

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:

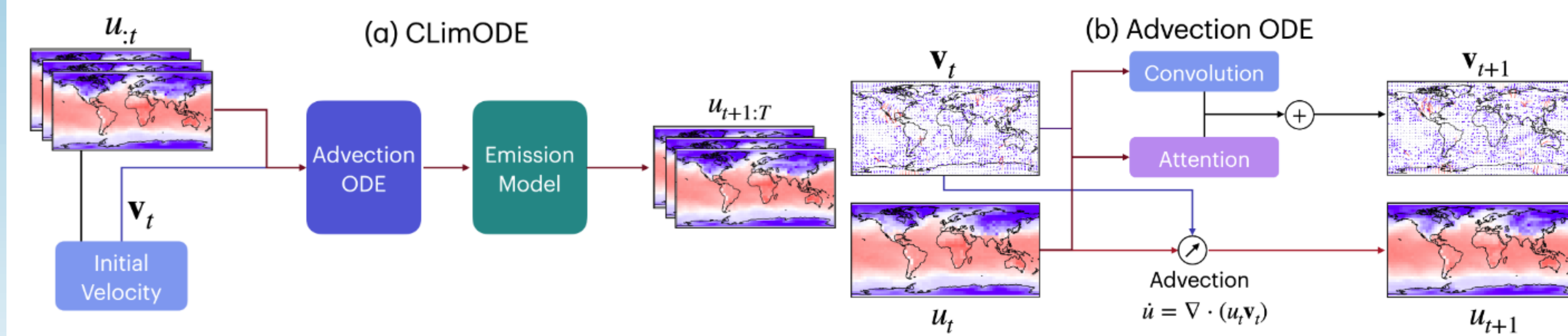
$$\underbrace{\frac{du}{dt}}_{\text{time evolution } \dot{u}} + \underbrace{\mathbf{v} \cdot \nabla u + u \nabla \cdot \mathbf{v}}_{\text{advection}} = \underbrace{s}_{\text{sources}},$$

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. We learn the flow \mathbf{v} as a neural network that uses both global attention and local convolutions and address source variations via a probabilistic emission model that quantifies prediction uncertainties.

Method

Network Architecture:



Loss Function: Negative log-likelihood of the observations $\mathbf{y}_i \in \mathbb{R}^{K \times H \times W}$ at times t_i :

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

Overview

Experiments & Results