ClimODE: Climate Forecasting With Physics-informed Neural ODEs

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Problem Definition and Contribution

Goal: Enhancing climate forecasting by integrating physics-informed neural ordinary differential equations (ODEs) with uncertainty quantification.

Motivations:

- Existing models neglect the underlying physics, lack of uncertainty quantification and are computationally intensive.
- Enhance efficiency and effectiveness in global and regional weather prediction tasks.

Problem Formulation

Statistical Mechanics: Weather can be described as a spatial movement of quantities over time, governed by the partial differential continuity equation:

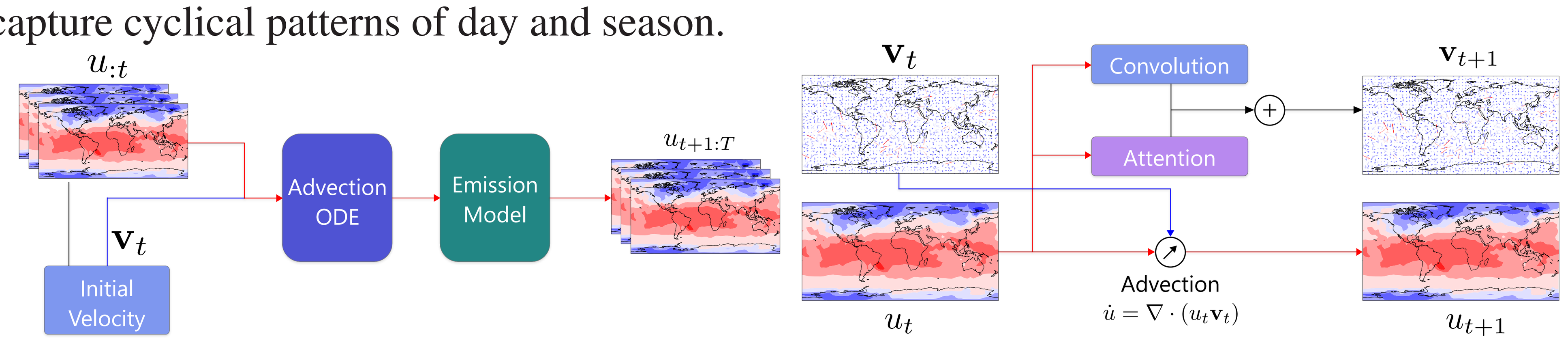
$$\underbrace{\frac{du}{dt}}_{\text{time evolution } \dot{u}} + \underbrace{\overbrace{\mathbf{v}\cdot\nabla u}^{\text{transport}} + \overbrace{u\nabla\cdot\mathbf{v}}^{\text{compression}}}_{\text{advection}} = \underbrace{s}_{\text{sources}},$$

where $u(x,t)$ is a quantity evolving over space $\mathbf{x}$ and time t driven by a flow's velocity $\mathbf{v}(\mathbf{x},t)$.

Main Idea: We solve the continuity equation over entire Earth as a system of neural ODEs.

Method

Network Architecture: Spatiotemporal embedding encodes time and location information to capture cyclical patterns of day and season.



(a) ClimODE (b) Advection ODE

Initial Velocity Inference:

$$\hat{\mathbf{v}}_k(t) = \underset{\hat{\mathbf{v}}_k(t)}{\arg\min}\left\{\left\|\tilde{\dot{u}}_k(t) + \mathbf{v}_k(t)\cdot\tilde{\nabla}u_k(t) + u_k(t)\tilde{\nabla}\cdot\mathbf{v}_k(x,t)\right\|_2^2 + \alpha\left\|\mathbf{v}_k(t)\right\|\right\}$$

Advection ODE: Modeling the dynamic evolution of quantities at specific locations by transforming second-order PDEs into first-order ODEs:

$$\begin{bmatrix}\mathbf{u}(t)\\ \mathbf{v}(t)\end{bmatrix} = \begin{bmatrix}\{u_k(t_0)\}_k\\ \{\mathbf{v}_k(t_0)\}_k\end{bmatrix} + \int_{t_0}^{t}\begin{bmatrix}\{-\nabla\cdot(u_k(\tau)\mathbf{v}_k(\tau))\}_k\\ \{f_\theta(\mathbf{u}(\tau),\nabla\mathbf{u}(\tau),\tau(t),\psi)_k\}_k\end{bmatrix} d\tau$$

Flow Velocity: Modeling local and global effects using a hybrid network:

$$\dot{\mathbf{v}}_k(x,t) = f_{\text{conv}}\left(\mathbf{u}(t),\nabla\mathbf{u}(t),\mathbf{v}(t),\psi\right) + \gamma f_{\text{att}}\left(\mathbf{u}(t),\nabla\mathbf{u}(t),\mathbf{v}(t),\psi\right)$$

Emission Model: Accounting for uncertainty and value changes in climate estimates:

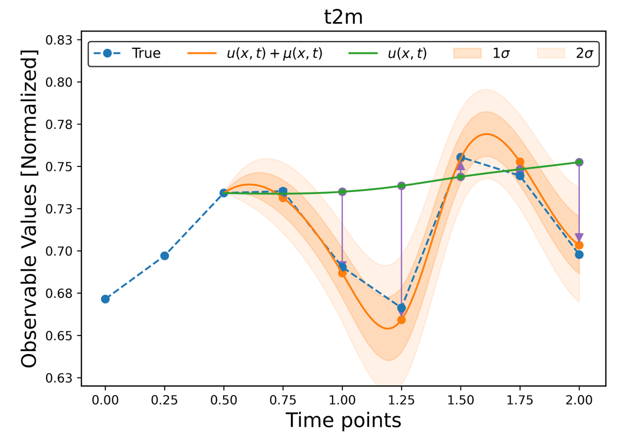
$$u_k^{\text{obs}}(\mathbf{x},t) \sim \mathcal{N}\left(u_k(\mathbf{x},t)+\mu_k(\mathbf{x},t),\sigma_k^2(\mathbf{x},t)\right), \quad \mu_k(\mathbf{x},t),\sigma_k(\mathbf{x},t) = g_k\left(\mathbf{u}(\mathbf{x},t),\psi\right)$$

Loss Function: Gaussian negative log-likelihood:

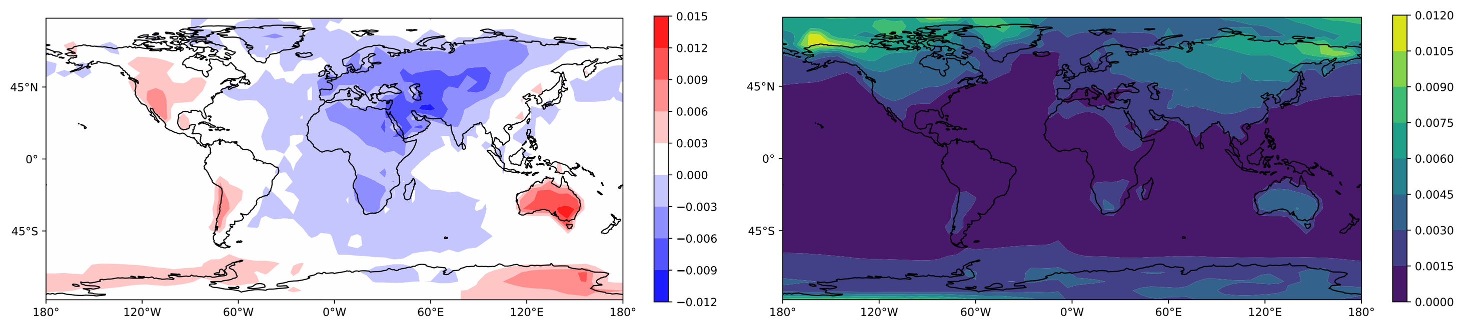
$$\mathcal{L}_\theta = -\frac{1}{NKHW}\sum_{i=1}^{N}\left(\log\mathcal{N}\left(\mathbf{y}_i|\mathbf{u}(t_i)+\boldsymbol{\mu}(t_i),\operatorname{diag}\boldsymbol{\sigma}^2(t_i)\right) + \log\mathcal{N}_+\left(\boldsymbol{\sigma}(t_i)|\mathbf{0},\lambda_\sigma^2 I\right)\right)$$

Experiments & Results

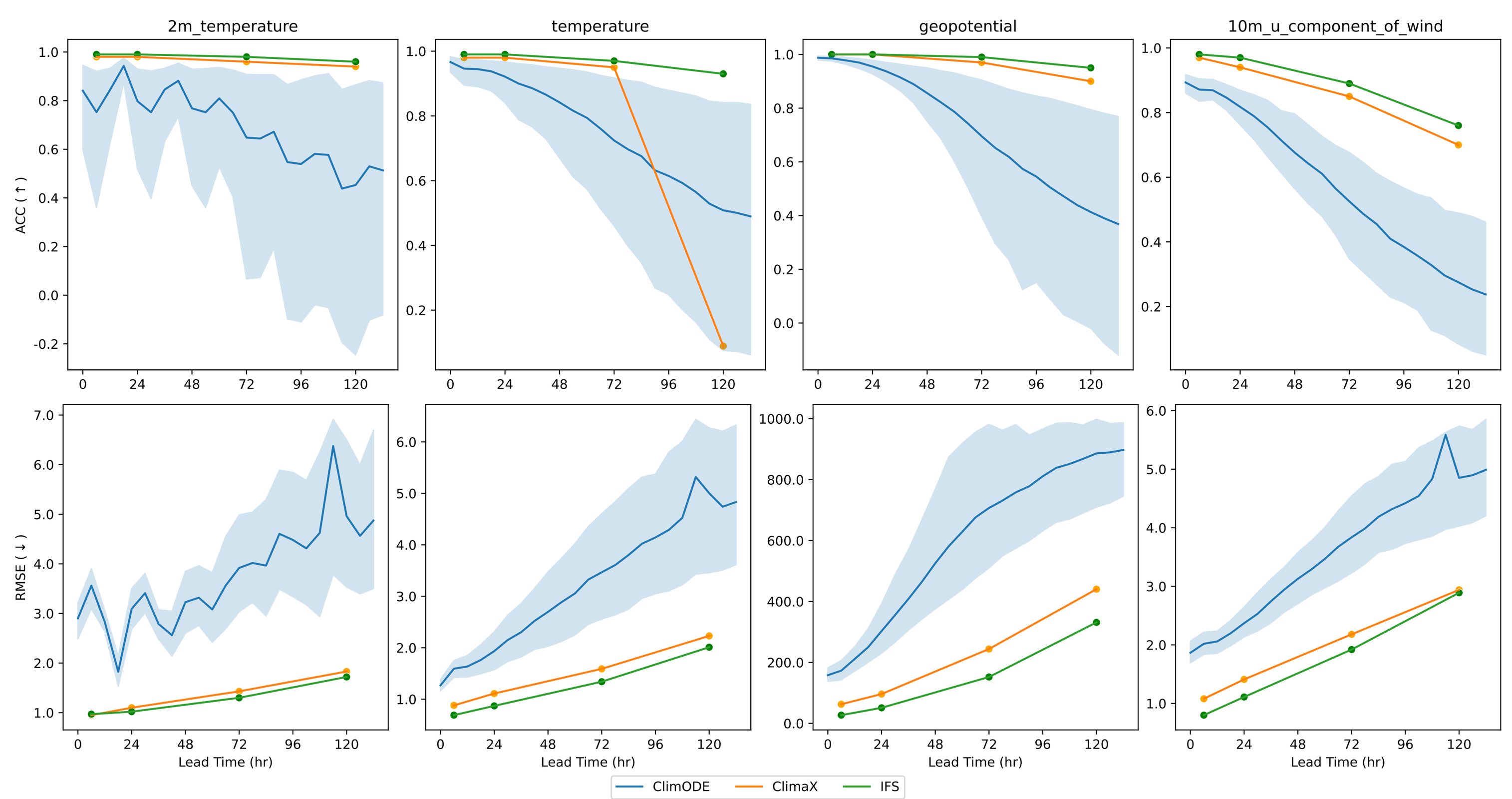
Effect of Emission Model:



(a) Bias $\mu(\mathbf{x},t)$ (b) Std $\sigma(\mathbf{x},t)$



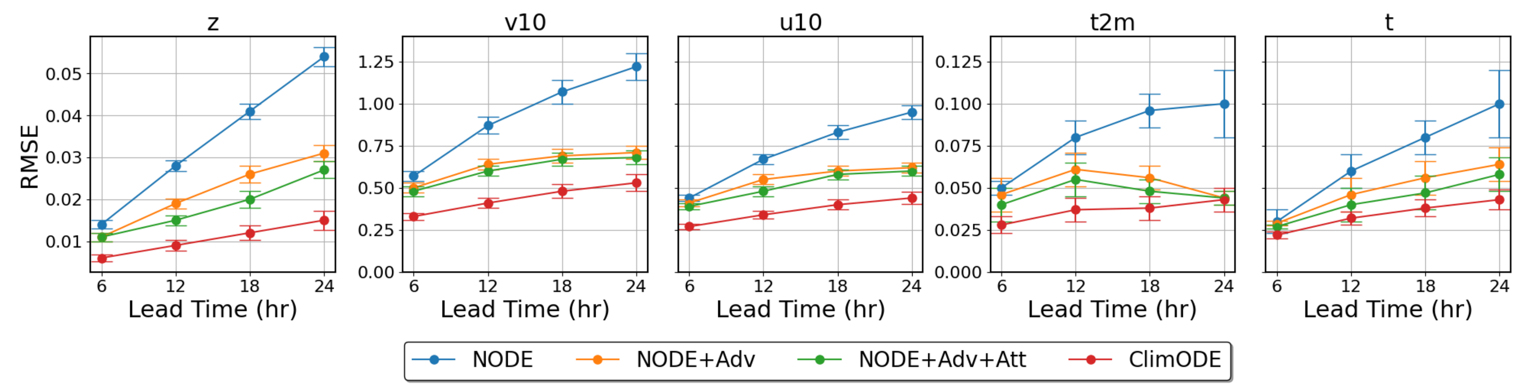
Quantitative Results and Comparison on ERA5:



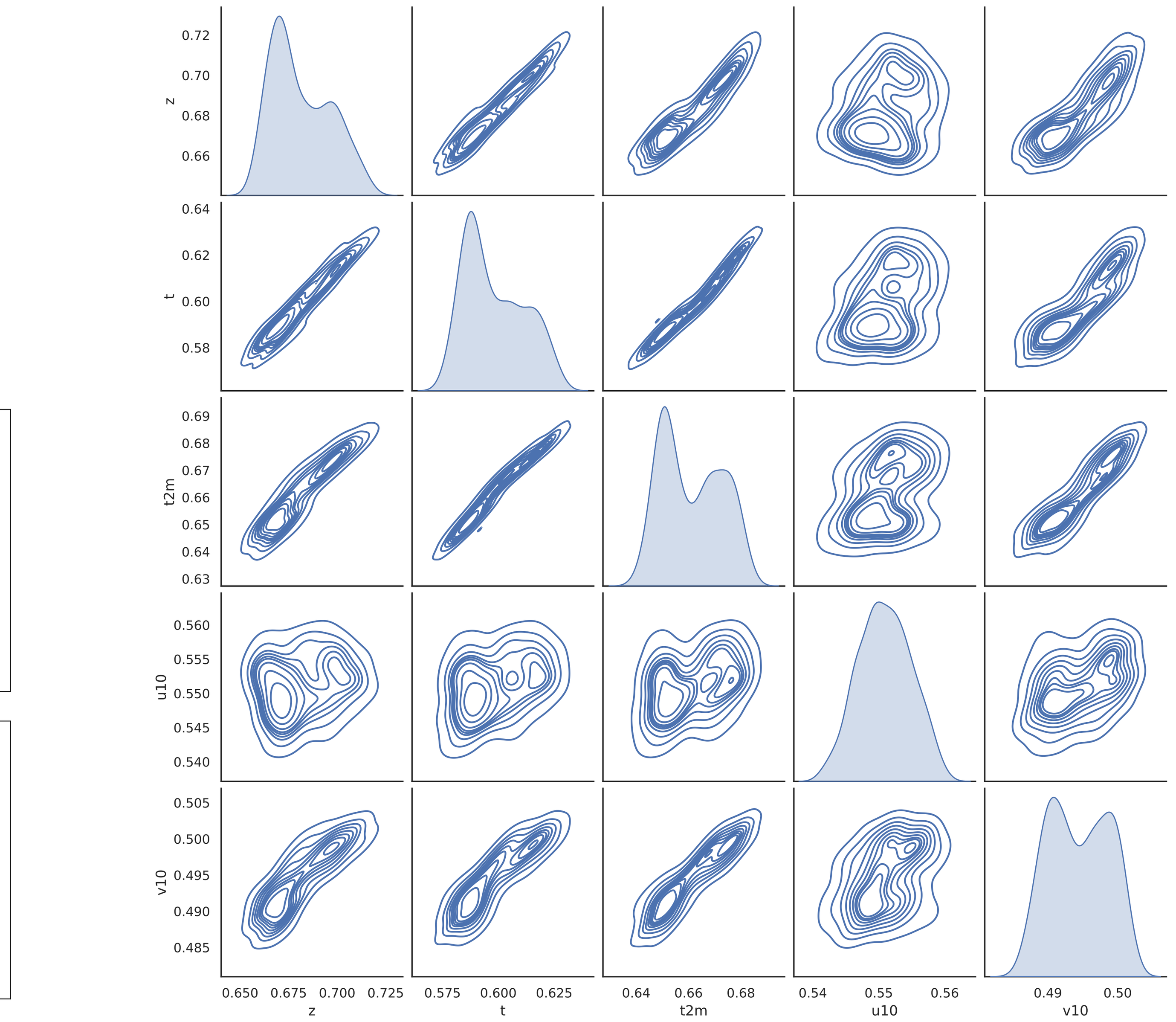
Effect of ODE Solver (per batch, on a single A100):

Solver	Euler		RK4		Implicit Adams	
Adjoints	w	w/o	w	w/o	w	w/o
Time (s)	0.27	0.18	0.34	0.31	0.69	0.45
VRAM (Gb)	10.20	15.70	11.80	17.80	13.70	30.10

Effect of Individual Components:



Quantifying Climate Interdependencies:



Critics

Paper:

- Lacks comparison to other models, such as FourCastNet, FuXi or Pangu-Weather (WeatherBench2)
- Is the comparison against ClimaX fair?
- Benchmark only up to 36 hours while state-of-the-art methods reported results for up to 10 days ahead
- Why choose ResNet over U-Net to model Gaussian prior for capturing both aleatoric and epistemic variance in the Emission Model?

Implementation:

- Concerns about data leakage
- Absence of shuffling in original code - impact?
- Unclear handling of residual architecture and dropout
- Code quality critique: Concerning coding standards
- Using Euler scheme to solve the ODE is known to be unstable but is a good compromise in terms of accuracy and efficiency