Learning Extreme Temperature Regimes

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Introduction

- Climate distribution is shifting and **extreme events are happening more frequently**
- Collected observations of extreme temperature events **do not comprise a substantial corpus**
- Physics-based simulation of such events is **expensive due to their low return rate**

Generative Modeling of Extreme Events

- Synthesize **statistically similar** scenarios of extreme conditions
- Help analyze likely extreme event **evolution patterns** and study their **impact regions and damages**
- **Stress test and prepare** for disaster scenarios
- **Plan** infrastructure and design management policies **according to changing climate**

Conditional Generative Modeling

- K-dimensional spatio-temporal climate process

$$u(\boldsymbol{x},t) = \big(u_1(\boldsymbol{x},t), \dots, u_K(\boldsymbol{x},t)\big), \qquad u_k\colon \Omega \times \mathbb{R} \to \mathbb{R}$$

  Time $t \in \mathbb{R}$ and location $\boldsymbol{x} \in \Omega = [-90^\circ, 90^\circ] \times [-180^\circ, 180^\circ]$
- ***Restricted*** climate process $u_{\mathcal{X}}(t) = \big(u(\boldsymbol{x},t)\big)_{\boldsymbol{x}\in\mathcal{X}}$ to region $\mathcal{X}$
- ***Query function q***: measure of $u_{\mathcal{X}}(t)$ e.g. average temperature over $\mathcal{X}$
- Query values partitioned to ***Q target classes***
- Each $u_\Omega(t)$ in the dataset is labeled y according to the corresponding partition of $q(u_{\mathcal{X}}(t))$
- Consecutive years of ERA5 dataset treated as independent observations
- Label according to the quartile bin index corresponding to $q(u_{\mathcal{X}}(t))$

Uniform Quantile ClimODE

Stochastic Differential Equation with **advection** based drift function and Gaussian observation likelihood

$$du_k(\boldsymbol{x},t) = -\nabla \cdot \big(u_k(\boldsymbol{x},t)\boldsymbol{v}_k(\boldsymbol{x},t)\big)dt + \mu_\theta(\boldsymbol{x},y)dt + \sqrt{2\Sigma}\, dB_t$$
$$\boldsymbol{v}_\theta(\boldsymbol{x},t) = F_\theta\big(u(\boldsymbol{x},t), \nabla u(\boldsymbol{x},t), \psi(\boldsymbol{x},t)\big)$$

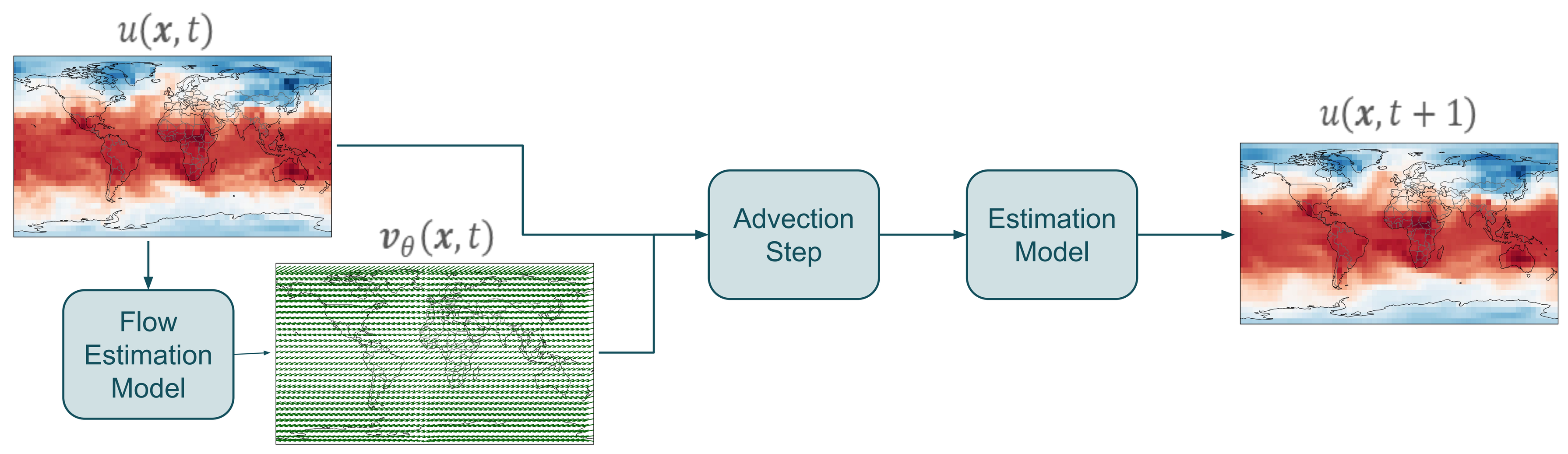

Figure 2: UQClimODE model: One step ahead prediction

- Extension of ClimODE climate model [Verma+'24]
- **Conditioned on uniformly partitioned quantiles:** label data according to day-of-year quartile binning partitions
- **Flow parametrization:** with parametrization of the flow vector field we enable one-step ahead prediction with **teacher forcing**, simplifying the training process
- **Tokenized observations:** improved scalability, account for spherical structure of the globe and attention to local and distant information with UNet architecture
- **Decoupling seasonality and volatility:** modeling seasonality through advection equation and daily volatility with gaussian likelihood

Long-Term Prediction

- UQClimODE is **comparable to baselines for short-term prediction** with daily observations and no contextual information
- Modifications make ClimODE stable for long-term prediction **over 90-days with bounded estimation error**

Model	Lead time (days) 1	3	7	14	30	90
ClimODE (24)	**0.010** ± **0.010**	**0.017** ± **0.018**	0.034 ± 0.041	NaN	NaN	NaN
daily (24)	0.017 ± 0.017	0.025 ± 0.027	0.034 ± 0.039	0.079 ± 0.072	NaN	NaN
daily (6)	0.017 ± 0.021	0.022 ± 0.026	0.027 ± 0.037	0.031 ± 0.041	0.052 ± 0.061	NaN
daily (4)	0.019 ± 0.022	0.023 ± 0.026	**0.026** ± **0.032**	**0.029** ± **0.036**	0.041 ± 0.049	NaN
nocontext (24)	0.022 ± 0.062	0.028 ± 0.064	0.035 ± 0.069	0.052 ± 0.076	0.108 ± 0.169	NaN
nocontext (6)	0.033 ± 0.076	0.036 ± 0.077	0.039 ± 0.079	0.047 ± 0.081	0.077 ± 0.089	NaN
UQClimODE	0.015 ± 0.01	0.024 ± 0.027	0.031 ± 0.034	0.034 ± 0.037	**0.035** ± **0.037**	**0.034** ± **0.036**

Table 1: CRPS comparison of UQClimODE and ClimODE variants for global forecasting

Guided Generation

- Generate conditional on first and last quartiles
  → cold and hot temperature averages over the target region

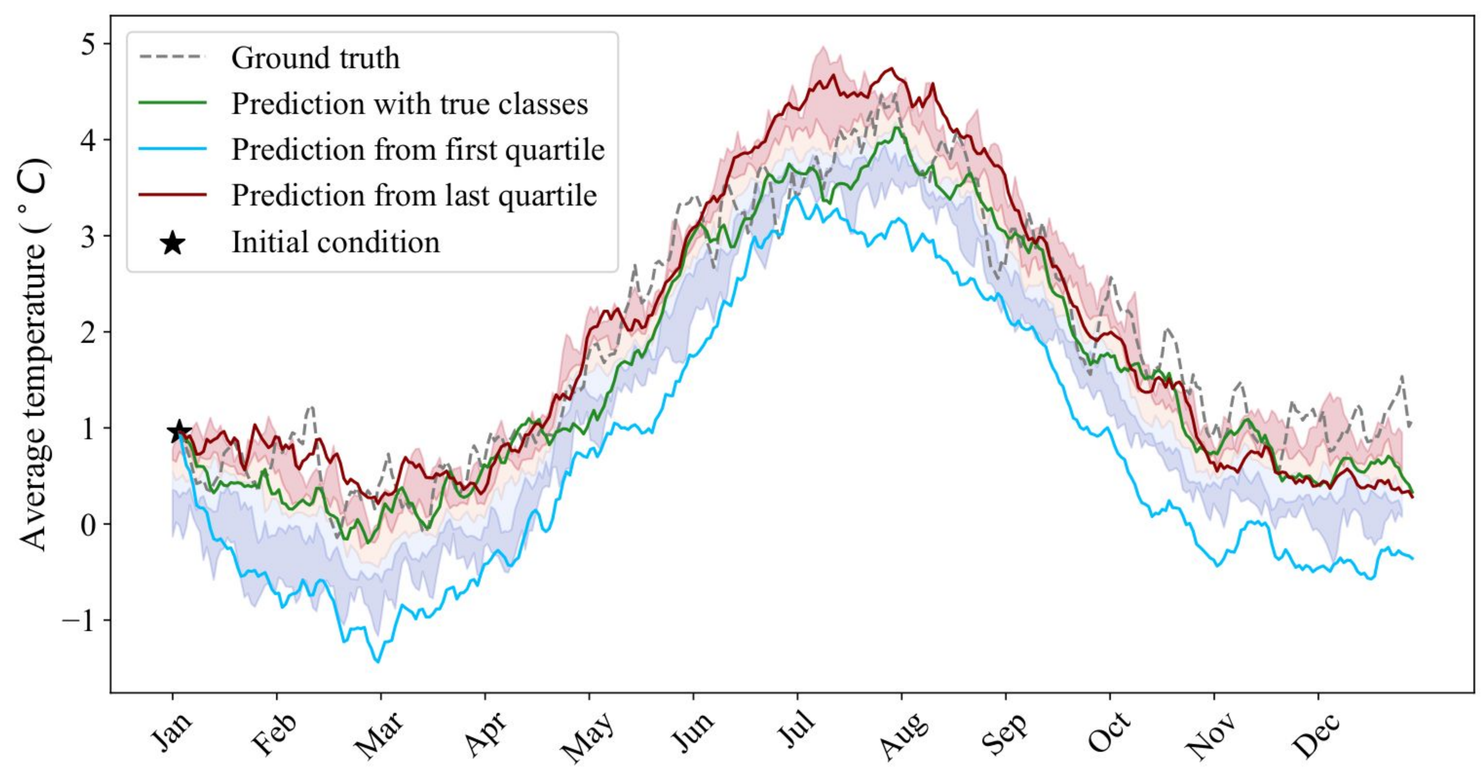

Figure 3: 365-days global temp. average most likely prediction

Temp. Maps with Regional Targets

- Different patterns of cold and hot values with sufficiently long lead time

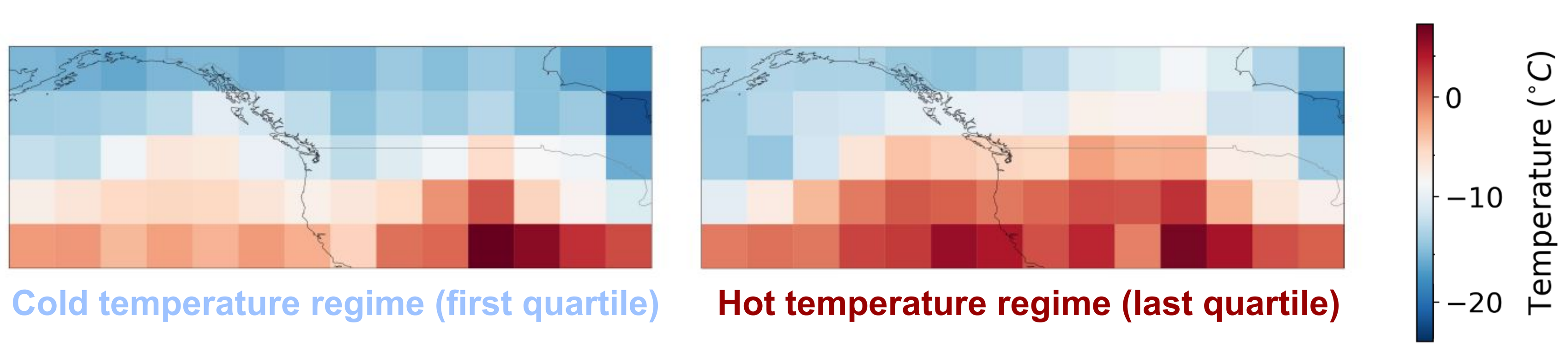

Figure 4: Most likely temp. maps over Pacific Northwest region with 10-day lead

References

- Yogesh Verma, Markus Heinonen, and Vikas Garg. ClimODE: Climate and weather forecasting with physics informed neural ODEs. In The Twelfth International Conference on Learning Representations, 2024.