Mapping the U.S. Weather: Climate Forecasting with Deep Learning

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Abstract

Weather prediction is crucial for **modeling climate change**. Traditionally, Numerical Weather Prediction models (NWP) are the driving force for forecasting weather, but they are limited by high computational costs in solving complex **Partial Differential Equations** (PDE). The performance of **data-driven Neural Operators** poses an alternative tool that's **magnitudes faster** at **climate forecasting**. Even without knowing the specific governing PDE of climate, Neural Operators can learn the *mapping* from past weather to future weather attributes from data with **high accuracy**. This project explores the performance and accuracy of **Fourier Neural Operator** and **U-Net** in forecasting weather attributes including temperature using data from the ERA5 dataset with a high resolution of 0.25°.

Background

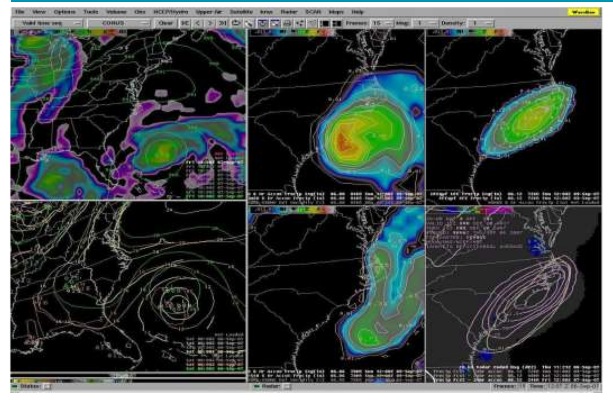
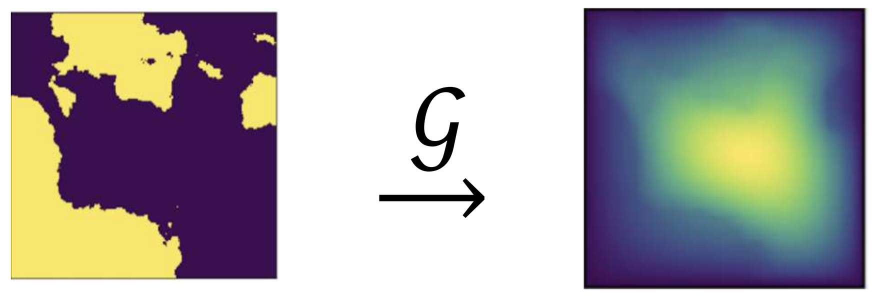


Figure 1: Numerical weather prediction models solve PDEs from physics and fluid dynamics which requires high computation and supercomputers for calculations. However, these models rely on underlying mathematical models. If the models are not correct, NWP would not have high accuracy (National Center for Environmental Information).



Input: coefficient function

Output: solution function

$$\mathcal{G}: \mathcal{A} \times \theta \longrightarrow \mathcal{U}$$

Figure 2: Neural operators learn the mapping between infinite dimensional function spaces. This approach is completely data-driven. Without knowing a specific PDE, Neural Operators still learn to map input functions $a \in \mathcal{A}$ to the correct solution functions $u \in \mathcal{U}$ with parameters θ given data generated from the input functions.

Models

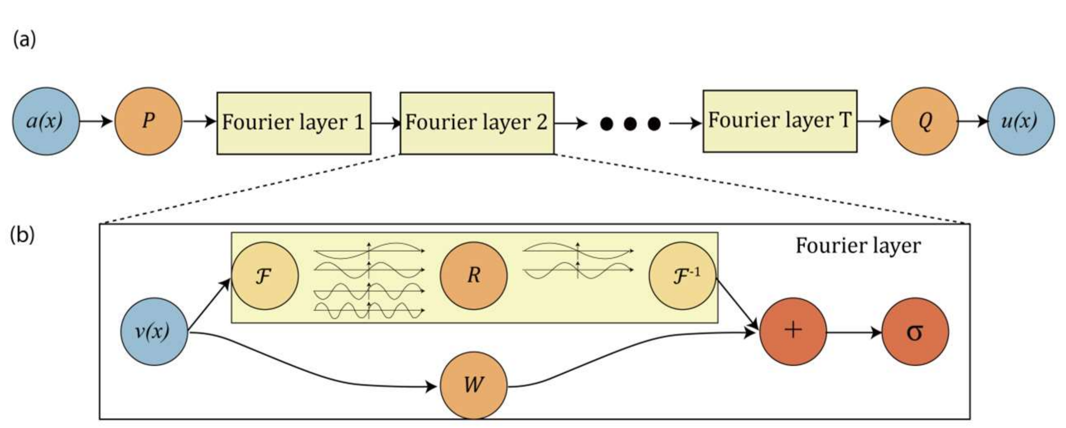


Figure 3a): Design of **Fourier Neural Operator**. *P* and *Q* are linear transformations to change dimensions.

Figure 3b): Implementation of Fourier layer. Fast Fourier Transformation *F*, linear transformation *R*, then Reverse Fast Fourier Transform F^{-1}. Nonlinear activation function like ReLU or GeLU. (Li, et. al 2021)

$$\big(\mathcal{K}(\phi)v_t\big)(x) = \mathcal{F}^{-1}\Big(R_\phi \cdot (\mathcal{F}v_t)\Big)(x)$$

Figure 4: Mathematical formulation of the Fourier Layer where *K* is the integral operator of standard Neural Operators and *x* is input

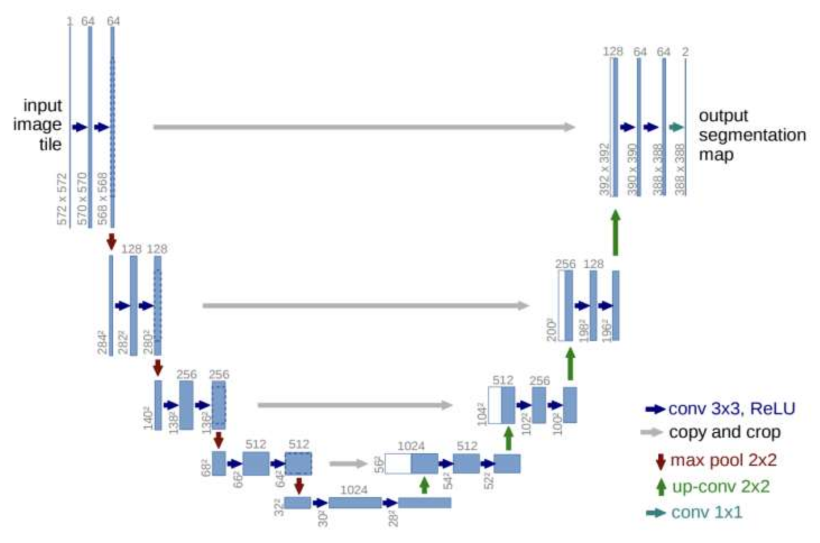


Figure 5: The architecture of **U-Net**. Input for experiments are weather data at different latitude, longitude and time steps. (Ronneberger et. al 2015)

Training Methods

- **Training Data**: Data used for testing and training are taken from the ERA 5 reanalysis dataset compiled by the ECMWF. Data are extracted from a **bounding box** based on latitude and longitude at 0.25 step size, at 4 times a day each 6 hours apart. A **time step** refers to all the data at latitude and longitude of a specific time.
- **Prediction Generation**: The Deep Learning model is fed data at one time step and outputs the prediction at the next timestep. The prediction is then compared with ground truth (actual data).

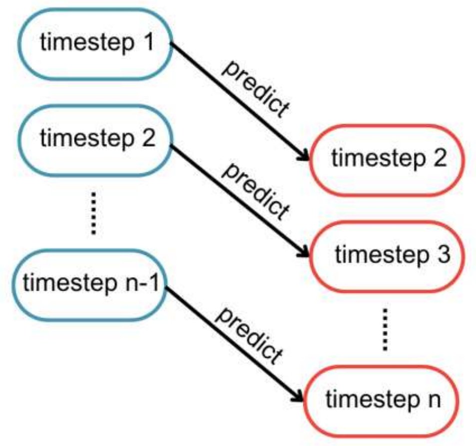


Figure 6: Left column is the training data (blue) and right column is the ground truth data (red). The model takes in one timestep and makes a prediction of **temperature 2 meters above the surface** at the next time step, which is the temperature **after 6 hours**.

- **Performance Evaluation**: A relative L2 loss is used to measure the error between the model's prediction value and the actual values. We want to **minimize** this value.

$$\frac{\|\hat{y}_\theta - y\|}{\|y\|}$$

Figure 7: Formula to construct the loss function, where $\hat{y}_\theta$ is the prediction value from parameters θ and y is the actual data value.

Results

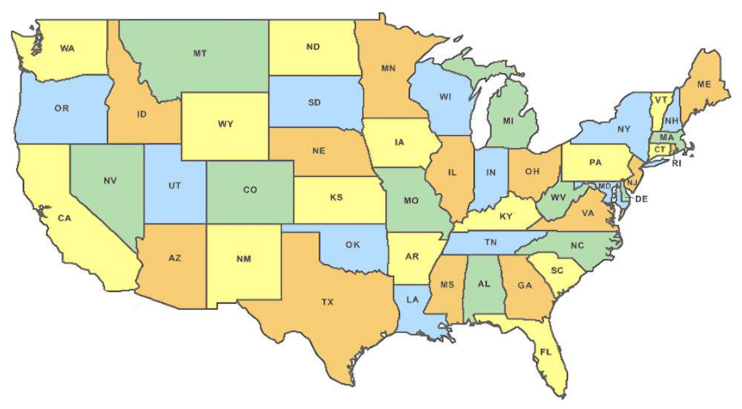


Figure 8: Bounding box used for the United States: 50N, 24S, -124W, -65E. There are 105 latitude and 237 longitude points.

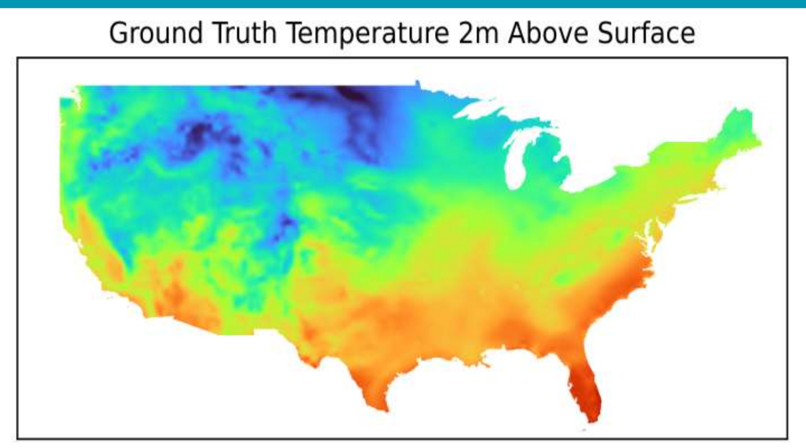
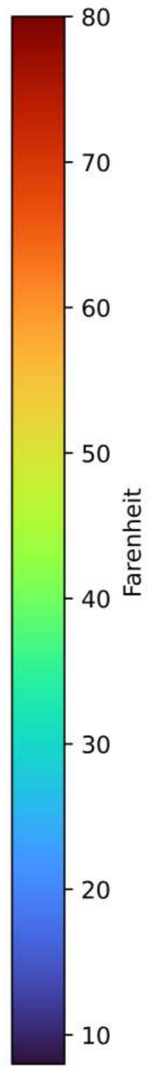
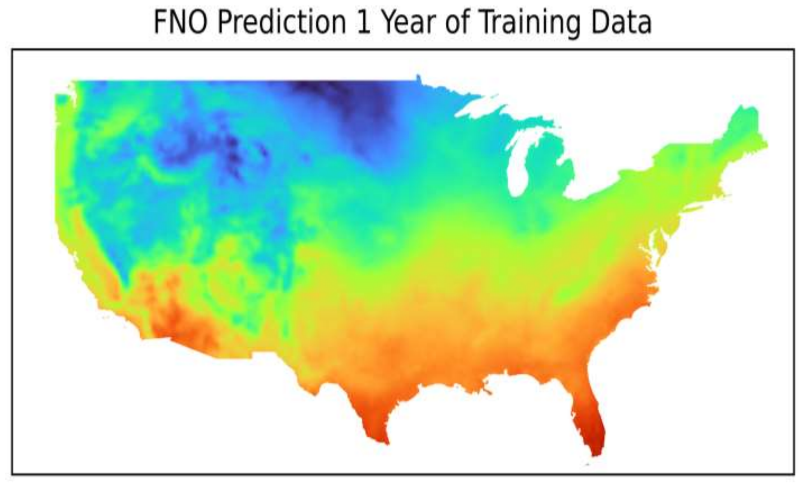


Figure 9: Actual temperature of United States at January 01 2023, 6:00 A.M.





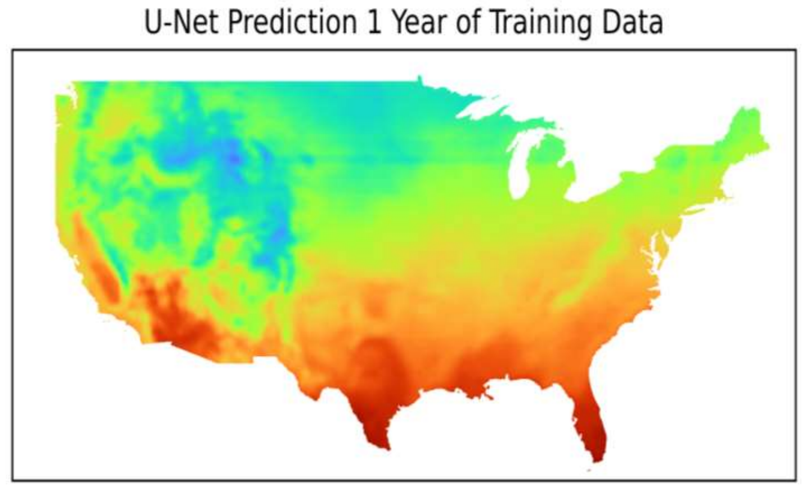
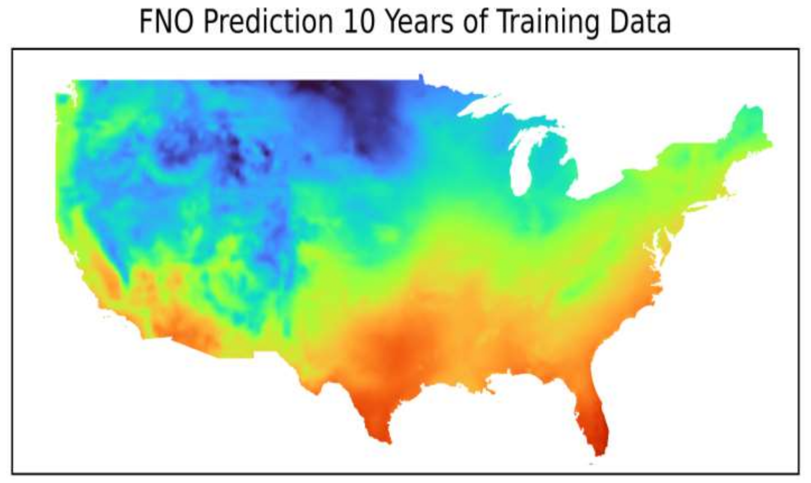


Figure 10&11: Models trained on 13 attributes over 2023 data



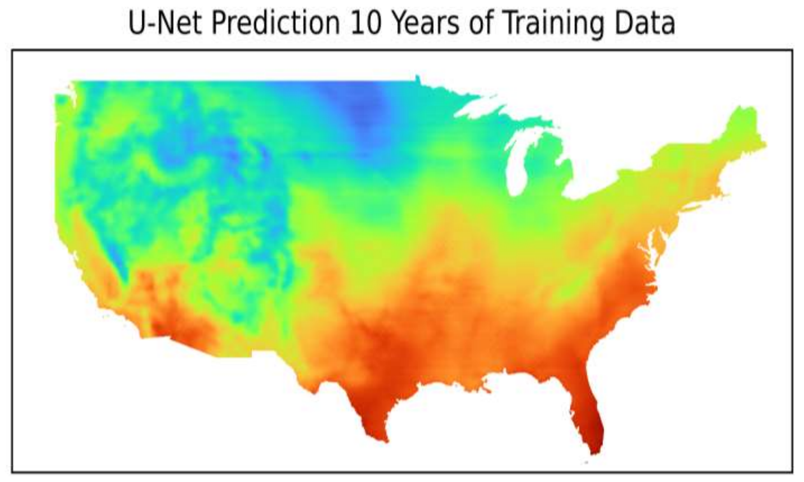
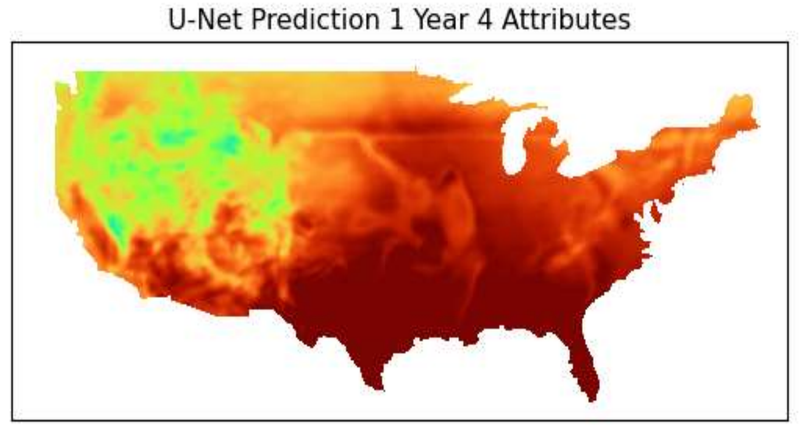
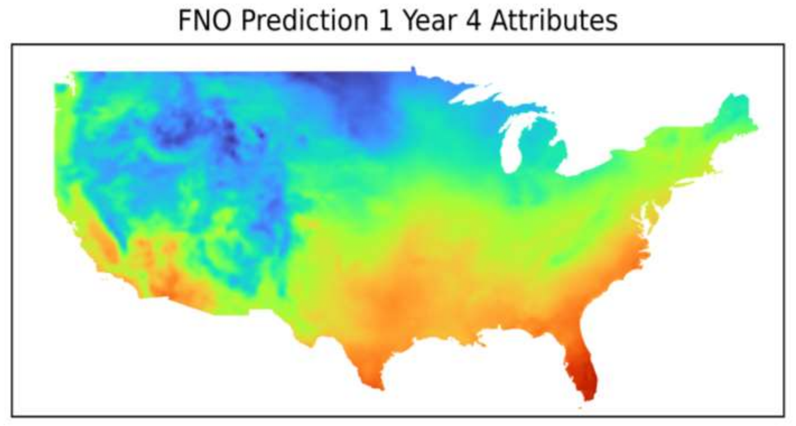


Figure 11&12: Models trained on 4 attributes over 2012-2021 data

Results





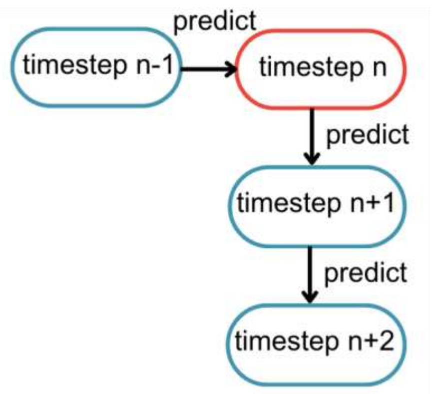
	FNO	U-Net
1 yr 4 attributes	0.0066	0.0449
	25%↓	67%↓
1 yr 13 attributes	0.0049	0.0146
	18%↑	30%↓
10 yr 4 attributes	0.0058	0.0102

Figure 13: Loss function values of FNO and U-Net under different volume of training data and attributes.

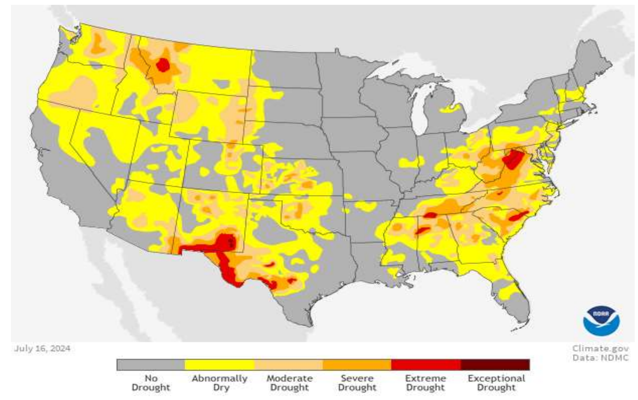
Summary

- FNO has shown great performances at **predicting weather of the next 6 hours**.
- U-Net's performance is worse than FNO's, with a higher error rate in both 1 year and 10 years of training data. The errors were also more obvious at the beginning of the predictions.
- U-Net's performance increases with **more volume of training data**, while FNO's performance did not improve much and even decreased. Past data weren't as accurate for FNO to predict current weather.
- Both models make noticeable errors at predicting weather at upper middle regions of the plot including Minnesota, North Dakota.
- Even though the attributes have different units, the model still has a decent loss at predicting temperature (Kelvin) **without the need** to convert to the same units.
- Neural Operators have demonstrated decent performance at climate forecasting without needing any mathematical models or PDEs of the climate like Numerical Weather Prediction models do.

Future Works



- We can try to predict **multiple time steps**, like the next 24 hours using autoregressive models (**Figure 14**).



- With more training data, we can **predict severe weather events** such as hurricanes, heat waves, droughts. (**Figure 15**, Climate.gov).

Acknowledgements

This project was funded by the State University of New York (SUNY) and the Stony Brook SUNY SOAR summer research program. I would like to thank Lisa Ospitale, Diana Champney and Dr.Ashley Barry for running the program and supporting everyone in it. I'm also grateful for Dr.Daniene Byrne, Dr.Christine Veloso and Risa Stein from SBU CSTEP who encouraged me through the journey of doing research.

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