CondensNet: A Physically-Constrained Hybrid Deep Learning Model for Stable Long-Term Climate Simulations

Xin Wang*[a], Jianda Chen[b], Juntao Yang[c], Jeff Adie[c], Simon See[c], Kalli Furtado[d], Chen Chen[d], Troy Arcomano[e], Romit Maulik[f], Wei Xue[b], Gianmarco Mengaldo†[a]

[a] *National University of Singapore,* xin.w24@nus.edu.sg, mpegim@nus.edu.sg

[b] *Tsinghua University,* chenjd21@mails.tsinghua.edu.cn, xuewei@tsinghua.edu.cn

[c] *NVIDIA, Singapore,* yjuntao@nvidia.com, jadie@nvidia.com, ssee@nvidia.com

[c] *Centre for Climate Research Singapore,* kalli_furtado@nea.gov.sg, chen_chen@nea.gov.sg

[c] *Argonne National Laboratory, US,* tarcomano@anl.gov

[d] *Pennsylvania State University, US,* rmaulik@psu.edu

*Presenting author
†Corresponding author

1. Introduction

Small-scale precipitation and cloud processes are crucial for climate modeling yet challenging for traditional general circulation models (GCMs) [1, 2]. While super-parametrization improves accuracy by embedding cloud-resolving models in GCMs, it incurs substantial computational costs [3]. Deep learning approaches offer efficient alternatives but struggle with water vapor condensation processes, causing simulation instability [4, 5, 6]. We introduce CondensNet, a hybrid framework that incorporates adaptive physical constraints to address water vapor oversaturation, delivering accurate precipitation predictions while maintaining numerical stability in long-term climate simulations.

2. Method

2.1 Methodology and Platform

We integrate CondensNet within the Community Atmosphere Model (CAM5.2) [7], where the standard convection parameterization is replaced by a DL-based emulator trained on super-parametrized CAM (SPCAM) [3, 8] outputs (Figure 1, panel a). At each simulation step, the host GCM (CAM) supplies essential climate state variables (e.g., temperature, humidity, and solar insolation) to CondensNet and receives prediction tendencies from CondensNet.

2.2 CondensNet

Our CondensNet model (Figure 1, panel b) consists of two integrated neural networks with distinct tasks. These are *BasicNet* and *Condensation Correction Network (ConCorrNet)*. The former is a ResMLP model that predicts basic tendencies of water vapor ($\mathrm{d}Q$) and dry-static-energy ($\mathrm{d}s$), capturing fundamental cloud physics. The latter is designed to adaptively correct BasicNet's predictions by enforcing physical constraints associated with water vapor saturation through explicit correction terms. Con-

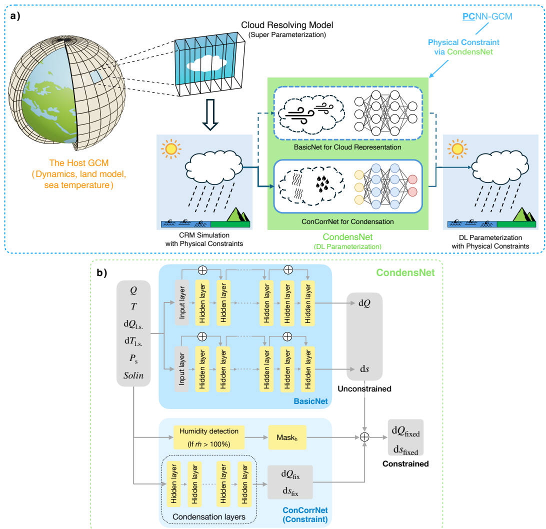

Fig. 1: Methodology a) and Architecture b) of the CondensNet.

densNet predicts physically constrained tendencies that comply with the saturation adjustment mechanism. We employ a humidity detection module to identify grid points where relative humidity (rh) exceeds 100%, creating a humidity mask ($\mathrm{Mask_h}$) that lets ConCorrNet focus on these regions, and adaptively learn whether and how much to fix from training data. The humidity mask ($\mathrm{Mask_h}$) is defined as:

$$\mathrm{Mask_h}(\mathrm{lon}, \mathrm{lat}, \mathrm{lev}) = \begin{cases} 1, & \text{if } rh > 100\% \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

ConCorrNet computes correction terms $\mathrm{d}Q_{\mathrm{fix}}$ and $\mathrm{d}s_{\mathrm{fix}}$ based on the excess water vapor above condensation threshold:

$$\mathrm{d}Q_{\mathrm{fixed}} = \mathrm{d}Q - \mathrm{Mask_h} \odot \mathrm{d}Q_{\mathrm{fix}} \quad (2a)$$

$$\mathrm{d}s_{\mathrm{fixed}} = \mathrm{d}s + \mathrm{Mask_h} \odot \mathrm{d}s_{\mathrm{fix}}, \quad (2b)$$

This ensures that excess water vapor is appropriately condensed, with corresponding latent heat re-

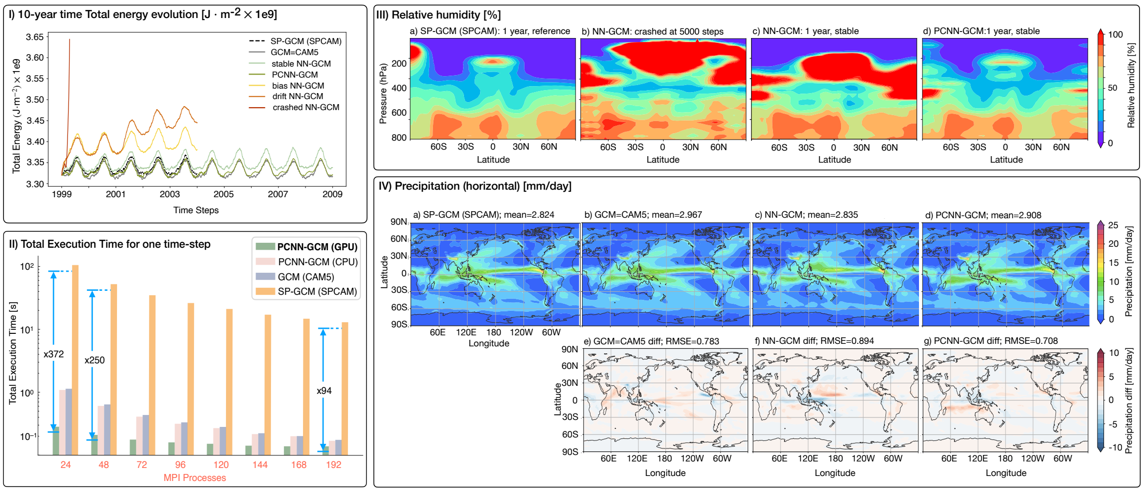

Fig. 2: Results of CondensNet. Panel I) is the 10-year total energy evolution for SPCAM, CAM5, NN-GCM, and PCNN-GCM, respectively; Panel II) is the computional performance; Panel III) is the Relative humidity for SPCAM reference (a), NN-GCM model failing after 5000 time steps (b), stable NN-GCM (c), and new PCNN-GCM featuring CondensNet (d); Panel IV) is the annual means (1999-2003) precipitation (a–d) for SPCAM, CAM5, NN-GCM, and PCNN-GCM, respectively, and corresponding differences with respect to SPCAM reference (e–g).

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2.3 *Training details*

BasicNet comprises 7 residual blocks (14 layers total) with 512-width in hidden layers, while ConCorrNet includes 6 residual blocks (12 layers) with sigmoid activations. During training, we freeze BasicNet's parameters and optimize ConCorrNet using two loss functions:

1. **Overall Loss** measures the difference between final predictions and SPCAM data.
2. **Condensation Correction Loss** focuses specifically on correction terms in regions marked by the humidity mask.

By optimizing both losses simultaneously, CondensNet effectively learns the necessary physical constraints, resulting in predictions consistent with SPCAM data while maintaining simulation stability.

3. Results

The PCNN-GCM (CondensNet integrated with GCM) achieves long-term stable simulations, better precipitation, and more physical representation compared with NN-GCM, as well as highly efficient computational performance.

Long-term simulation stability. Figure 2, panel I, shows that PCNN-GCM's total energy evolution closely follows the SPCAM reference, avoiding the energy surges that lead to crashes in unstable NN-GCM configurations.

Computational performance Crucially, PCNN-GCM delivers these improvements with substantial computational efficiency. Figure 2, panel II, demonstrates that GPU-accelerated PCNN-GCM achieves up to 372× speedup.

Physical Constraint. The relative humidity profiles (Figure 2, panel III) show that CondensNet-featured PCNN-GCM effectively solves water vapor over-saturation, closely resembling SPCAM patterns and significantly improving upon standard NN-GCM implementations.

Multi-year precipitation. Precipitation (Figure 2, panel IV) from PCNN-GCM achieve an RMSE of 0.708 compared to NN-GCM's 0.894.

4. Conclusion

We presented CondensNet, a physics-constrained deep learning framework for hybrid ML modeling that successfully addresses the problems of water vapor oversaturation and stability plaguing previous approaches. Integrating adaptive physical constraints through our ConCorrNet architecture ensures physical, numerically stable, and efficient simulation. Our results demonstrate that PCNN-GCM achieves long-term stable simulations with improved precipitation representation compared to traditional GCMs and unconstrained neural network emulators. The hybrid approach effectively balances the advantages of both data-driven methods (computational efficiency, accuracy) and physics-based modeling (physical consistency, stability). This work highlights the promise of physics-guided machine learning for climate science applications, potentially enabling more accurate climate projections at reduced computational costs.

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