# Envisioning the Role of Physics-Informed Neural Networks in Atmospheric Science: Advancements, Challenges, and Future Prospects

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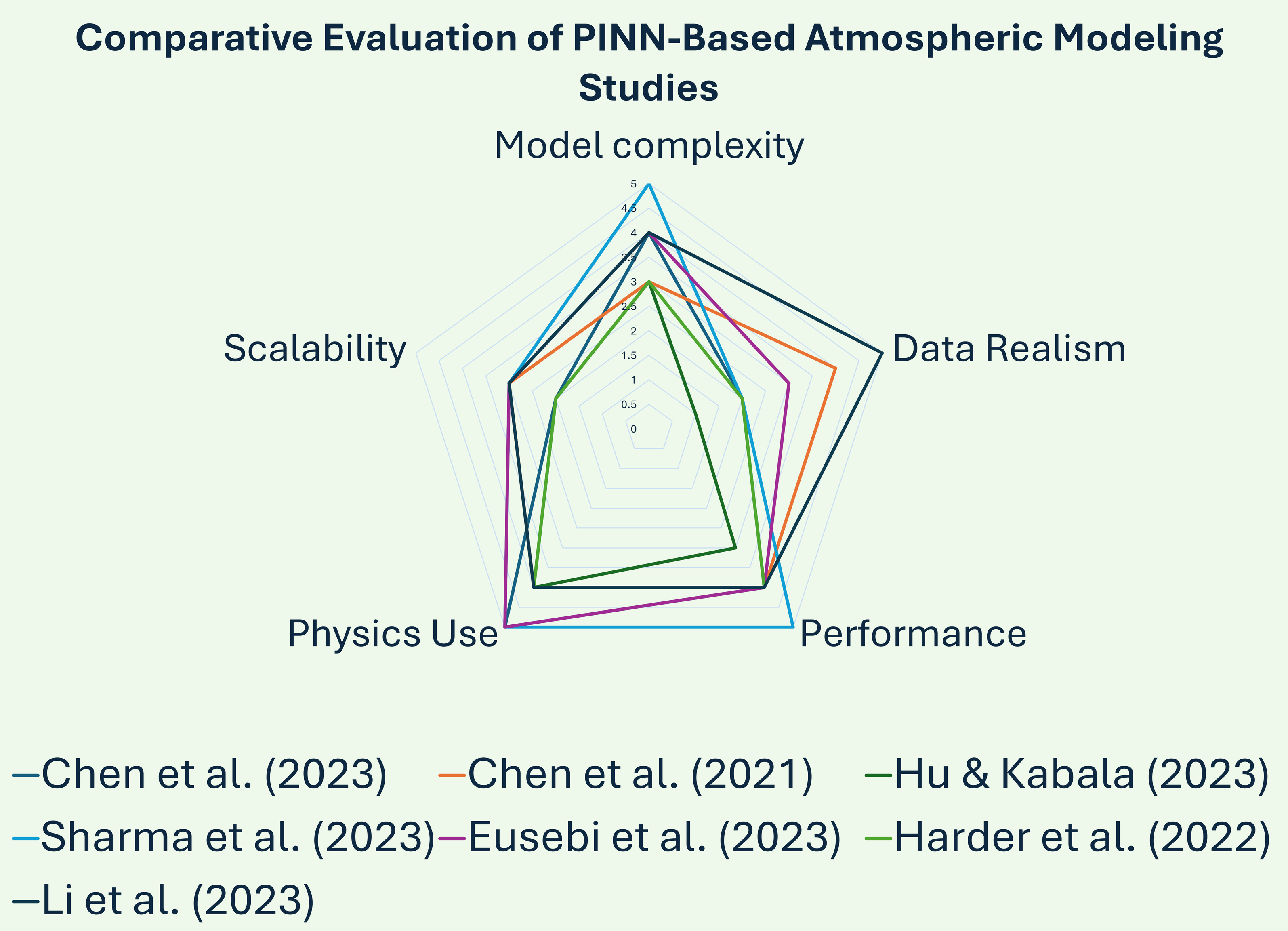
## INTRODUCTION

Physics-Informed Neural Networks (PINNs) are a class of machine learning models that incorporate physical laws—typically expressed as partial differential equations (PDEs) directly into the neural network training objective. This coupling allows the network to enforce physical consistency during learning, making PINNs particularly advantageous in domains where labeled data are sparse but governing equations are well established, such as in atmospheric and climate sciences. Despite these strengths, most implementations have relied on standard multilayer perceptron (MLP) architectures, which suffer from well-known limitations including spectral bias toward low-frequency components, difficulties capturing sharp gradients, and instability when learning stiff or highly nonlinear dynamics. These architectural constraints hinder generalization across multiscale processes and often necessitate extensive tuning or preprocessing.




| Application | HPKM-PINN Advantage (MLP + KAN Hybrid) | Potential Impact |
|---|---|---|
| **ENSO prediction** | KAN branch captures low/high-frequency modes; MLP preserves sequence memory | Better mid-/long-range prediction |
| **Temperature video prediction** | KAN enhances stability across sharp transitions | Smoother spatiotemporal fields, less drift |
| **Aerosol–cloud–precipitation** | Hybrid improves robustness to delay-diff equations | Better modeling of feedback-driven systems |
| **SOA chemistry (Amazon)** | Parallel mixing balances physical vs. data-driven behavior | Reliable across wet/dry season variability |
| **Hurricane data assimilation** | KAN captures fine structure; MLP stabilizes flow field | Improved 3D field reconstructions from sparse observation |
| **Aerosol microphysics** | Hybrid can apply physics constraints at different layers | Preserves conservation laws while refining predictions |
| **Air quality mapping** | KAN adds spatial expressivity, improves resolution in gaps | Finer resolution pollution mapping in remote areas |

## APPLICATIONS OF PINNS IN ATMOSPHERIC SCIENCE

The synthesized work spanning aerosol–cloud–precipitation interactions, climate modeling, secondary organic aerosol (SOA) formation, weather prediction, and hurricane intensity forecasting demonstrates the flexibility of Physics-Informed Neural Networks (PINNs) across diverse atmospheric applications. Many studies report computational advantages, including faster inference and reduced cost of solving complex PDEs, particularly in emulating sub grid processes. Most incorporate physical constraints directly into the loss function, while others explore architectural modifications to improve accuracy and convergence. Nonetheless, key challenges persist such as spectral bias, instability in stiff regimes, and difficulties with generalization across spatiotemporal scales. Additionally, the predominance of training on simulated datasets, while necessary for model development, limits the opportunity to fully assess performance against real-world atmospheric observations.

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