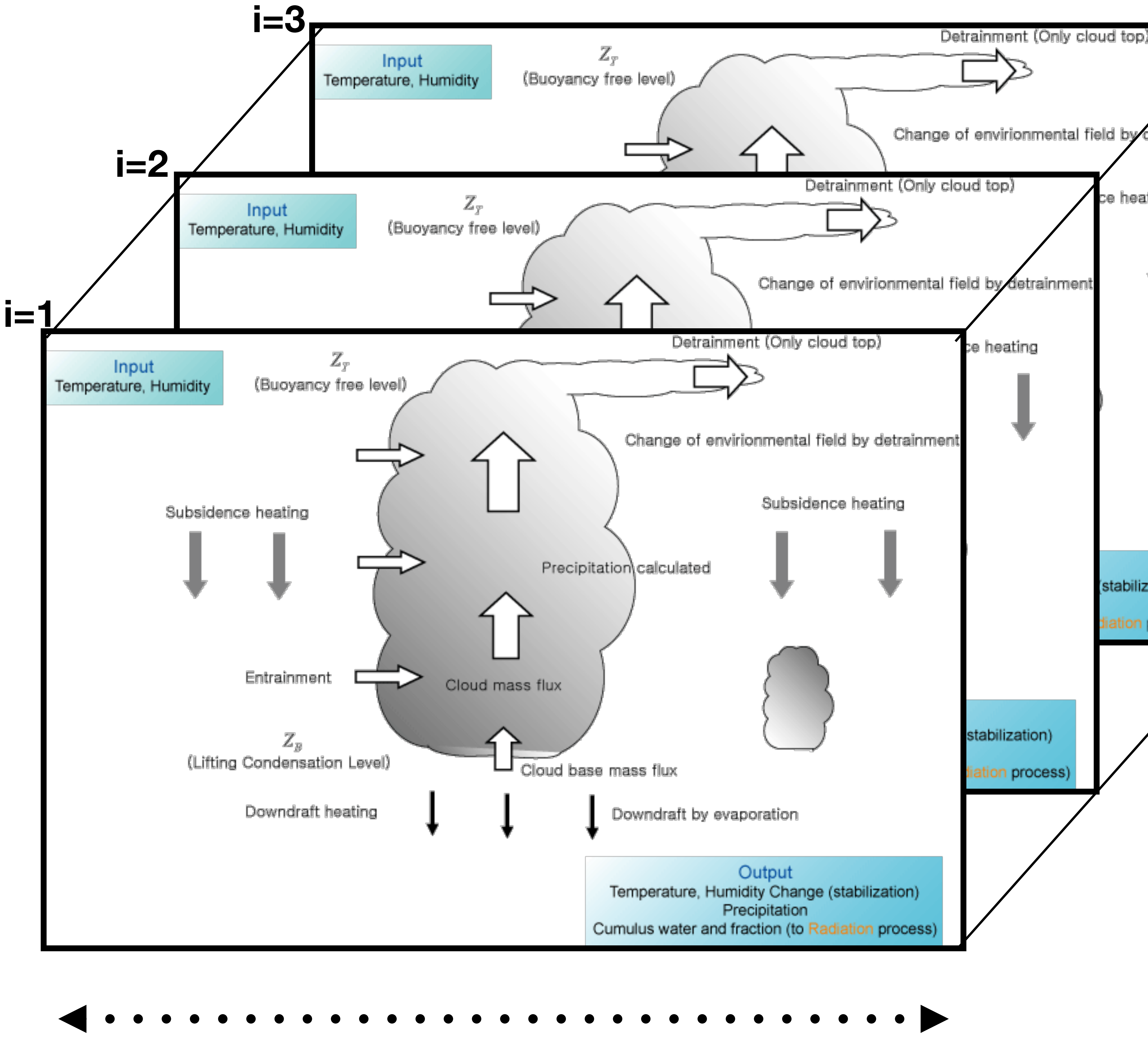
Model physics

Need to predict sources and sinks of prognostic variables **x** = {*T*, *q*, …} using predictors **x**’, *i.e.*,

$$\frac{d\mathrm{x}_{\mathrm{ij}}}{dt} = \frac{\partial \mathrm{x}_{\mathrm{ij}}}{dt}|_{\mathrm{dyn}} + \frac{\partial \mathrm{x}_{\mathrm{ij}}}{dt}|_{\mathrm{phys}}$$

Model physics acts as a (stochastic) operator to map predictors $\mathbf{x}_{\mathbf{ij}}$’ onto $\frac{\partial \mathrm{x}_{\mathrm{ij}}}{dt}|_{\mathrm{phys}}$.

$\mathbf{x}_{\mathbf{ij}}$’ ≡ {$\mathbf{x}_{\mathbf{ij}}$, others diagnosed from **x**}

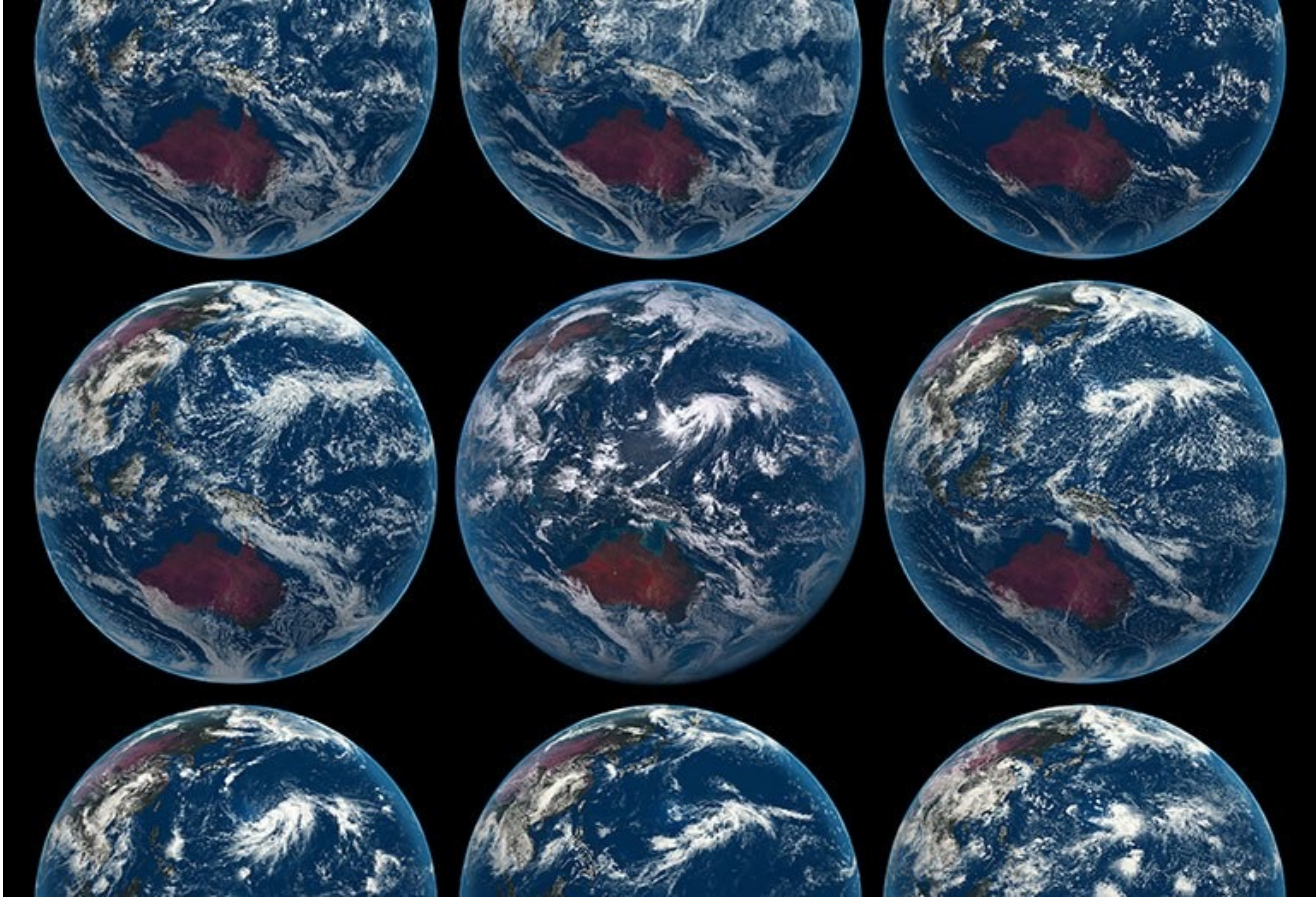


Model horizontal grid spacing

Why have model physics representations developed so slowly?

1. Phenomena are too complex for straightforward representation — we need to simplify substantially but don't know how
2. Scheme development+implementation is laborious
3. Offline evaluation hampered by lack of data
4. Online evaluation corrupted by other model errors

DYAMOND
<=5 km

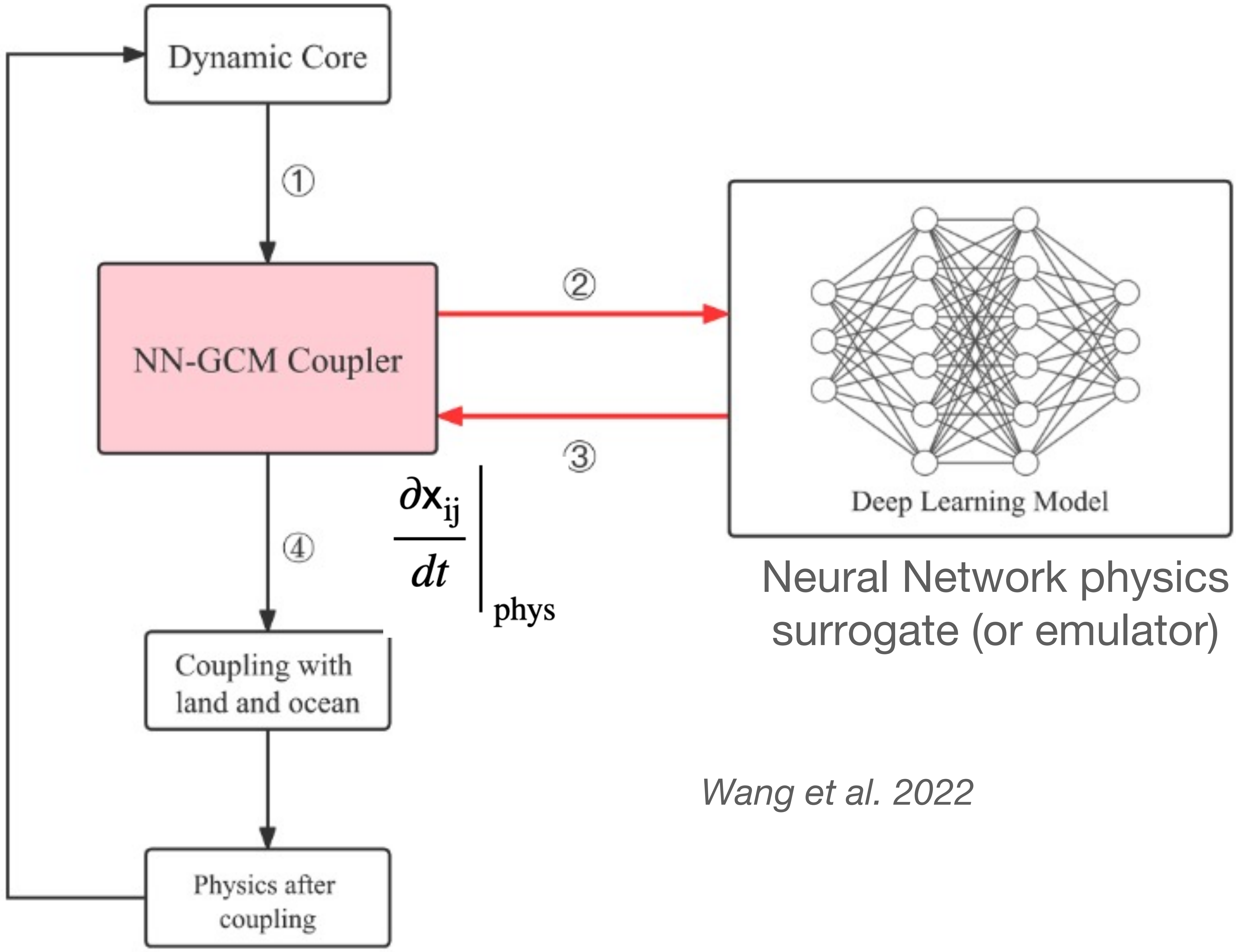


So let’s just resolve convection 😃

100 m	1 km	100 km
Three days	One year	10-member ensemble of a glacial cycle

😳

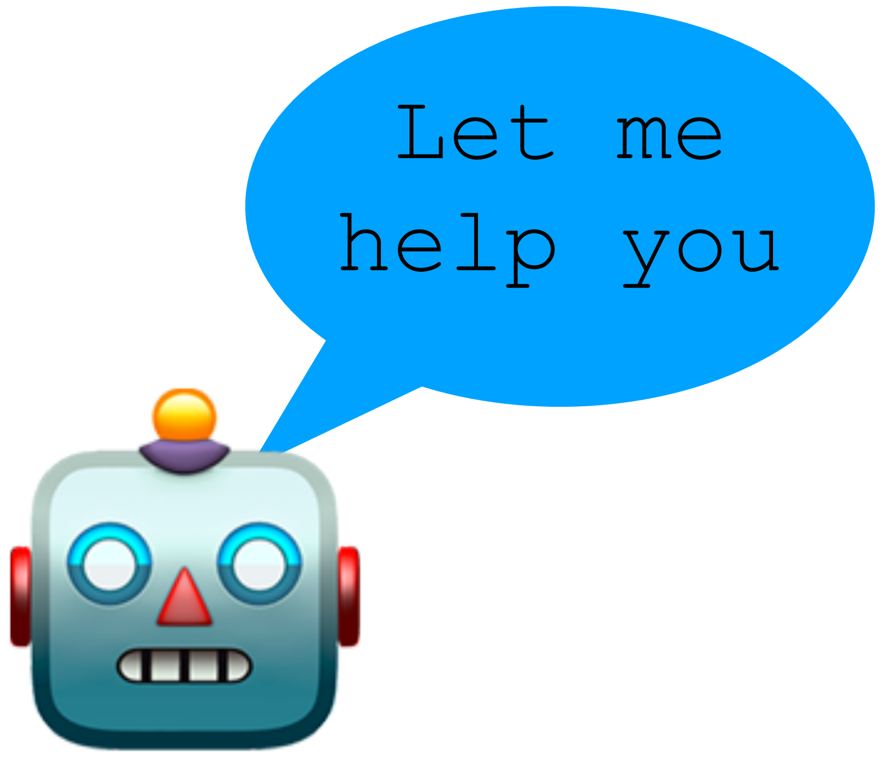
How can we test in more realistic and diverse situations?



Neural Network physics surrogate (or emulator)

Wang et al. 2022

Hybrid Climate Model



- Data for training the Machine Learning (ML)?
- How to put the ML into the (FORTRAN) GCM?
- How to rapidly test alternate ML models?

Offline AI surrogate performance
(Total Precipitation)

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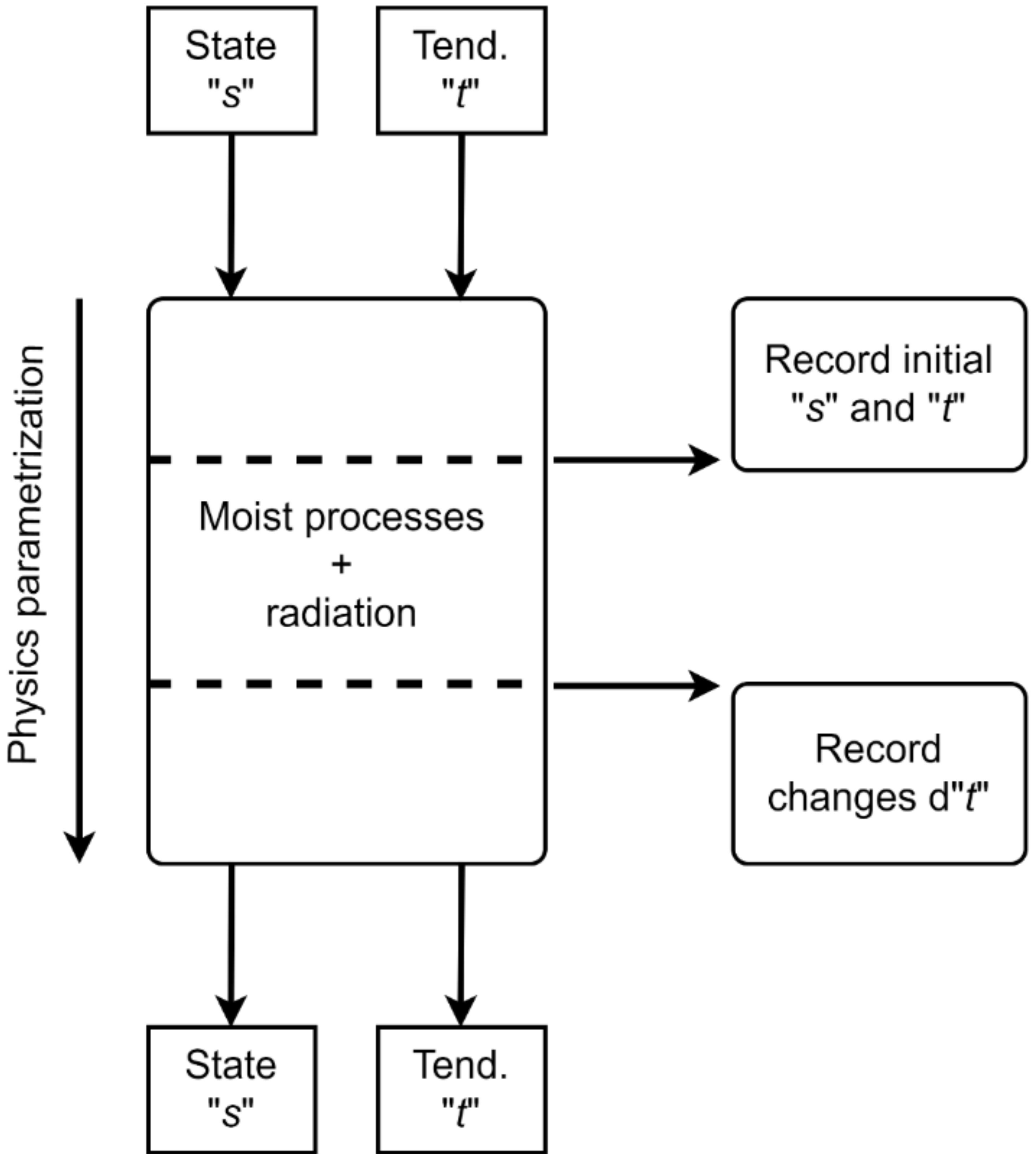
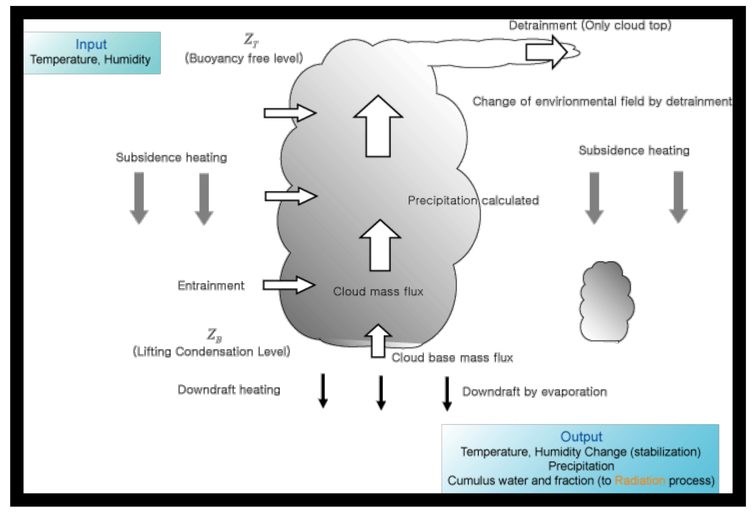
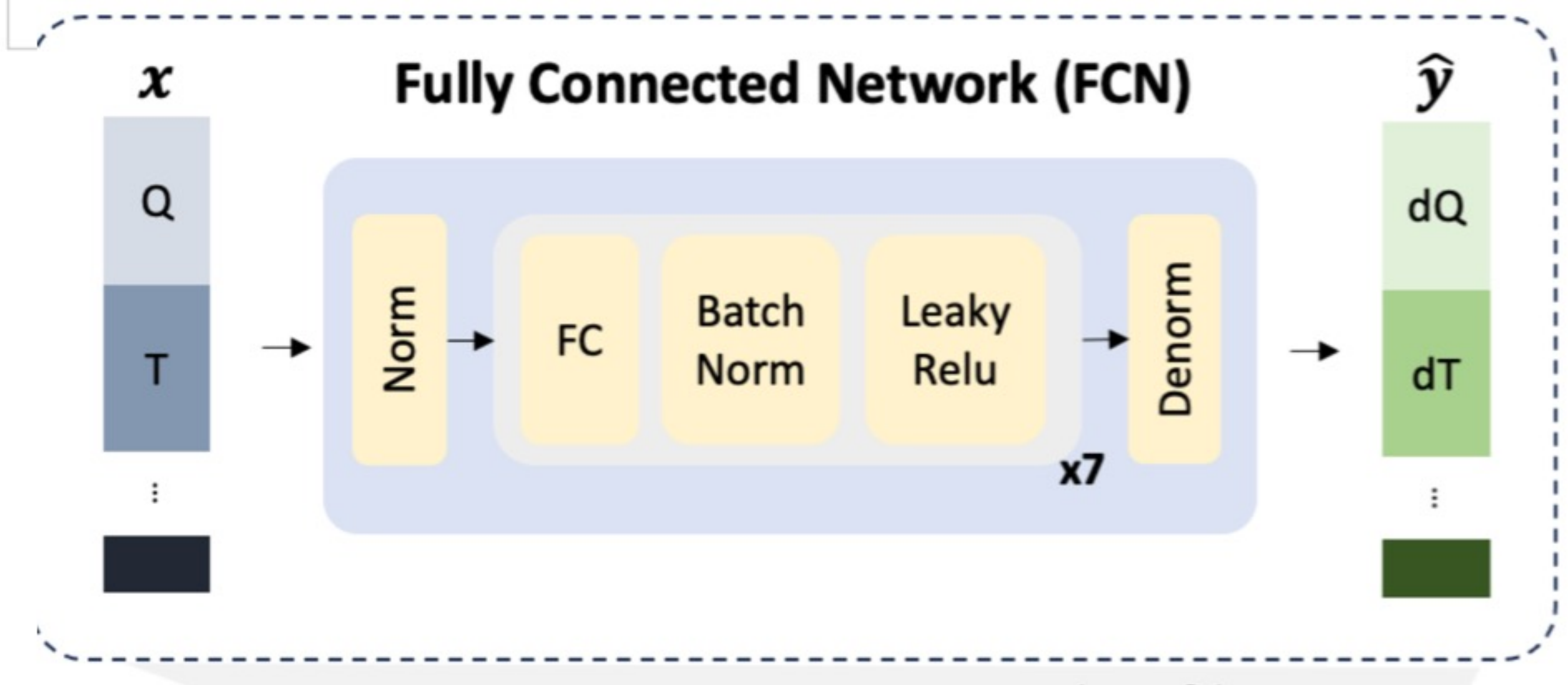


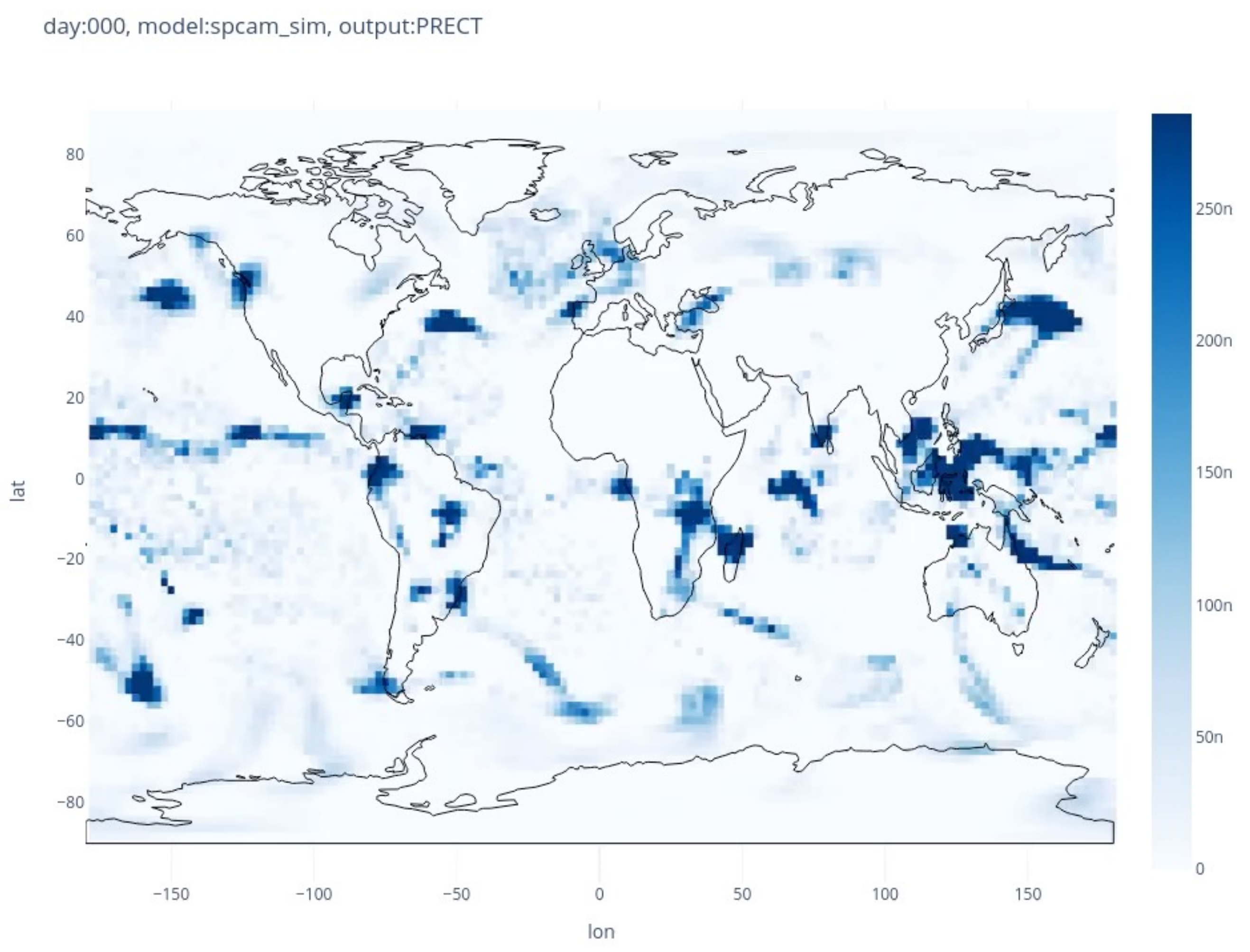


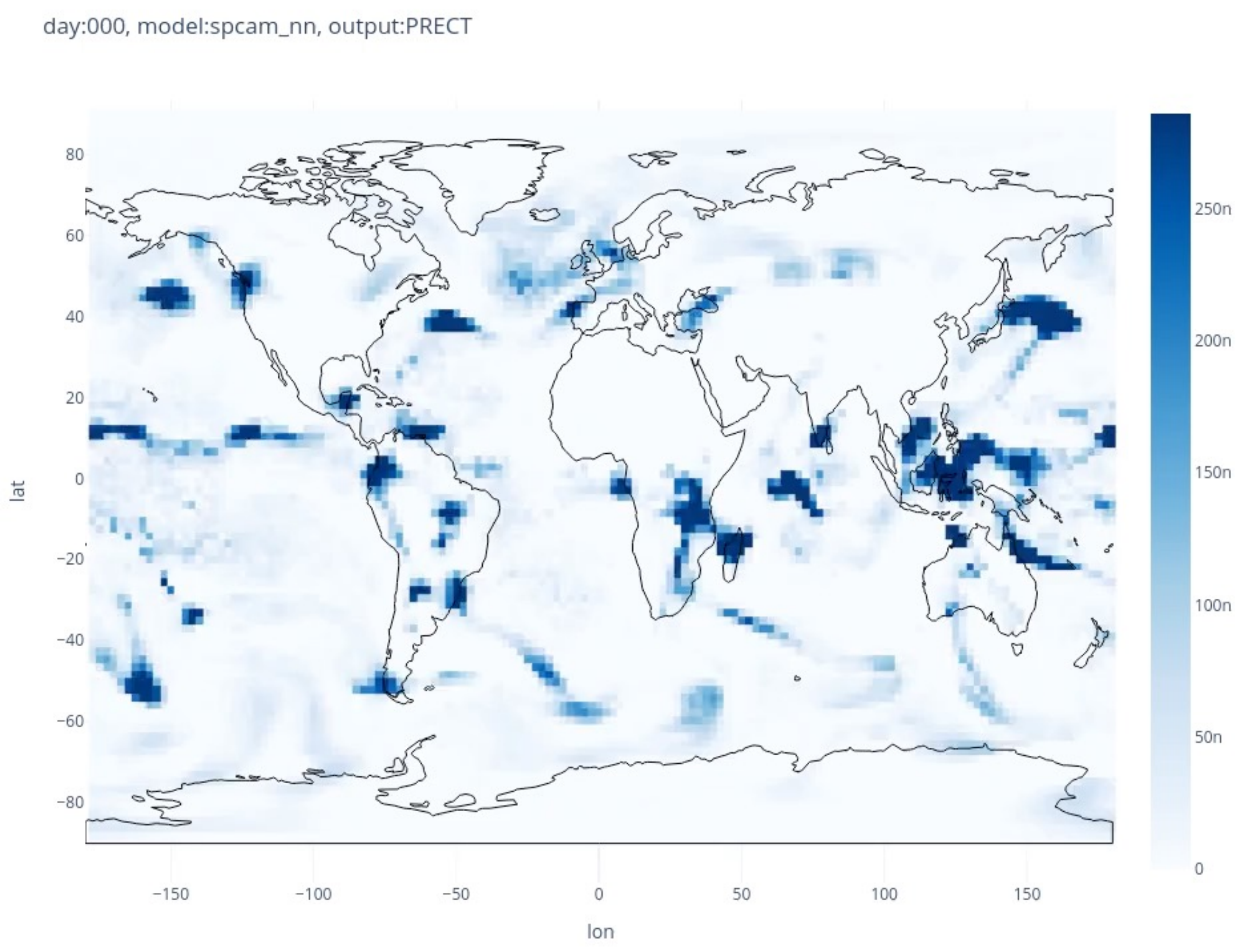


SPCAM Sim

Precipitation

SPCAM NN





Gaia Hybrid Model Integration
TorchClim Bridge Module

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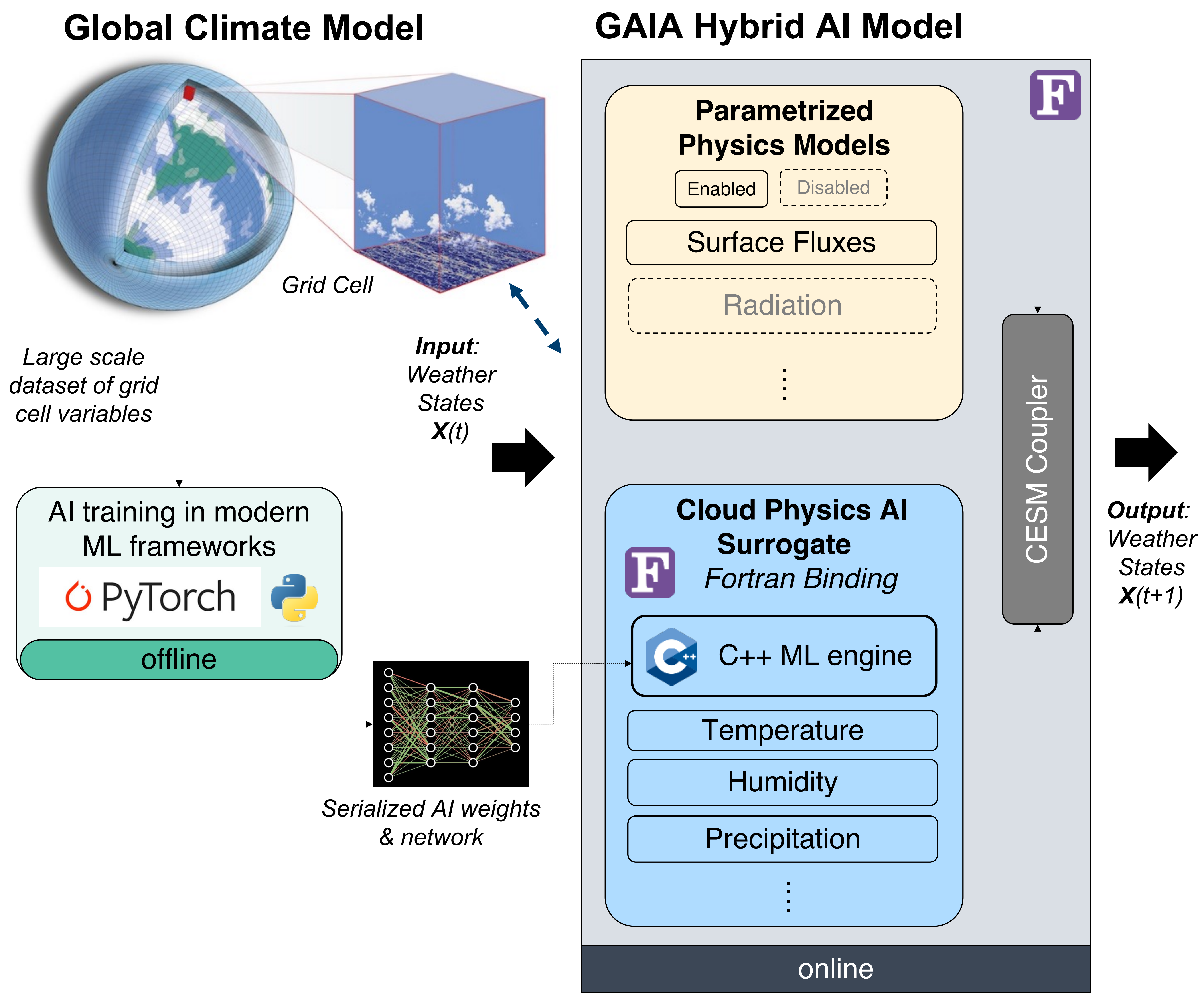


GAIA hybrid physics model integration bridge will enable new AI-based climate science research and developments

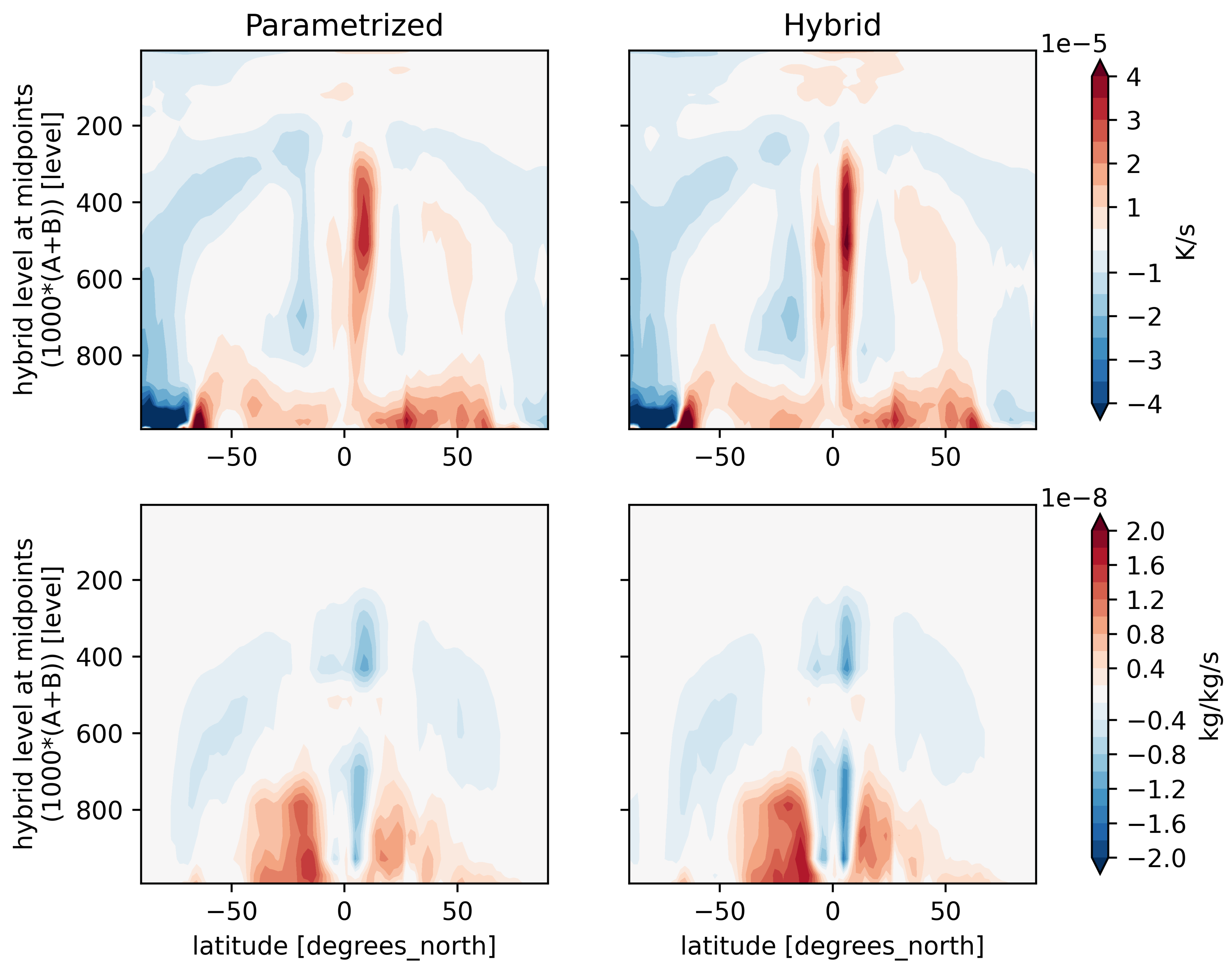
- Flexible integration of AI surrogates compatible with common ML frameworks w/o custom compilation
- Enables fast research and development of AI surrogates for the entire climate science community
- Highly customizable: configure AI surrogates to replace different physics parameterizations
- Same speed as standard model, faster with future optimization
- Validated integration with widely-used CSEM codebase & GCMs parallelization architectures

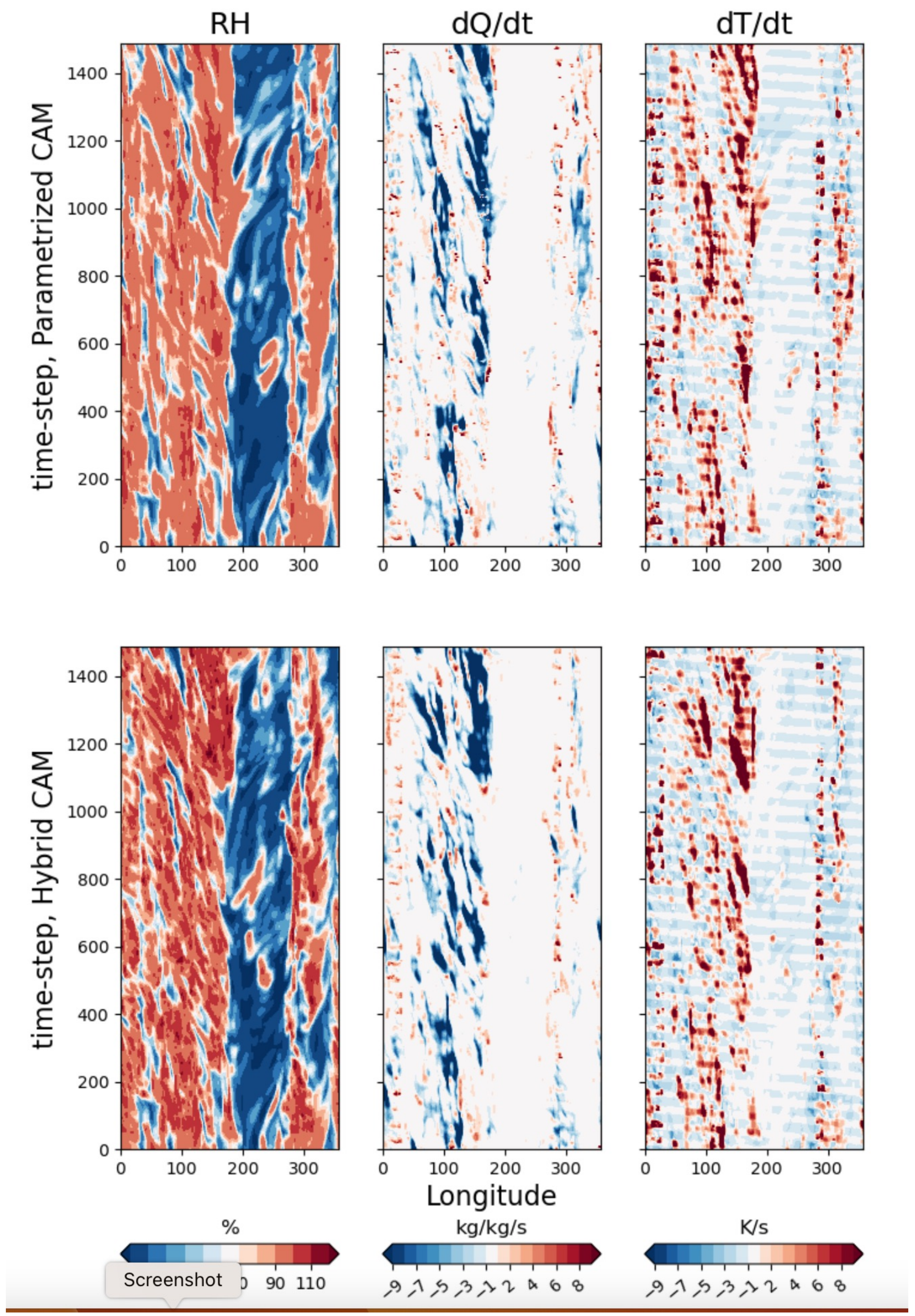
Fuchs et al., Geosci. Mod. Development

Gaia Hybrid Model Integration
Comparison with original physics

∂T/∂t

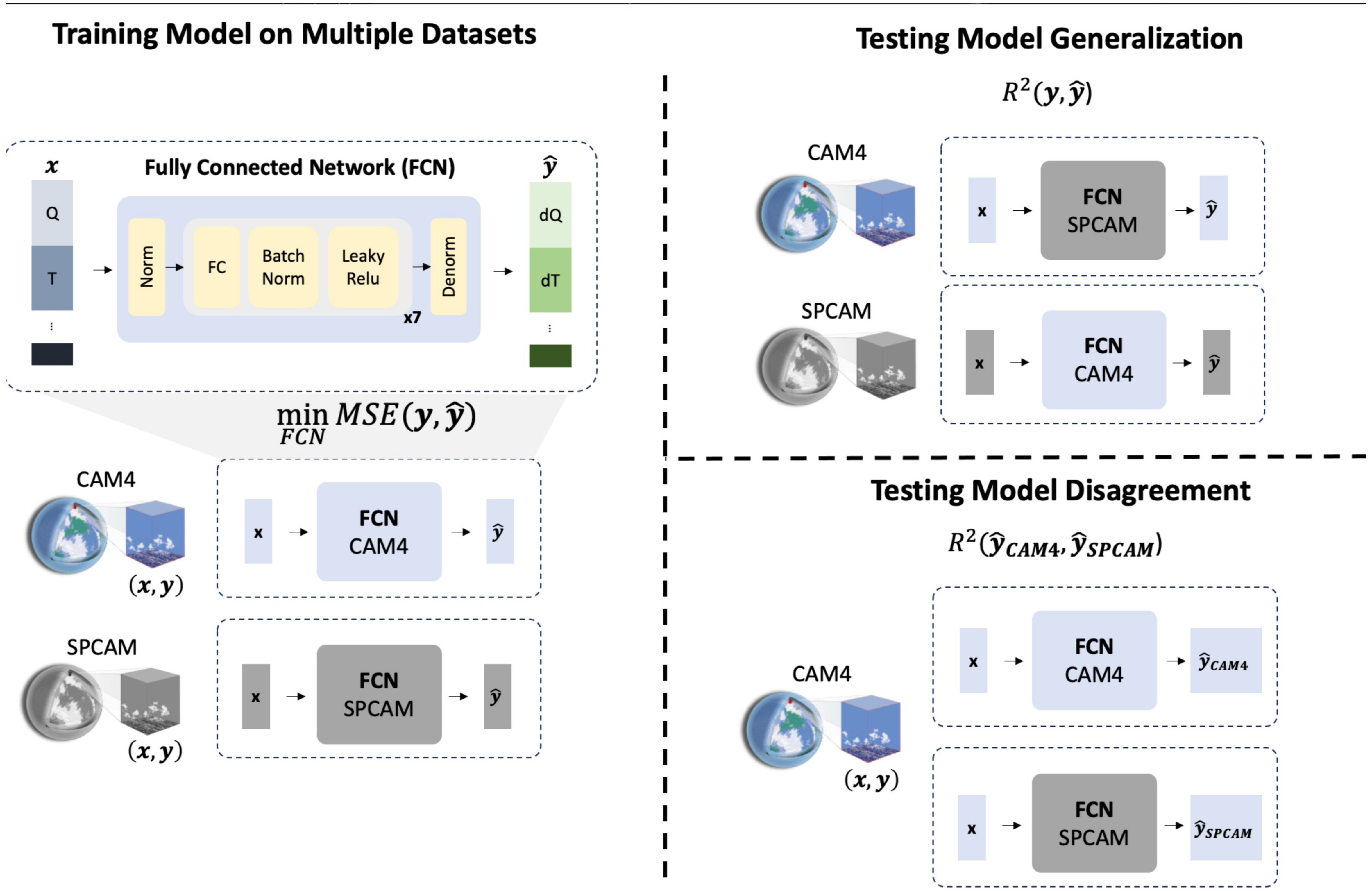
∂q/∂t





Gaia Hybrid Model Integration
Applications

- *If system were used in multiple GCMs:* easily swap (emulated) physics between models
- Emulate selected individual processes
- Evaluate new schemes or versions rapidly via an emulator—avoid integration costs
- Emulate LES models or observations (but usually don't have enough data!?)



Pre-training to use limited data

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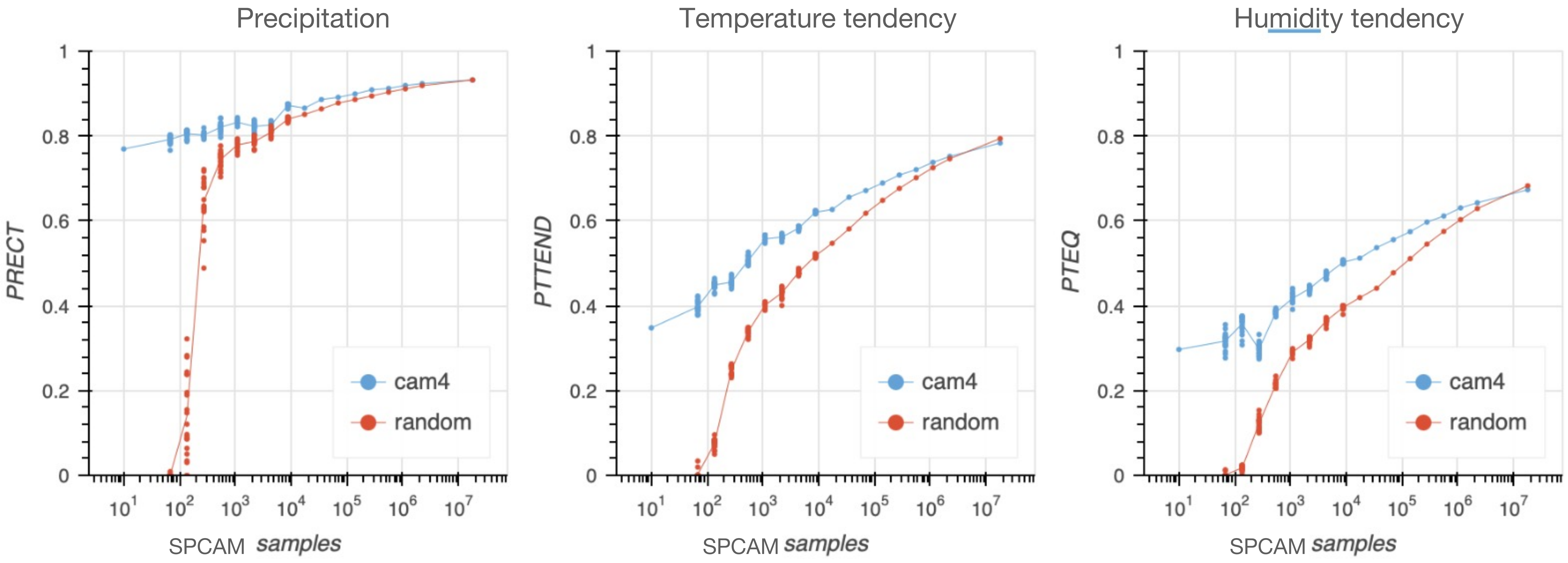
1. Pre-train the deepNN on data from CAM (10^7 data points)
2. Fine-tune this deepNN with small sample from SPCAM (10^1-10^7 data points)
3. How well can this fine-tuned NN emulate SPCAM?

LES can generate training sample, e.g.
Yu et al. 2023 (arXiv)



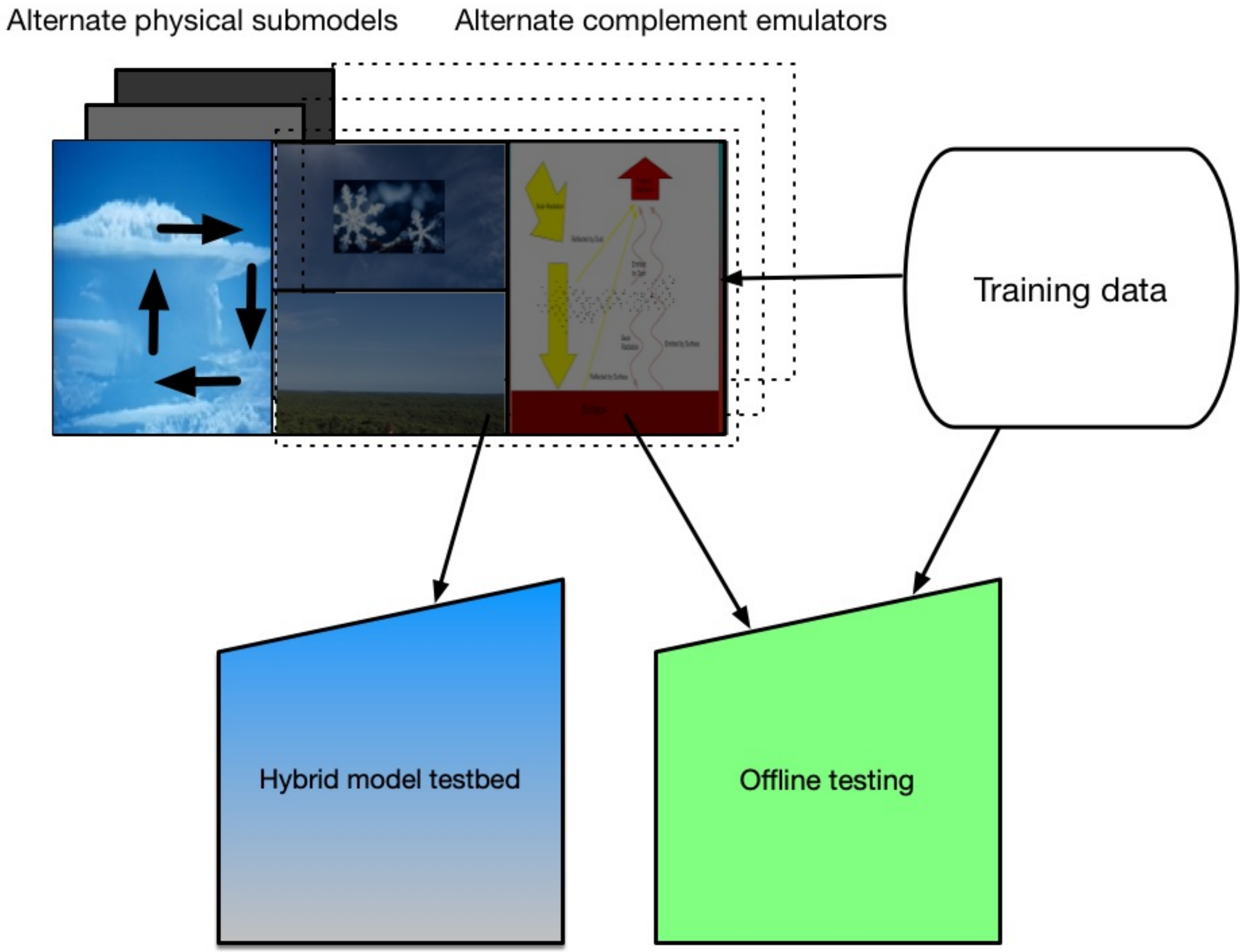
Pre-training on poor data reduces the amount of good data needed by 1-2 orders of magnitude

What can this be used for

- Speed up models by emulating expensive physics / resolution
- Learn processes from “quality” data (model/observations)
- Add new predictands online (e.g., downscaling, impacts)
- *Accelerate traditional model development*

Accelerating Model Development

- Combine concepts of "interpretable" and "physics-informed" machine learning
- Trial an error process on different structural assumptions/models
- Use ML to overcome the "scheme interaction" problem



Take home messages

- GCRMs will not do everything (in my lifetime anyway) and there is room to improve current atmospheric model parameterizations
- We have a new system for CAM ML that could be implemented into other models
- Machine learning offers a host of opportunities for achieving the holy grail of combining information across scales (LES/CRM, GCM, observations), through fine-tuning/transfer learning approaches, transpose models.
- It could be harnessed to aid, not replace, human learning.

https://egusphere.copernicus.org/preprints/2023/egusphere-2023-1954/

Thank you

From Alphacoders

AI Surrogate Inputs and Outputs

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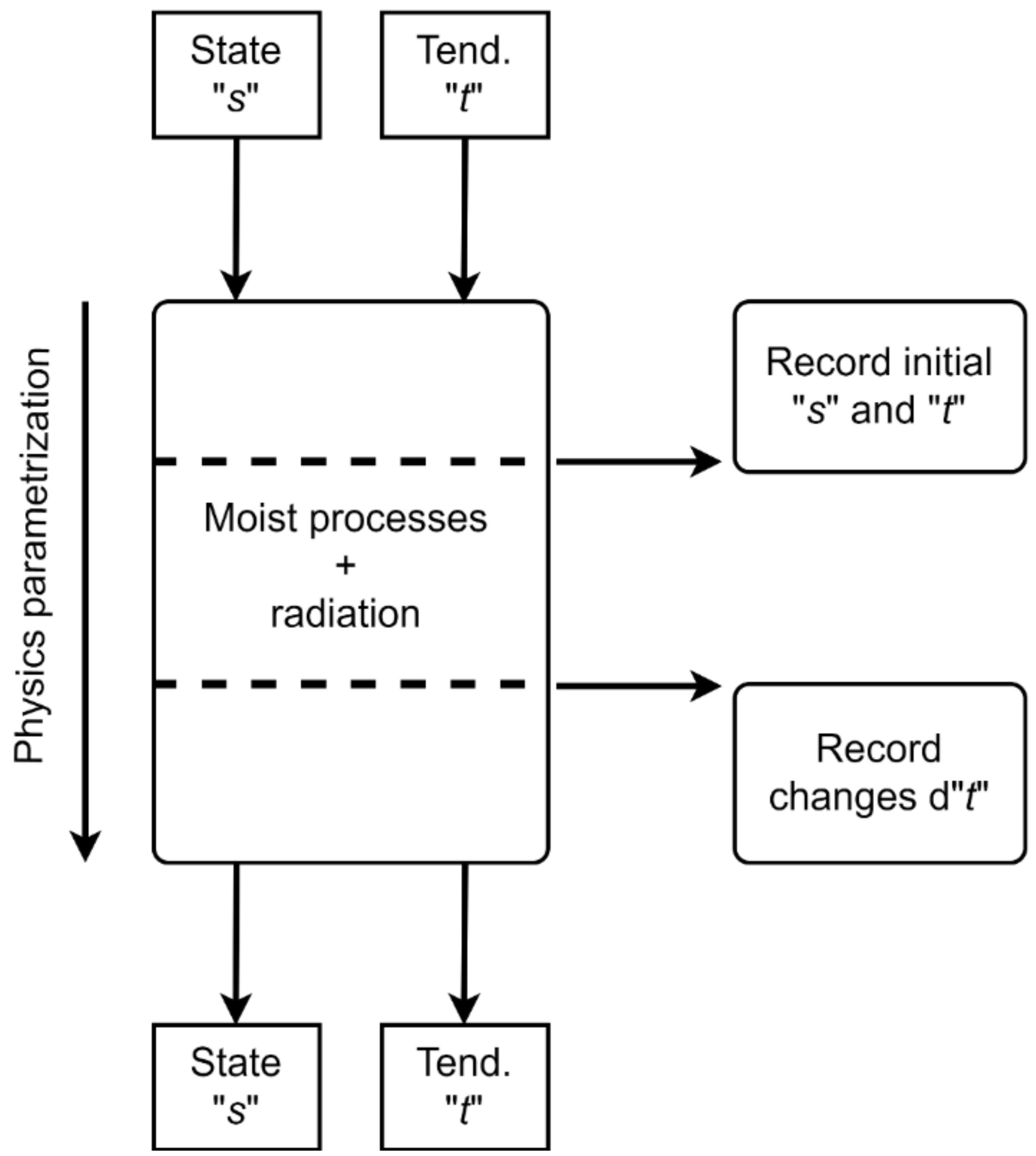

Inputs

- Specific Humidity (Q)
- Temperature (T)
- Zonal Wind (U)
- Meridional Wind (V)
- Vertical Velocity (OMEGA)
- Geopotential Height (Z3)
- Surface Pressure (PS)
- Solar Insolation (SOLIN)
- Sensible Heat Flux (SHFLX)
- Latent Heat Flux (LHFLX)
- Land Fraction (LANDFRAC)
- Ocean Fraction (OCNFRAC)
- Ice Fraction (ICEFRAC)
- Surface Temperature (TS)

Outputs

- Q Total Physics Tendency (PTEQ)
- T Total Physics Tendency (PTTEND)
- Net Solar Flux at Surface (FSNS)

Net Longwave Flux at Surface (FLNS)
Net Solar Flux at top of model (FSNT)
Net Longwave Flux at top of model (FLNT)
Downwelling Solar Flux at Surface (FSDS)
Downwelling Longwave Flux at Surface (FLDS)
Net Radiative Flux at Surface (SRFRAD)
Solar Downward Near Infrared Direct to Surface (SOLL)
Solar Downward Visible Direct to Surface (SOLS)
Solar Downward Near Infrared Diffuse to Surface (SOLLD)
Solar Downward Visible Diffuse to surface (SOLSD)
Total (Convective and Large-Scale) Precipitation Rate (liq + ice) (PRECT)
Convective Precipitation Rate (liq + ice) (PRECC)
Large-Scale (Stable) Precipitation Rate (liq + ice) (PRECL)
Convective Snow Rate (PRECSC)
Large-Scale (Stable) Snow Rate (PRECSL)

Additional AI evaluations & updates
Gradient map: no regularization

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