ClimODE: Climate Forecasting With Physics-informed Neural ODEs

Aymeric Delefosse   Mathis Koroglu   Charles Vin

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 and lack of uncertainty quantification.
- 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:

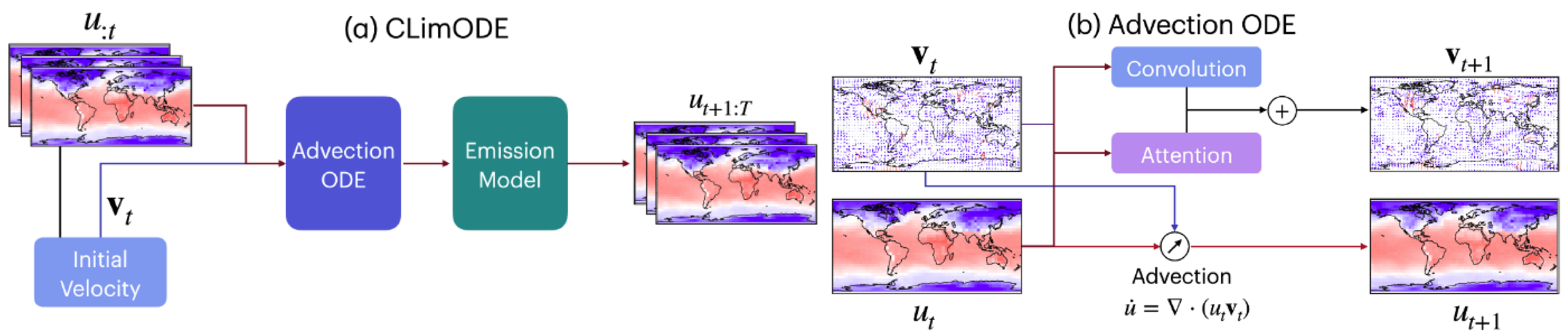
$$\underbrace{\frac{du}{dt}}_{\text{time evolution } \dot{u}} + \overbrace{\mathbf{v}\cdot\nabla u}^{\text{transport}} + \overbrace{u\nabla\cdot\mathbf{v}}^{\text{compression}} = \underbrace{s}_{\text{sources}},$$

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 :

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

Experiments & Results