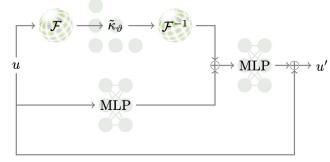


Introduction

Background

Weather forecasting is essential for various human activities, including agriculture, transportation, and disaster management. Traditional numerical weather prediction models, while effective, often encounter limitations due to the complexity of physical processes and significant computational demands. In recent years, deep learning–based neural networks have emerged as promising alternatives, offering potential improvements in efficiency and accuracy.

The Spherical Fourier Neural Operator (SFNO) model introduced the use of spherical harmonic transforms to maintain SO(3) rotational invariance, enhancing the stability of long-term forecasts and preventing early collapse.



The structure of a single SFNO block[1]

However, it still presents two critical limitations:

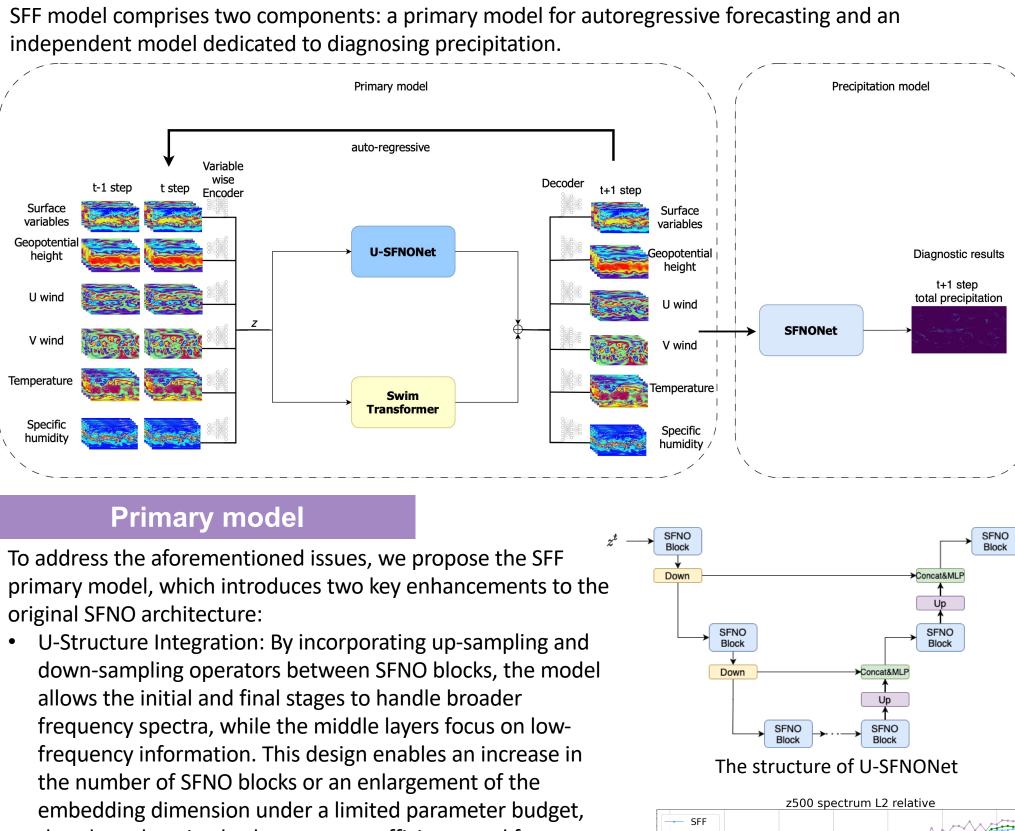
- The fixed model width limits both the model's depth and its scalability.
- Struggling to effectively capture high-frequency local features, reducing its ability to model fine-grained atmospheric variations.

Our works

We introduce Sphere Fusion Forecast(SFF), an advanced machine learning model that employs SFNO as its core operator. SFF is capable of performing rapid autoregressive forecasting and independently diagnosing total precipitation.

Experimental results show that SFF can produce stable 25-day forecasts in less than five minutes on a single NVIDIA H20 GPU. Key evaluation metrics such as root mean square error (RMSE) and anomaly correlation coefficient (ACC) for Z500, T2m, and T850—are comparable to those well-established IFS model and outperform the original SFNO. Moreover, in precipitation prediction, SFF demonstrates a forecast skill level on par with the IFS model.

Sphere Fusion Forecast (SFF): A Neural Operator Based Model for **Global Weather Forecasting**



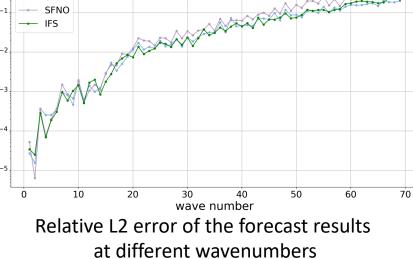
- thereby enhancing both parameter efficiency and forecast accuracy.
- Vision Transformer-base Residual Connection: We introduce a Vision Transformer-base architecture between the encoder and decoder as the skip connection, specialized to focus on local features. This scheme improves the model's capacity for local feature learning, producing more robust and accurate forecasts.

Precipitation model

Considering the discontinuous occurrence and development of precipitation, SFF employs an independent precipitation model which can be easier to learn the physical processes of precipitation. Furthermore, to improve the detection and prediction accuracy of heavy rainfall, we leverage classification weighting and extending the effective lead time of precipitation forecasts through joint training.

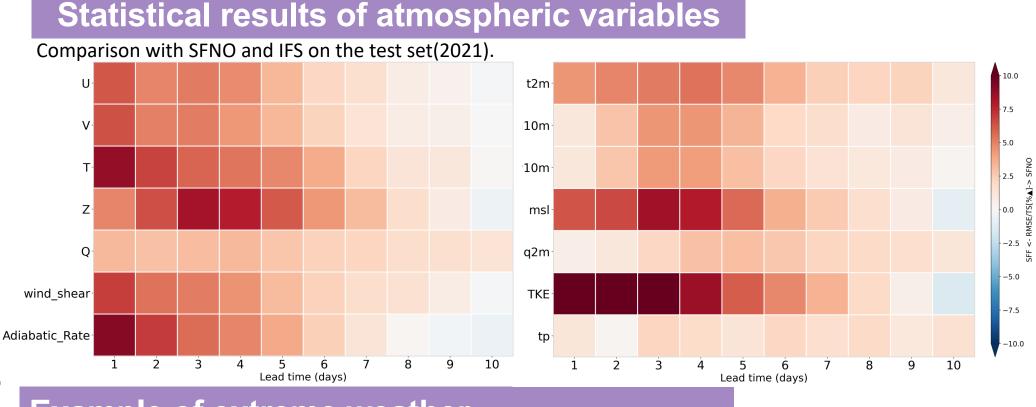
Qilong Jia, Chenyu Wang, Zhixiang Dai, Ivan Au Yeung, Hao Jing, Rita Zhang, Jian Sun, Wei Xue*

Method



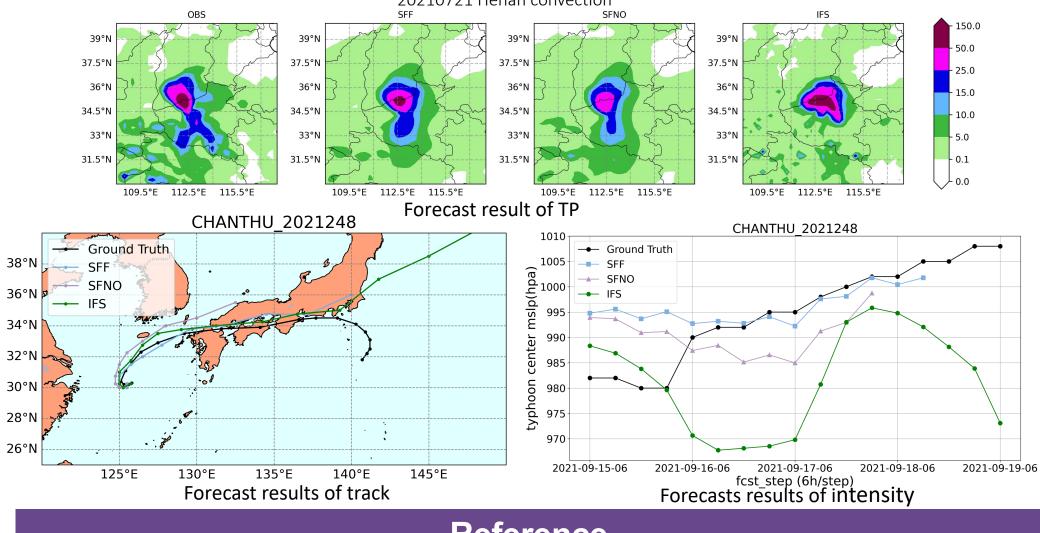
Setting

Models are trained on the ERA5 dataset at a 0.25° spatial resolution, aiming to predict atmospheric variables of 6 hours into the future. We utilize 43 years of ERA5 data (1979–2021): 1979 to 2019 for training, 2020 for validation, hyperparameter tuning, and model selection, while 2021 serves as an out-of-sample test set. Both models are trained for 40 epochs in the first stage and 4 epochs in the multi-step finetuning stage.



Example of extreme weather

Comparison with SFNO in forecasting performance for extreme-weather case—the convection in Henan, CHINA on 21 July 2021 and Typhoon CHANTHU on 15 September 2021. In both cases, the models start forecasting at 00:00 on the current day and perform autoregressive forecasts for 4 days. 20210721 Henan convection



1. Bonev, Boris, et al. "Spherical fourier neural operators: Learning stable dynamics on the sphere." International conference on machine learning. PMLR, 2023.

Session CL5.9 Hall X5 #X5.227

Experiments

Reference