Preliminary investigation on machine learning in numerical weather prediction at CEMC

Huadong Xiao, Hao Jing, Honglu Sun, Sa Xiao, Qifeng Lu
CMA Earth System Modeling and Prediction Centre

Introduction

Recent advances highlight machine learning's (ML) growing role in enhancing prediction accuracy and computational efficiency for numerical weather prediction (NWP). To harness this potential, we are integrating ML techniques into NWP workflows. We present the implementation and testing of ML-emulated physics parameterization schemes as a key integration example. We also introduce a data-driven forecasting model as an initial exploration of intelligent modeling and downscaling applications. The preliminary results show very promising for applying machine learning in the NWP area both for computational and forecasting performance.

Method

Basic idea: the neural networks learn a mapping between input and output fields of the conventional schemes/model.

$$\mathcal{F} = \{f|Y = f_\theta(x), \theta \in R^n\},\ \ y: target\ data, x: input\ data, \theta: model\ parameters$$

Dataset

1. Neural network emulation of physics parameterization

- Modify CMA-GFS v4.0 code to output all time-dependent variables either inputted to or outputted from the scheme
- Run forecasts with the CMA-GFS model regularly saving the global input and output data of the two parameterization schemes

Save input arguments → Physics parameterization → Save output arguments

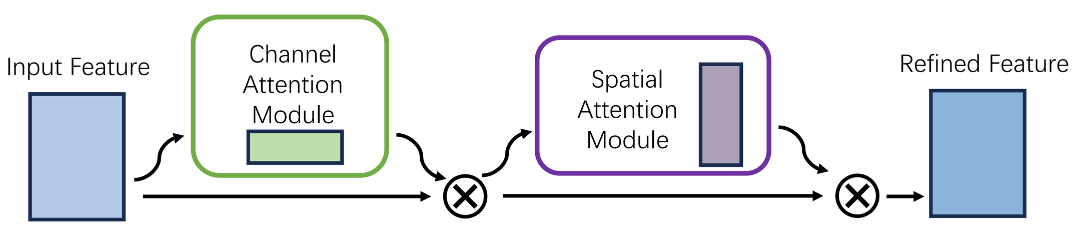
2. data-driven model

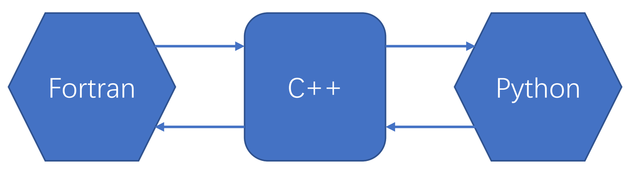
- Selected variables like u,v,w,q,t,p from the downloaded ECMWF global ERA5 data and ones tailed to China area, same variables from CMA-MESO reanalysis
- Data further divided by training, testing, and validating set.

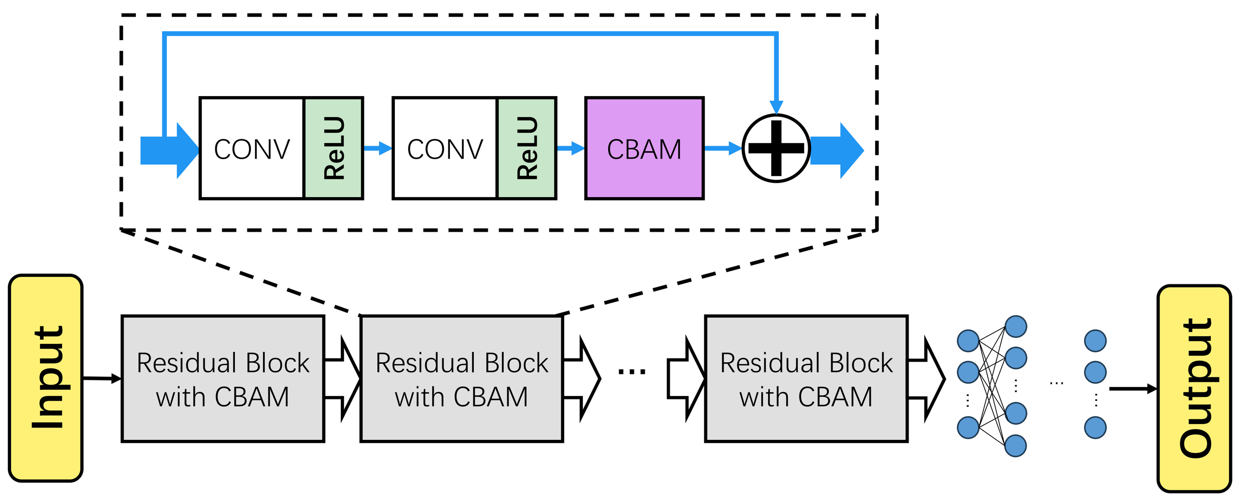
Machine learning methodologies

1. Neural network emulation

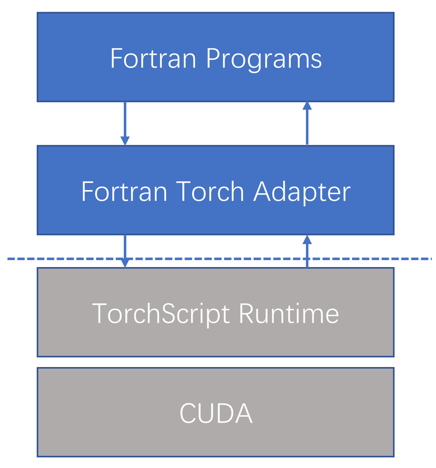
- Apply ResNet neural network to represent complex mapping from feature data to label data
- Enhance generalization and consistency of ML surrogate model by convolution attention module
- Use Fortran-Torch-Adapter to couple the ML model and NWP model







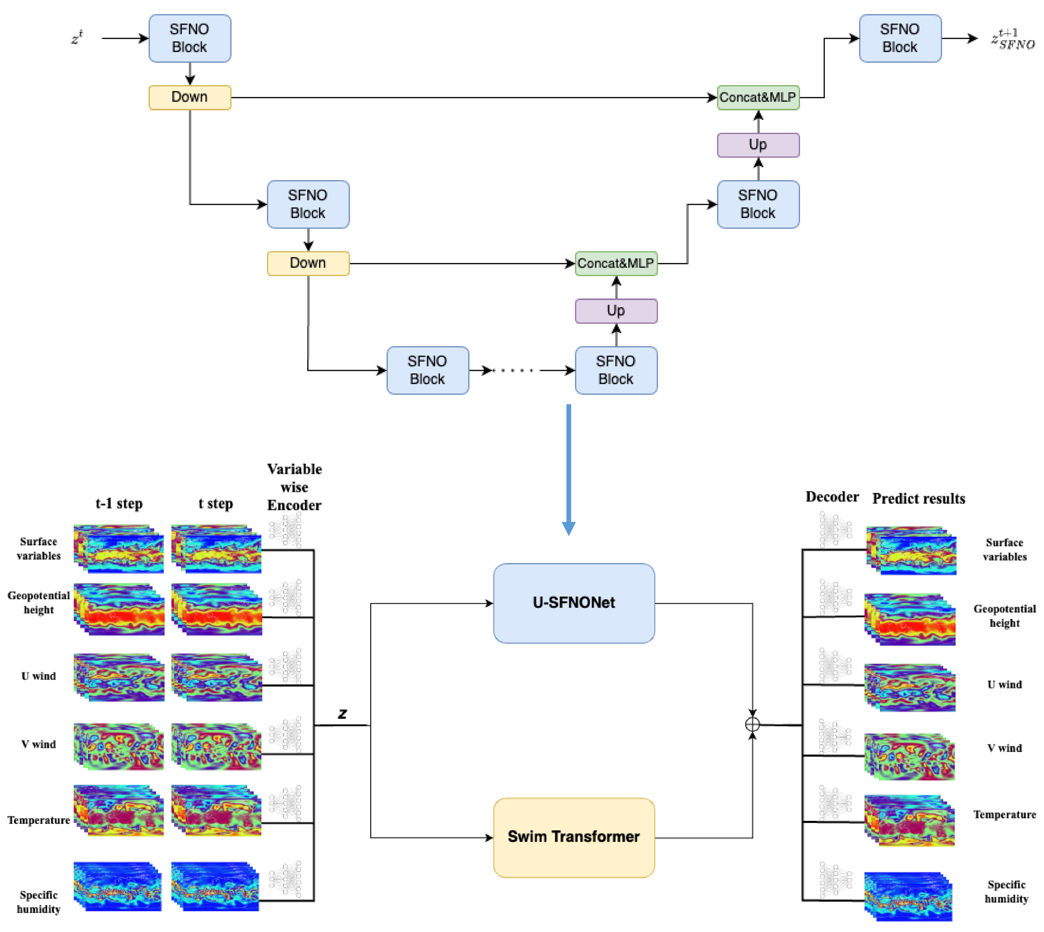
Schematic of neural network emulation of physics parameterization



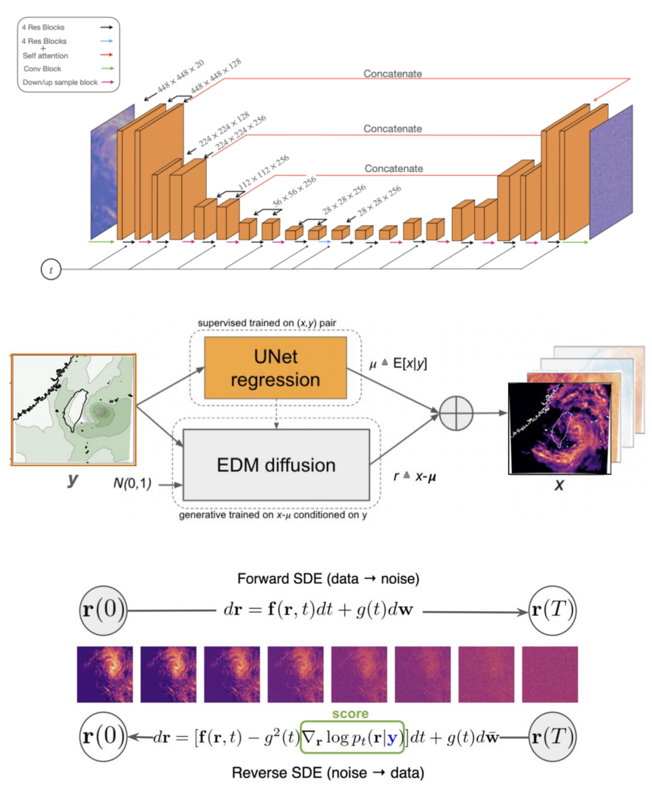
Integration ML scheme into NWP model (Mu et al., 2023)

2. Data-driven model

- Combined U-SFNOnet and Swin Transformer neural network for time series regression
- UNet and EDM diffusion network for downscaling/super resolution

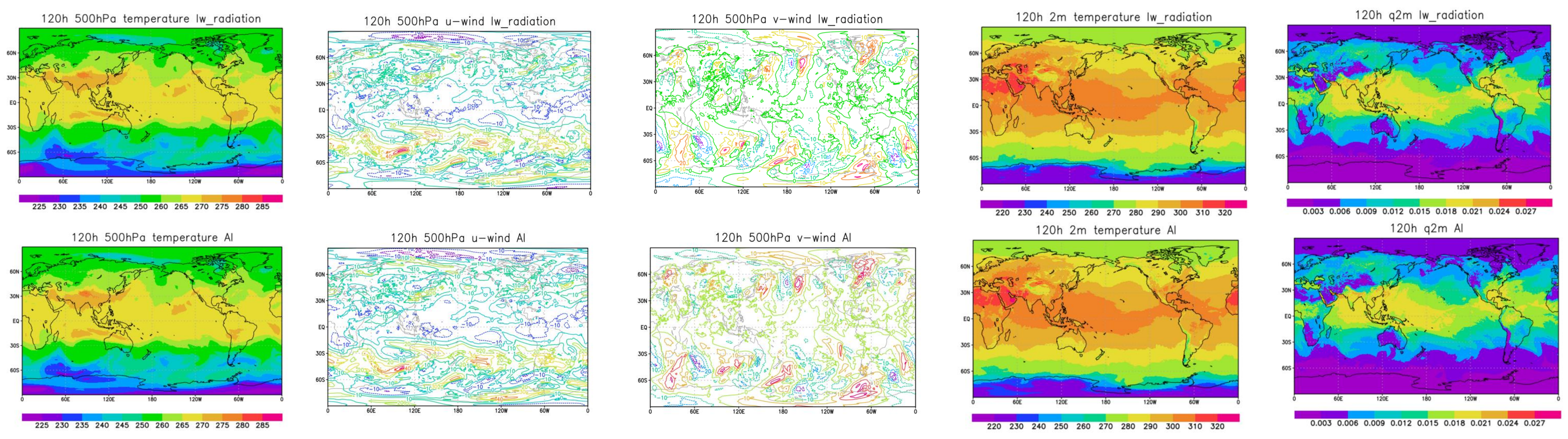


Structure of SFF AI forecasting model

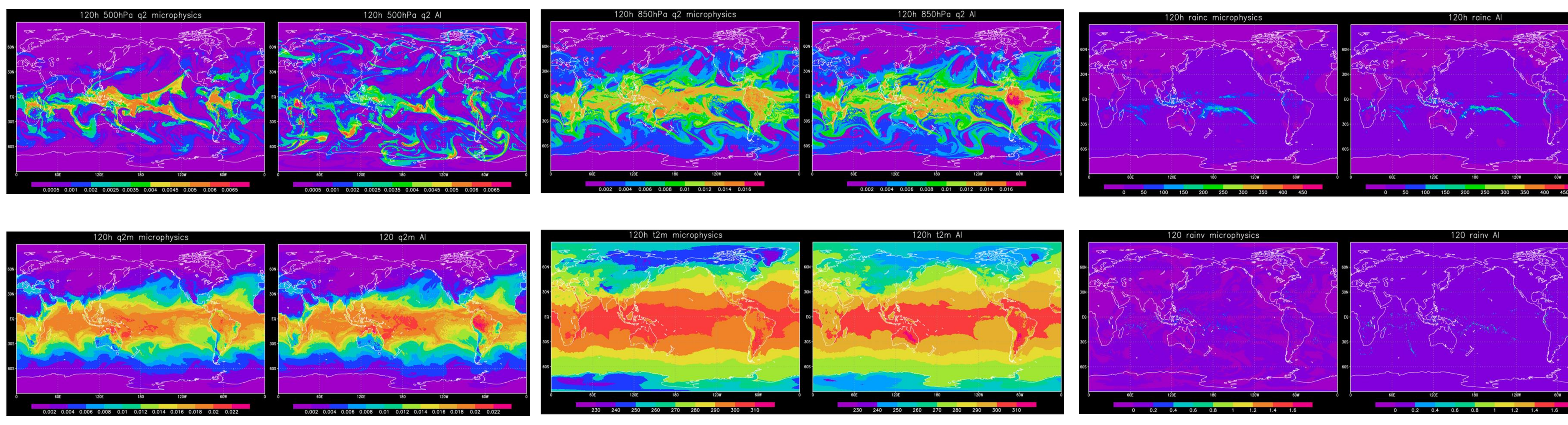


Workflow of CorrDiff for generative downscaling (Mardani et al., 2025)

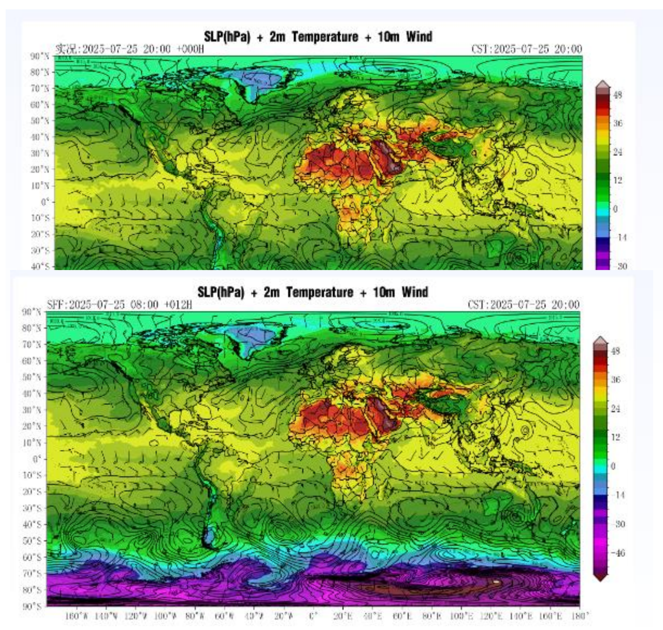
Result



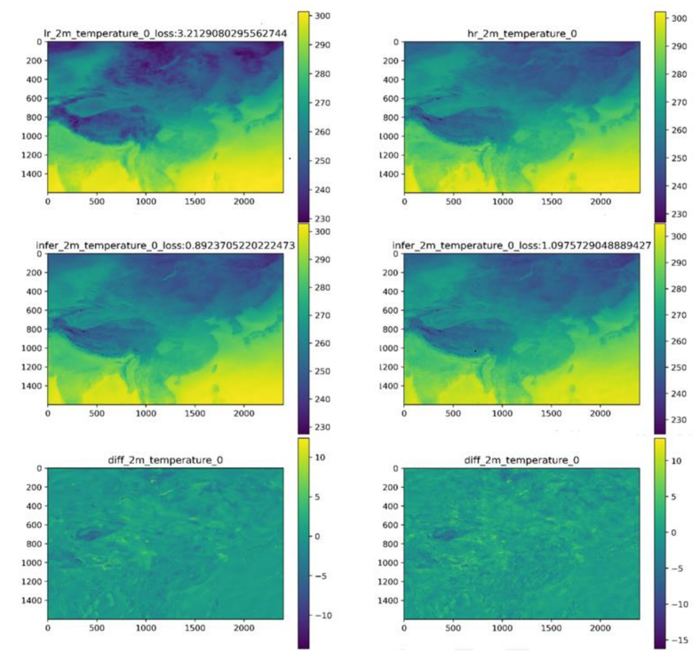
Temperature, u wind, v wind, 2m temperature, 2m moisture at 500hPa after 5days forecast for long wave radiation init: 2023070112(Top: NWP model, Bottom: AI inference)



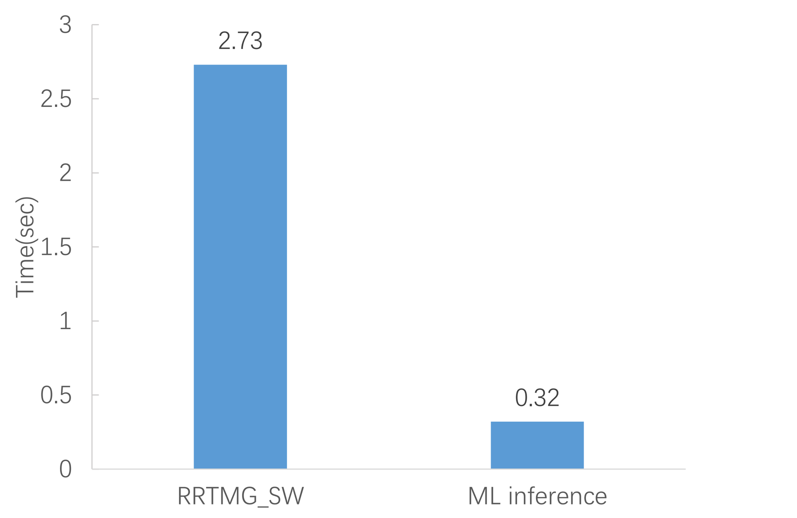
Comparison of 500Pa Q2, 850hPa Q2, 2m Z, 2m T, Rainc, and Rainv after 5days forecast for microphysics parameterization between mode(Left)l and AI emulation(right)

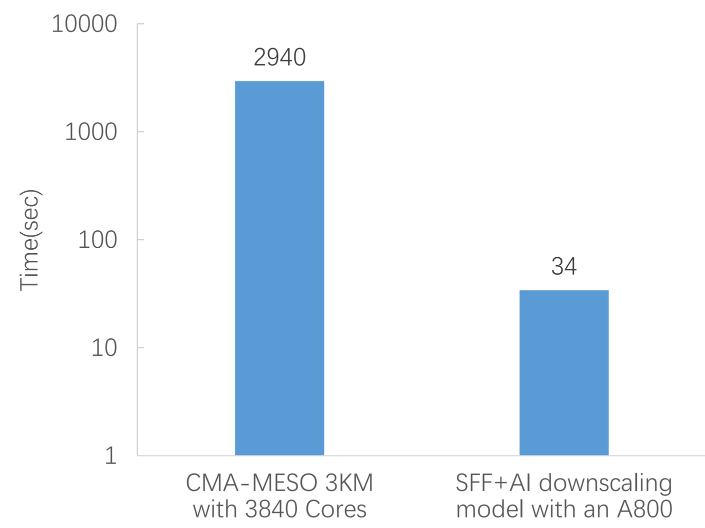


SLP, T2m, U10m for real-time condition(Top) and 12h forecast with data-driven model



T2m at low resolution, high resolution, U-NET inference, Corrdiff inference and difference between ML inference and high resolution (from left to right and top bottom)





Comparison for Computational performance(left: model physics vs neural network emulation, right: CMA-MESO model vs data-driven model

Conclusion

- Implemented neural network emulation of two physics parameterization schemes for online runs
- Developed a data-driven model for AI forecasting model with SFNO network and downscaling applications with UNet and diffusion model
- Initial results indicated very promising with the enhanced performance of forecasting and computation assisted by ML tools

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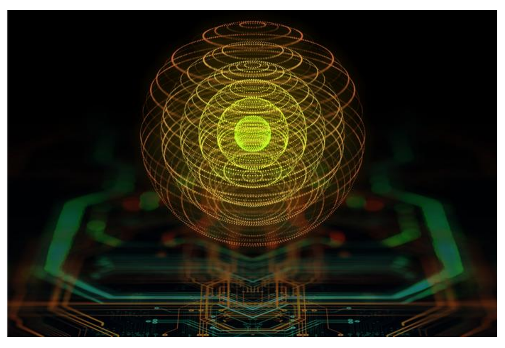

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