FengWu – Skillful Global Weather Forecasting Beyond 10 Days Lead

Lei Bai

Shanghai AI Laboratory

Who we are?

Shanghai AI Laboratory

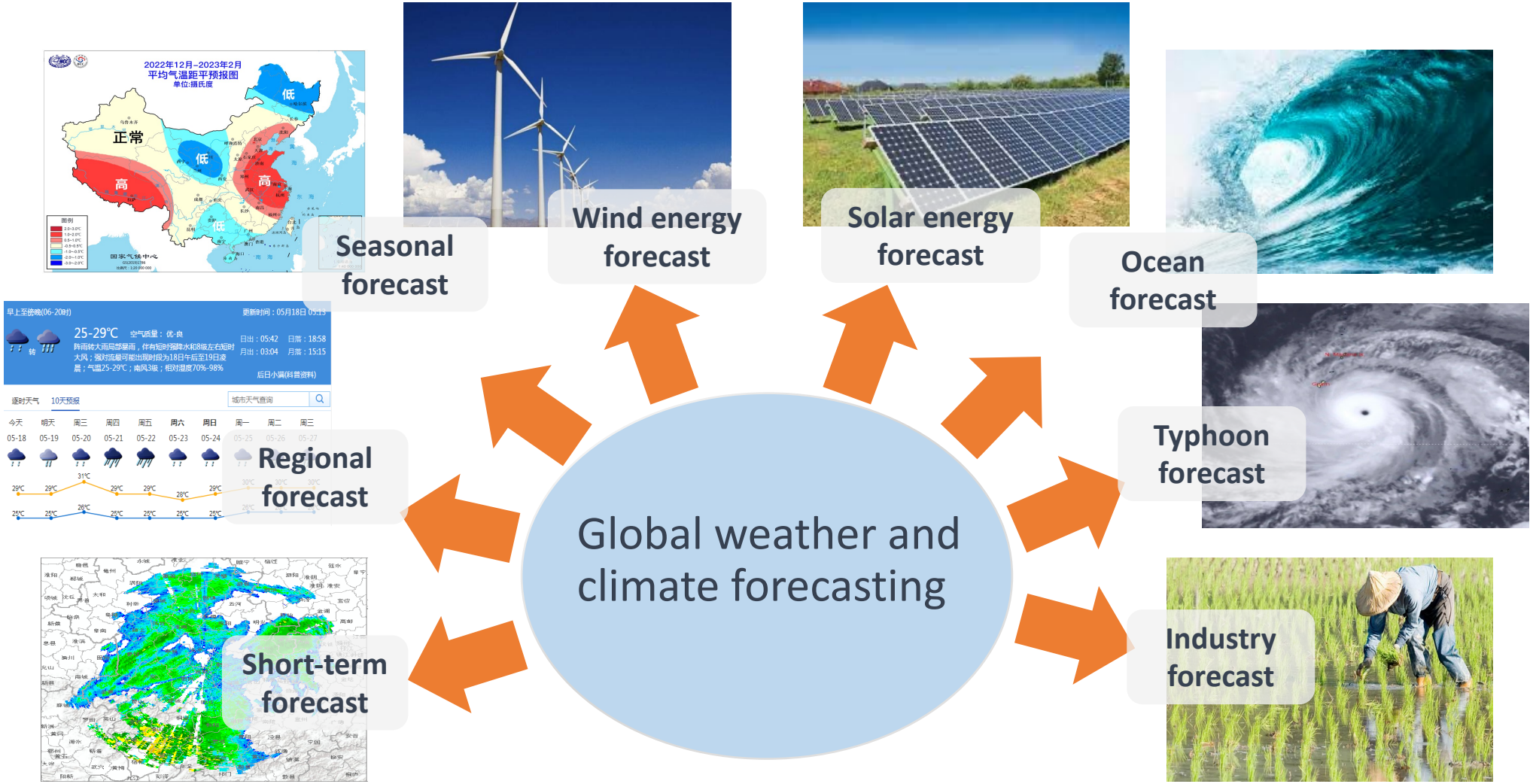
- Established in 2021, Shanghai
- Focusing on developing cutting-edge AI techniques
- CVPR 2023 best paper, Intern (foundational model for CV and LM), FengWu
- Open research with top tier universities (THU, PKU, SJTU, CUHK, NTU) and companies.

AI4Earth Team

- A research group at Shanghai AI Laboratory, co-lead by Prof. Wanli Ouyang and Dr. Lei Bai
- More than 20 research scientists, PhD students, and research interns

What are we doing?

❑ Build AI-powered chip for global weather and climate forecasting



ECMWF's ML Strategy: with **a very busy and FAST evolving landscape**

2018
ECMWF's ML scientific publication

Jan 2021
Machine Learning Roadmap

Feb 2022
Full medium-range NWP

Oct 2022
1km^2 global

Nov 2022
Tropical cyclones

Dec 2022
Extensive predictions

Jan 2023
Global & Limited Area

Apr 2023
7-day+ scores improve

ECMWF's
Peter Dueben and Peter Bauer publish a paper on using ERA5 at ~500km resolution to predict future z500.

ECMWF

Strategy to embed Machine Learning deeply into the ECMWF operational chain

Keisler - GraphNN 1°, competitive with GFS

NVIDIA – FourCastNet
Fourier+ , 0.25°

O(10^4) faster & more energy efficient than IFS

Jua.ai

1x1km global
48 hours lead time

5 minute timesteps

Huawei – PanguWeather
0.25° hourly product

"More accurate tracks" than the IFS.

Deepmind – GraphCast
0.25° 6-hour product

Predicts many variables and pressure levels with comparable skill to IFS.

Microsoft – ClimaX

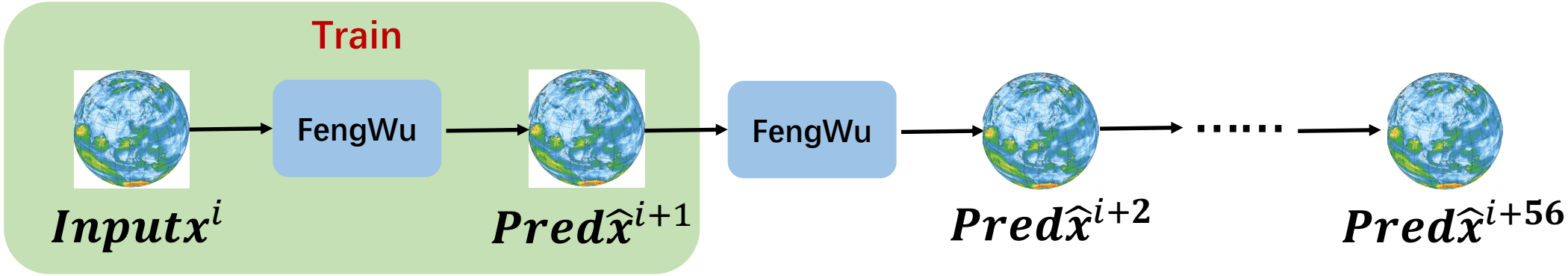
Forecasting various lead-times at various resolutions, both globally and regionally

FengWu – China academia + Shanghai Meteorological Bureau
0.25° 6-hour product

Improves on GraphCast for longer leadtimes (still deterministic)

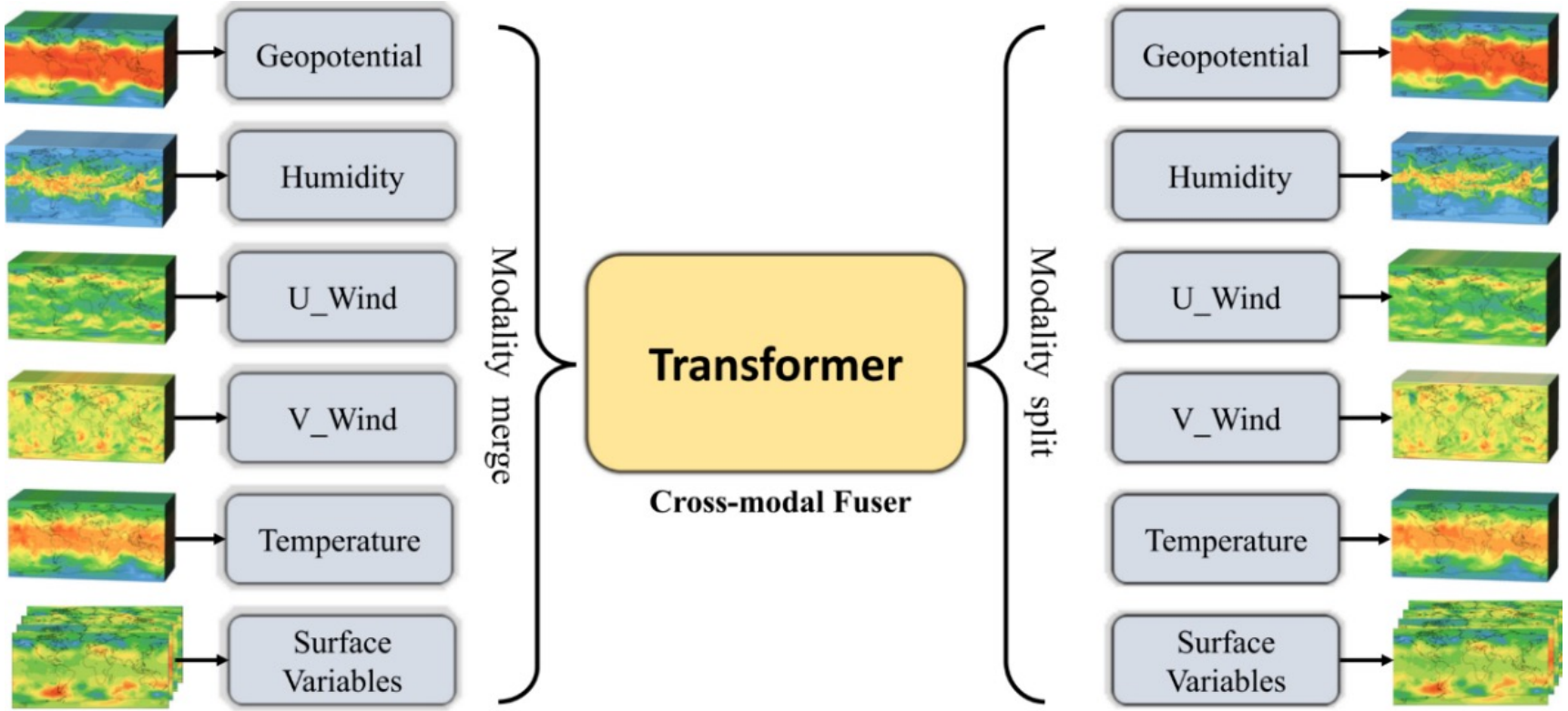
Problem and modeling

- **Problem : Predicting future global atmospheric conditions up to fourteen days ahead**
  - Resolution : **0.25**
  - Region : **Global**
  - Height level : **37 levels**
  - Atmosphere variables : geopotential、temperature、humidity、u component of wind、v component of wind
- **Modeling :**
  - Like physical model , the goal of FengWu is to predict the atmospheric variables at the next moment , and then all predictions are obtained by autoregressive method



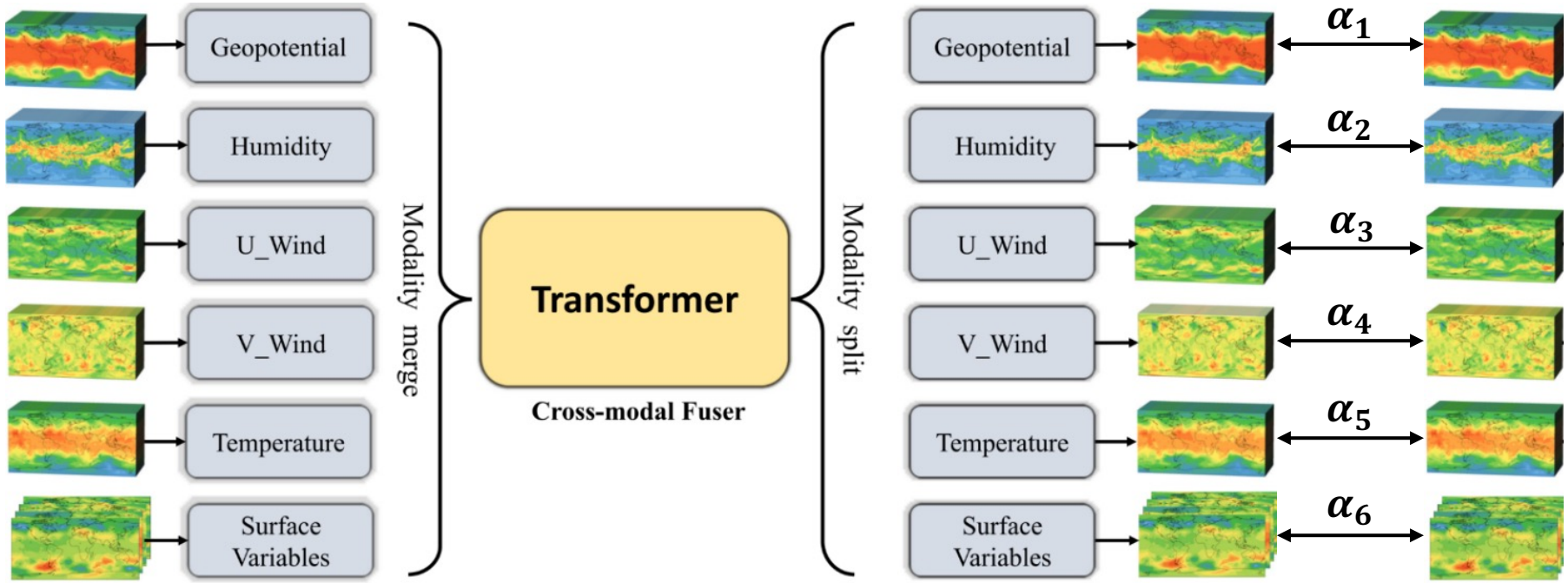
High-dimensional data representation

- **How to represent the high-dimensional weather data efficiently**
  - Multi-modal: treat each variable as a separate modality
  - Independent encoders and decoders
  - Cross-modal Fuser: learning the interactions among different variables



Network optimization

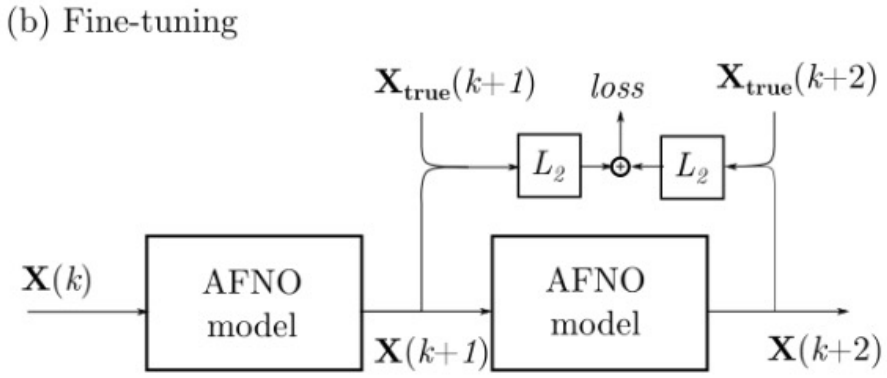
- **How to optimizee the network efficiently**
  - Multi-task learning : treat the optimization of each variable at each location as a task
  - Uncertainty loss: automatically generating the weights of each variable at each location based on the loss [1]



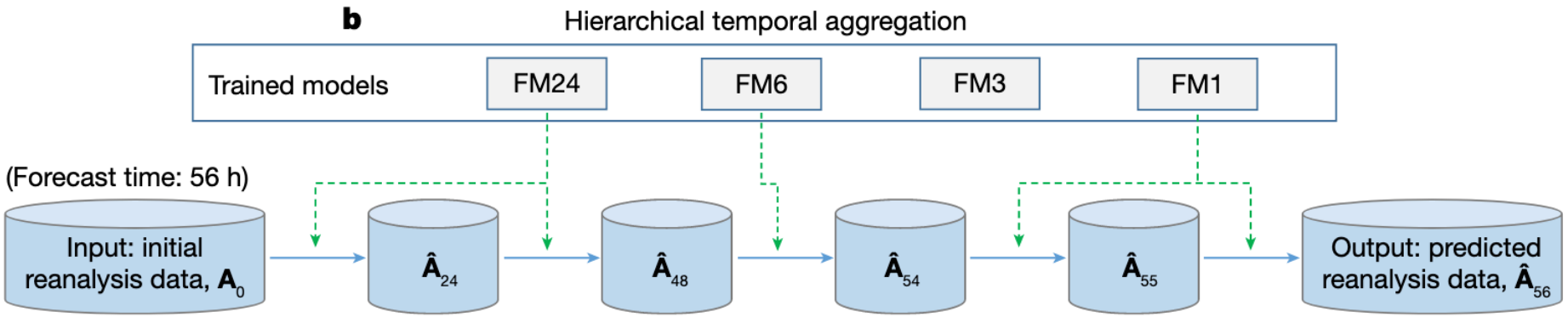
[1] Kendall, A., Gal, Y. and Cipolla, R., 2018. Multi-task learning using uncertainty to weigh losses for scene geometry and semantics. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 7482-7491).

How to achieve long-lead forecasting

- AutoRegressive Finetuning: FourCastNet and GraphCast

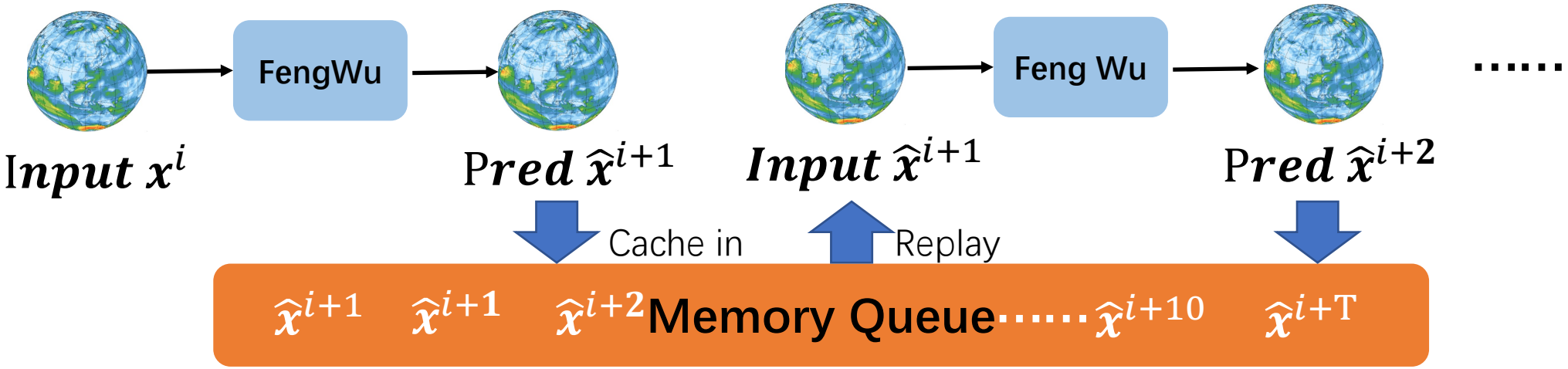


- Training with larger time steps: Pangu



How to achieve long-lead forecasting

- **How to achieve long-lead forecasting**
  - FourCastNet and GraphCast: Autoregressive finetuning
  - Pangu: Training with Larger time steps
  - FengWu: Replay buffer mechanism
    - The training of deep learning involves optimizing the network for a large number of iterations with the data sampled from the dataset
    - Replay buffer stores the predictions of prior iterations and samples training data from for the network optimization in the following iterations



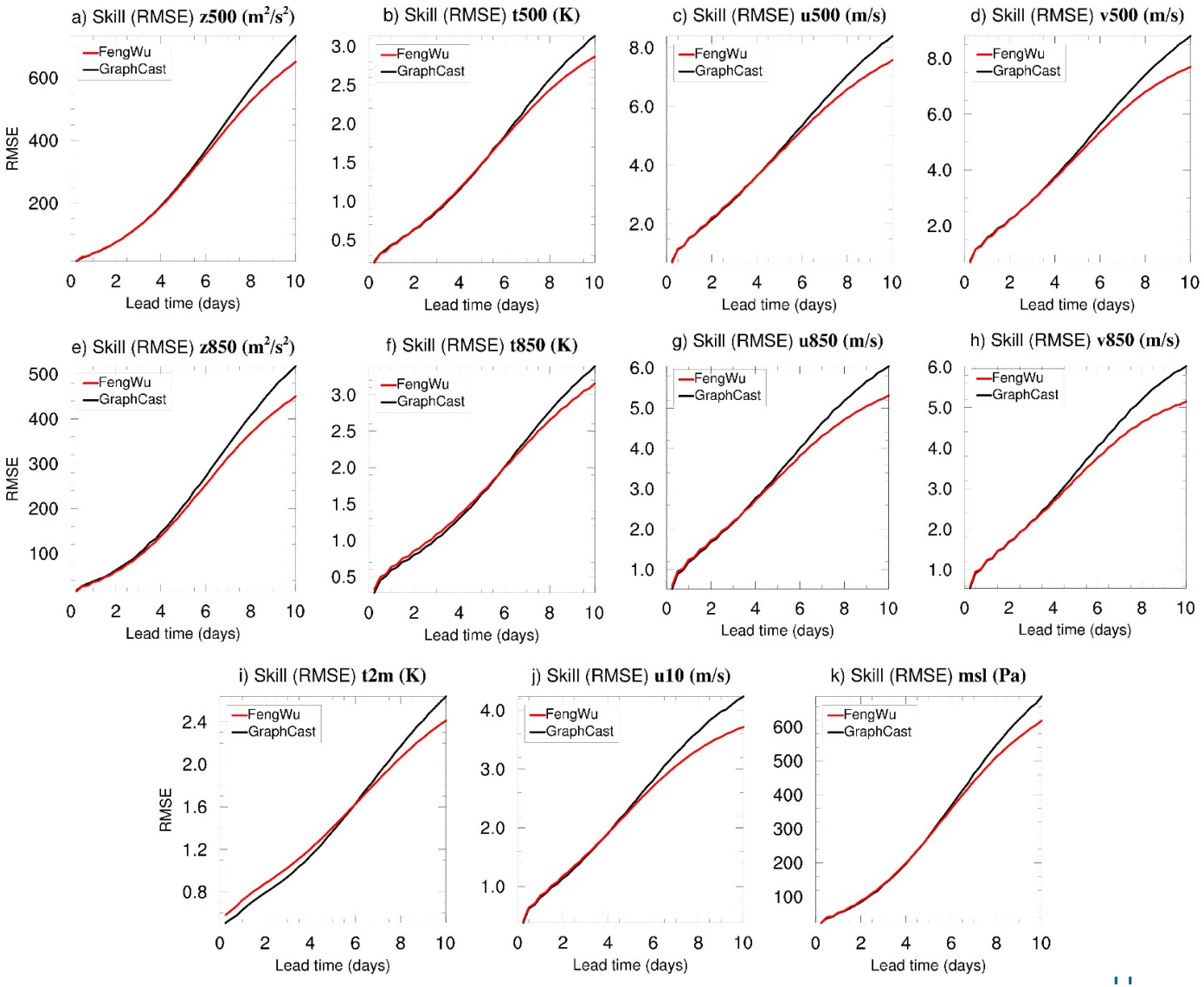
Training Details

- Data:
  - ERA5: the fifth generation ECMWF reanalysis for the global weather [1]
  - Six-hourly: original data is hourly and we only use 1/6 of it
  - Vertical levels: all 37 levels in the ERA5 data on pressure levels
  - Variables:
    - 5 atmospheric variables: geopotential, temperature, humidity, u component of wind, v component of wind
    - Surface variables: mean sea level pressure, 2-meter temperature, 10-meter u component of wind, and 10-meter v component of wind.
  - Spliting: 1979-2015 for training (37 years), 2016-2017 for validation, 2018 for testing
- Resource
  - 32 A100 GPUs
  - 17 Days

[1] https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=overview

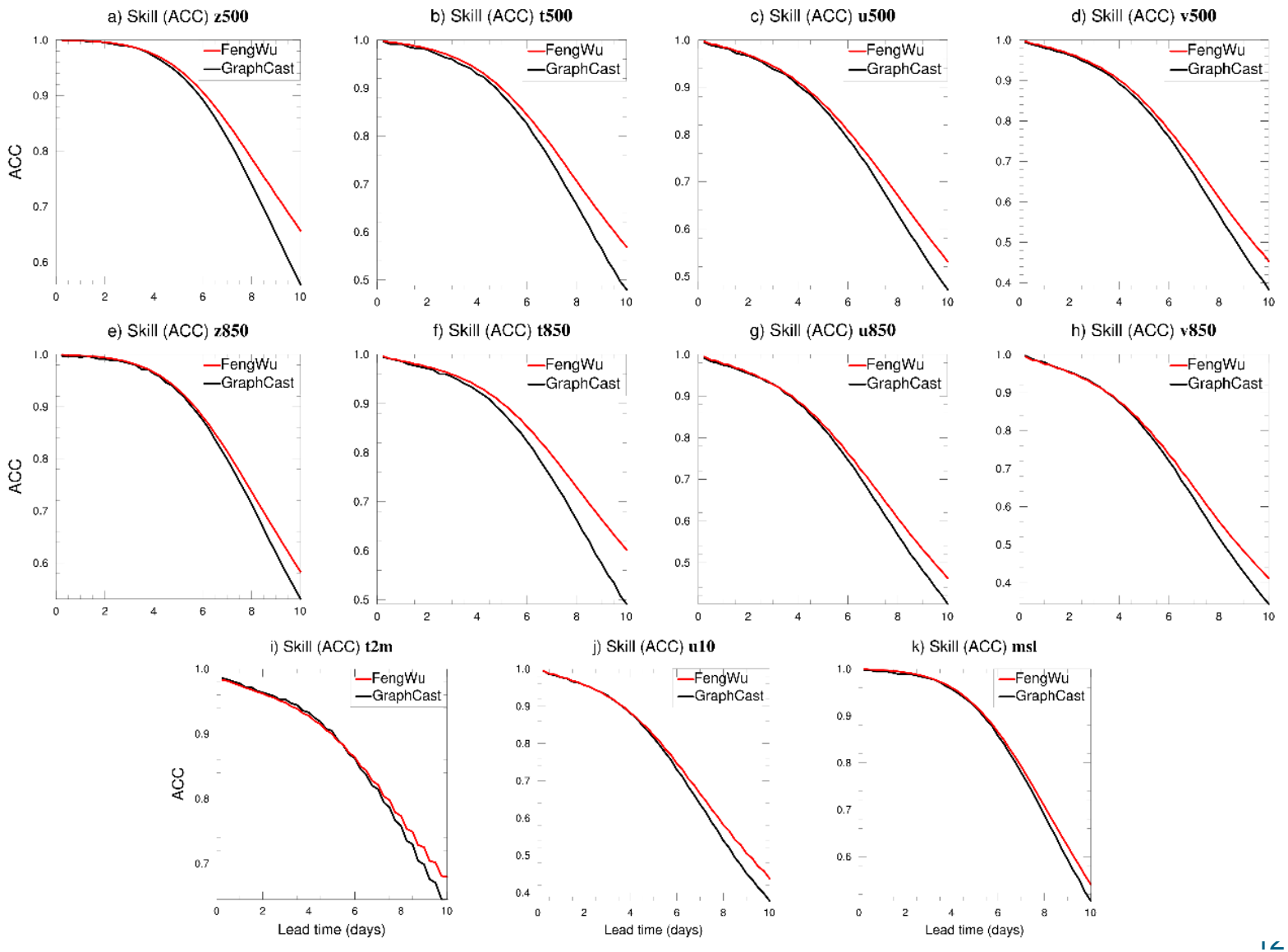
Performance of FengWu and GraphCast

- FengWu achieves better performance than GraphCast (**prior best model released by Deepmind** in Dec of 2022) on 80% of the metrics (lower RMSE indicating better prediction).
- FengWu reduces forecast errors by **10.87%** compared to GraphCast and by **19.4%** compared to IFS-HRES (**the best physical model from ECMWF)** for the ten days lead time.



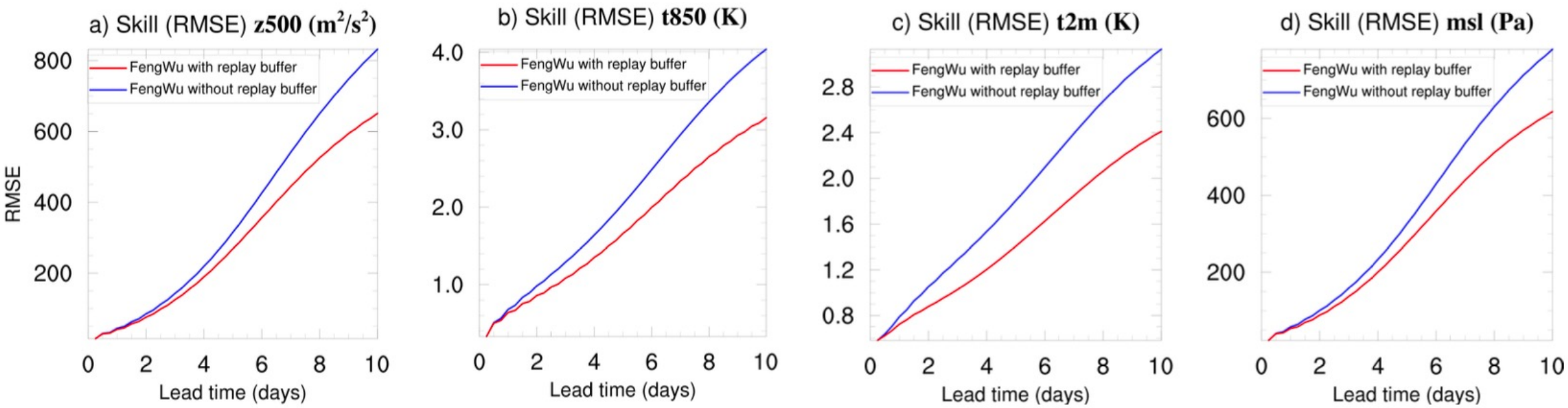
Performance of FengWu and GraphCast

- ACC of FengWu and GraphCast



Effect of the replay buffer

Effects of the autoregressive training with the proposed replay buffer mechanism (red lines) or without it(bluelines)



Visualization

- Predictions and errors visualization for Z500 and T850. Initialization time: 2018-Feb-11-00:00

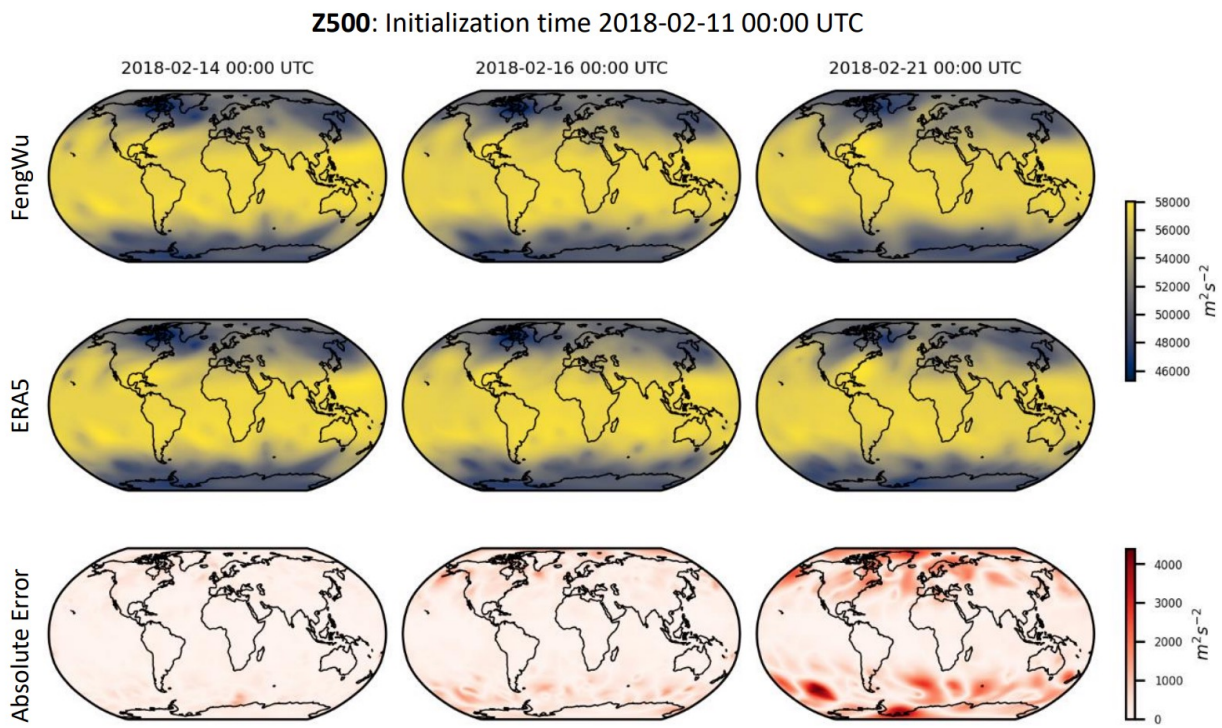


Figure 5: **Forecast images and absolute error for z500**. Figures of z500 on days 3, 5, and 10 are presented with initialization time at 2018-02-11 00:00 UTC. The subtitles at the top of the columns indicate the dates of prediction The first row and second row show FengWu and ERA5 ground truth, respectively. Row 3 shows the absolute error between FengWu and ERA5.

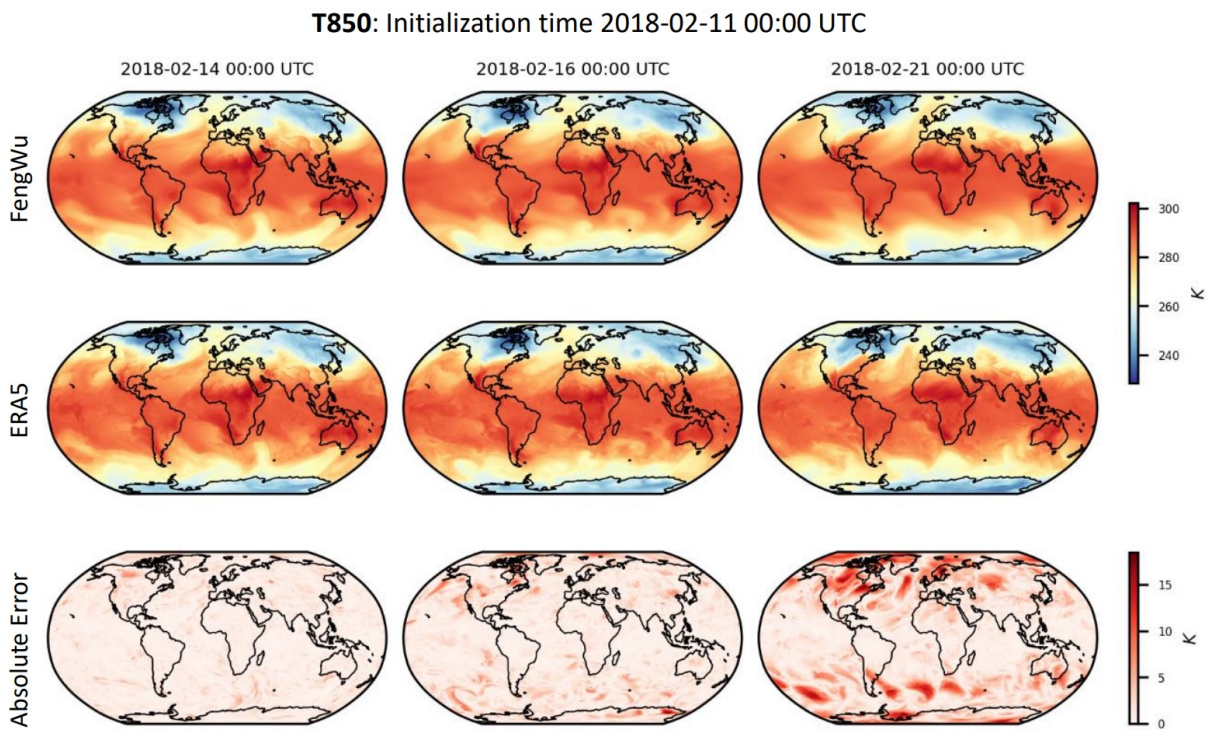
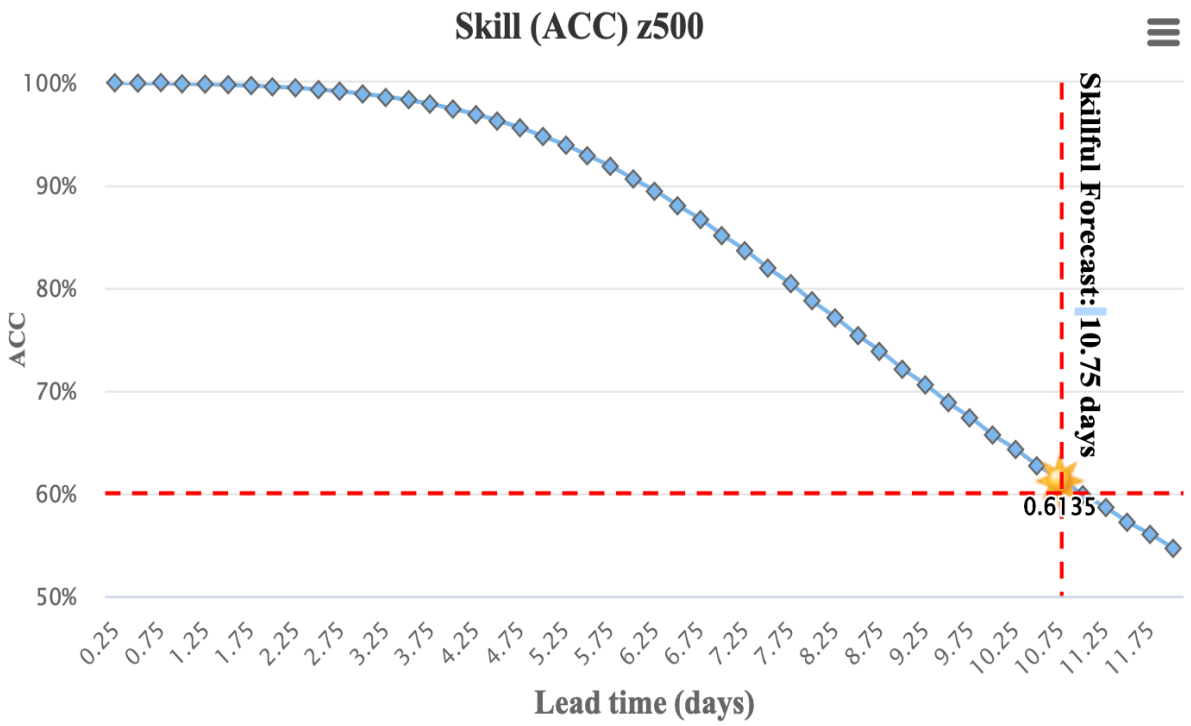
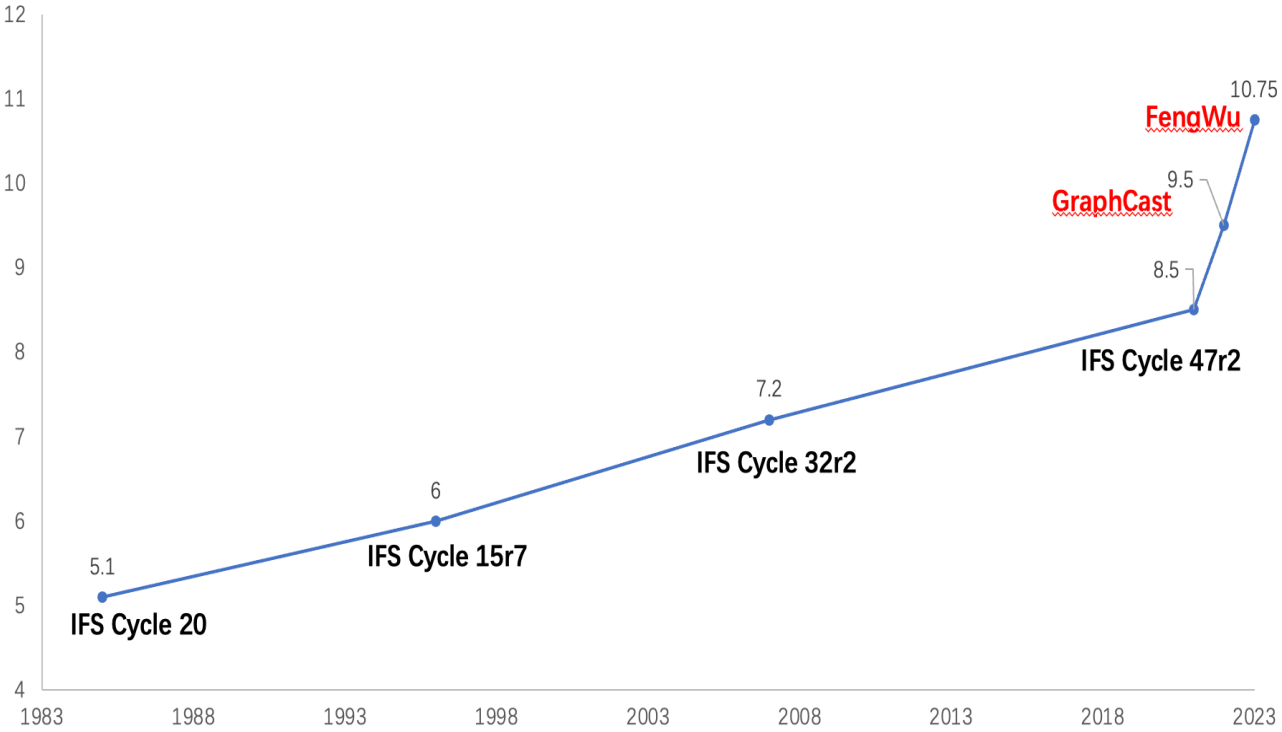


Figure 6: **Forecast images and absolute error for T850**. The plot demonstrates ERA5 ground truth and FengWu's prediction for T850, with forecast initialization 2018-02-11 00:00. Other settings are similar to Figure 5.

Core benefits

- **Long lead skillful forecasting**
  - **from 8.5 days to 10.75 days**
  - **Fast development**
- **Efficiency: Generating the predictions for the next 10 days of all regions in the world with 1 GPU cards with 30 seconds**

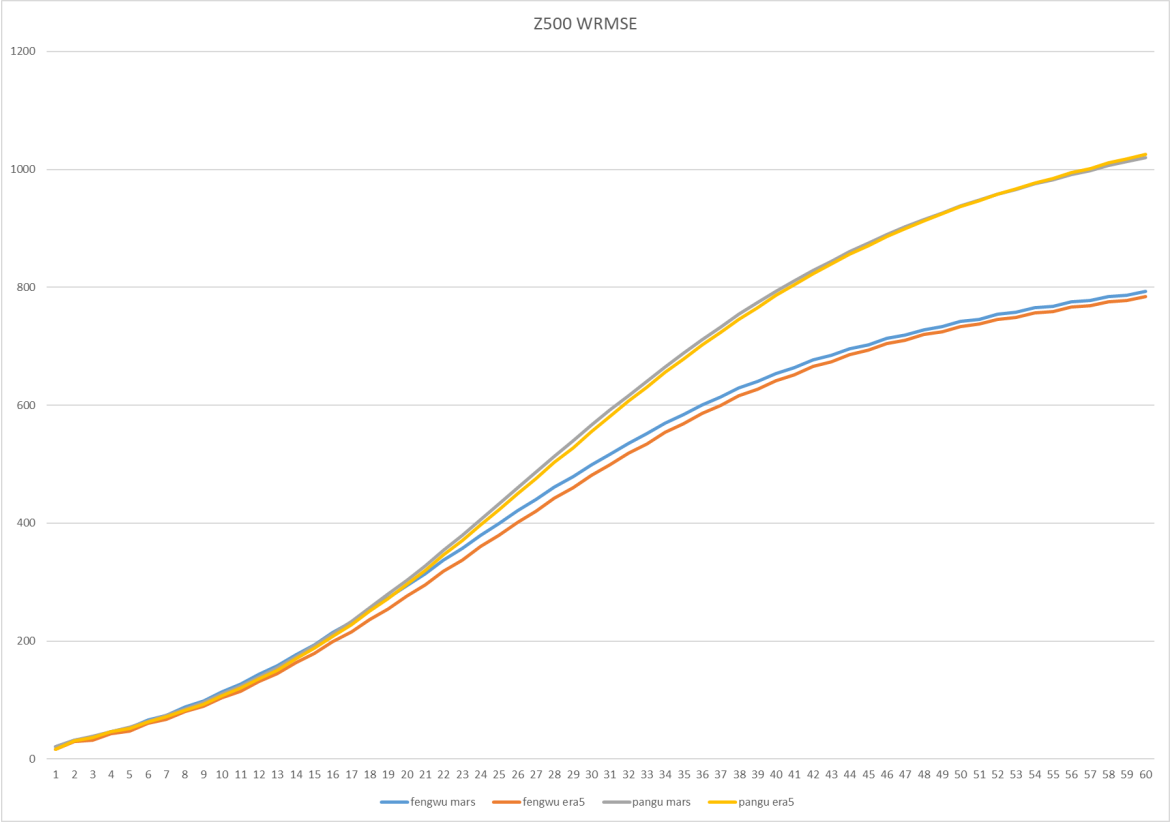




Towards operational forecast

A new version of FengWu is trained with 13 levels ERA5 data for operational forecast

Evaluated on the year of 2022 with both ERA5 inputs and operational analysis inputs



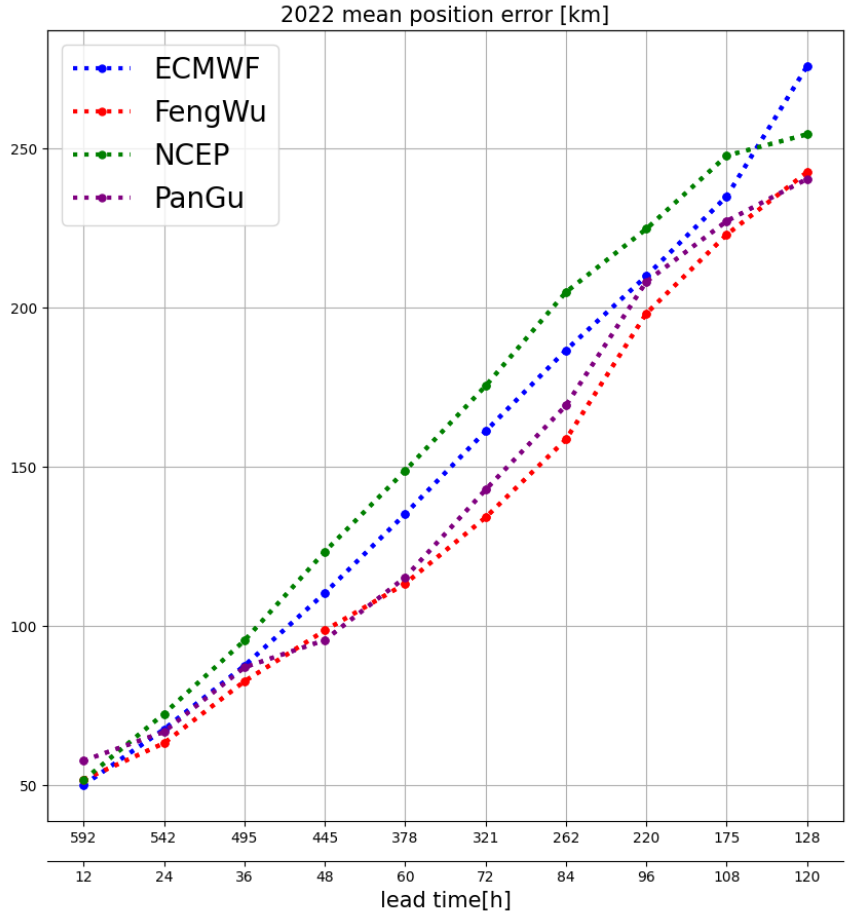
Z500 WRMSE

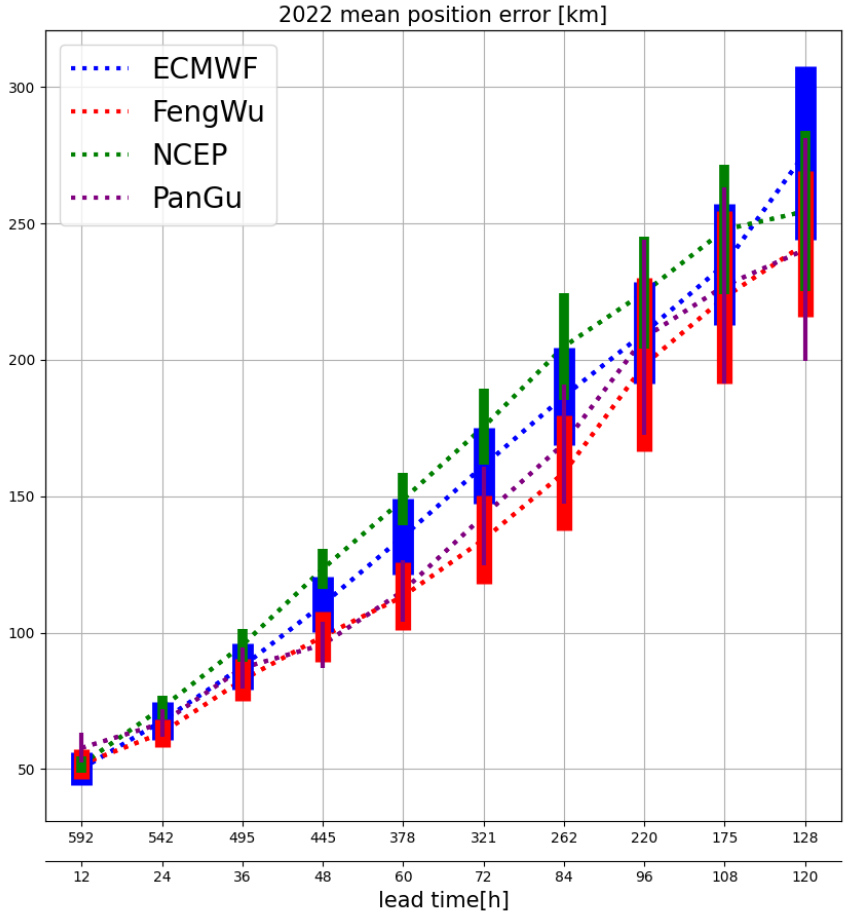
Z500 WACC

Towards operational forecast

FengWu achieves the best tropical Cyclones tracking performance within 5 days.

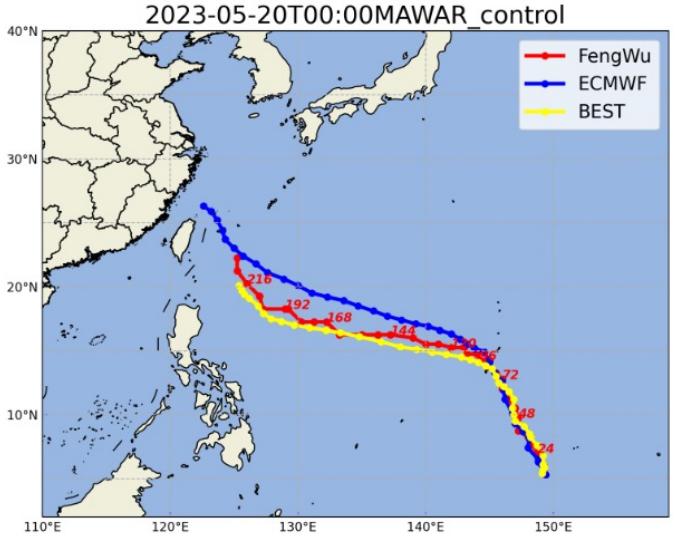
Evaluated on all the tropical Cyclone occurred in the year of 2022 (the same samples)

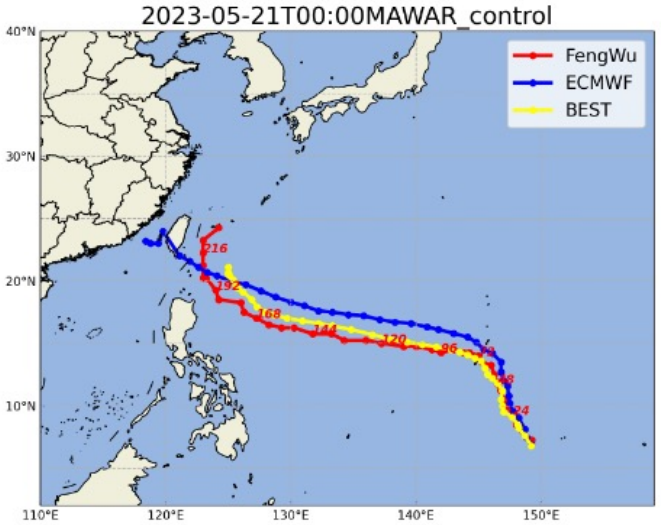


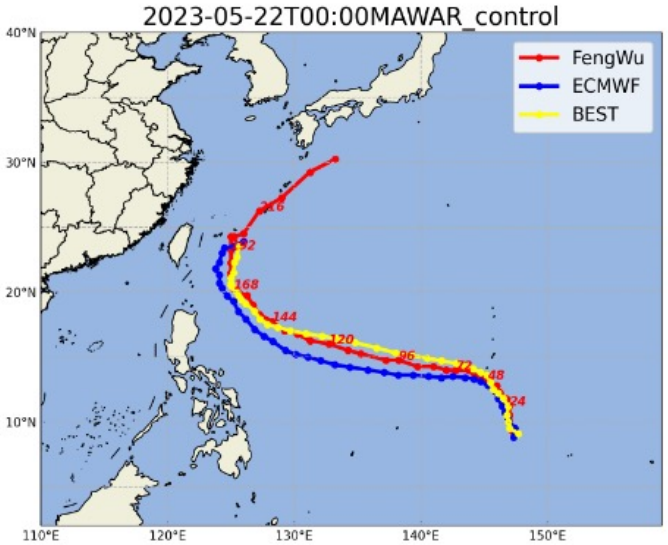


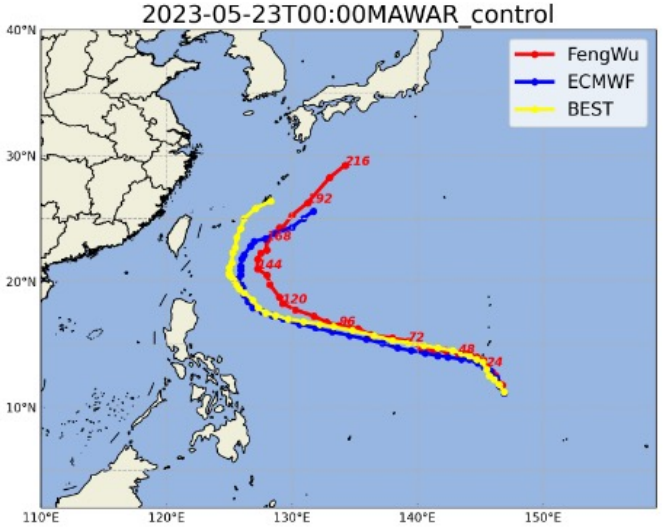
Towards operational forecast

Tropical Cyclone Track Prediction of Mawar



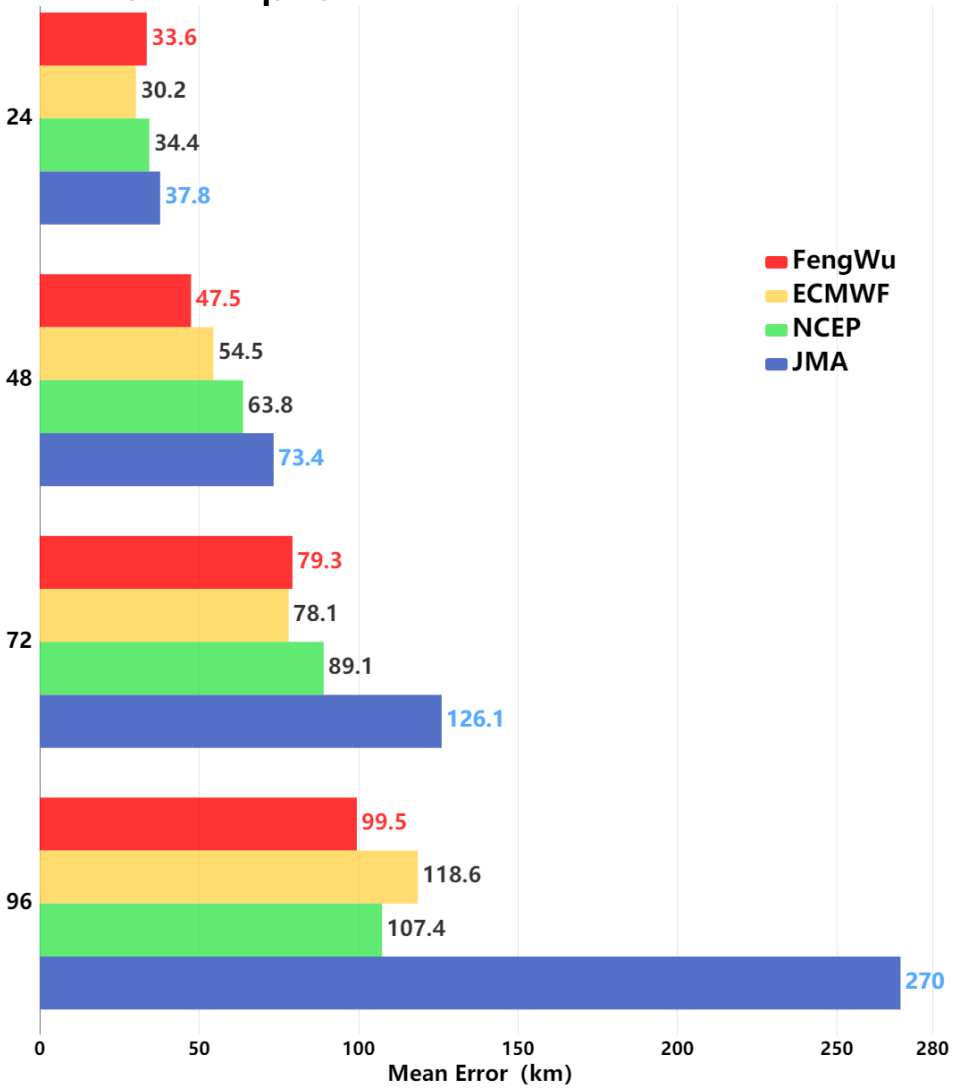




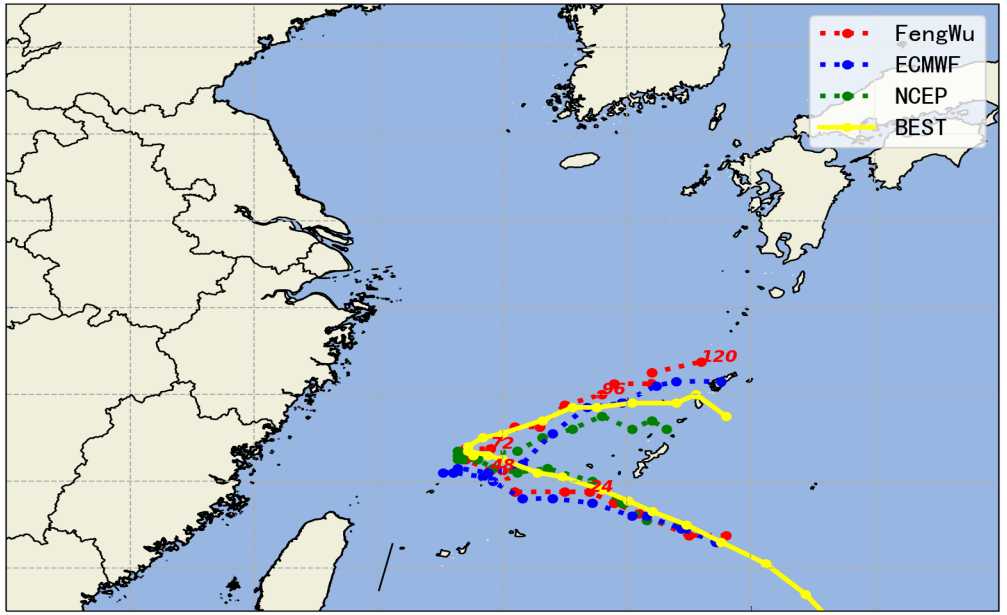


Operational Tropical Cyclone Prediction

Tropical Cyclone Track Prediction of Khanun (ensure same samples



2023-Aug-1-00:00:00



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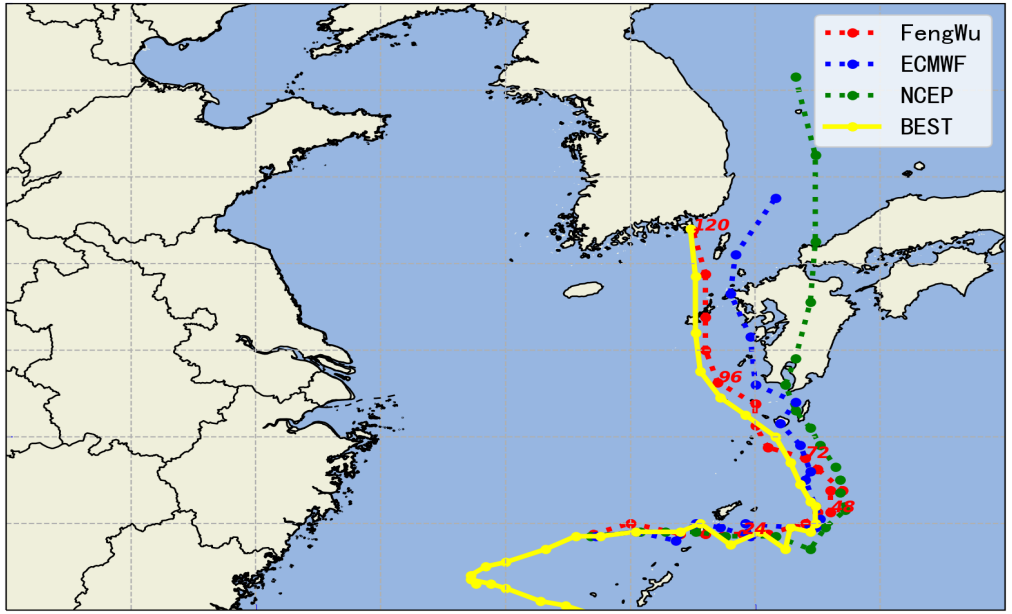
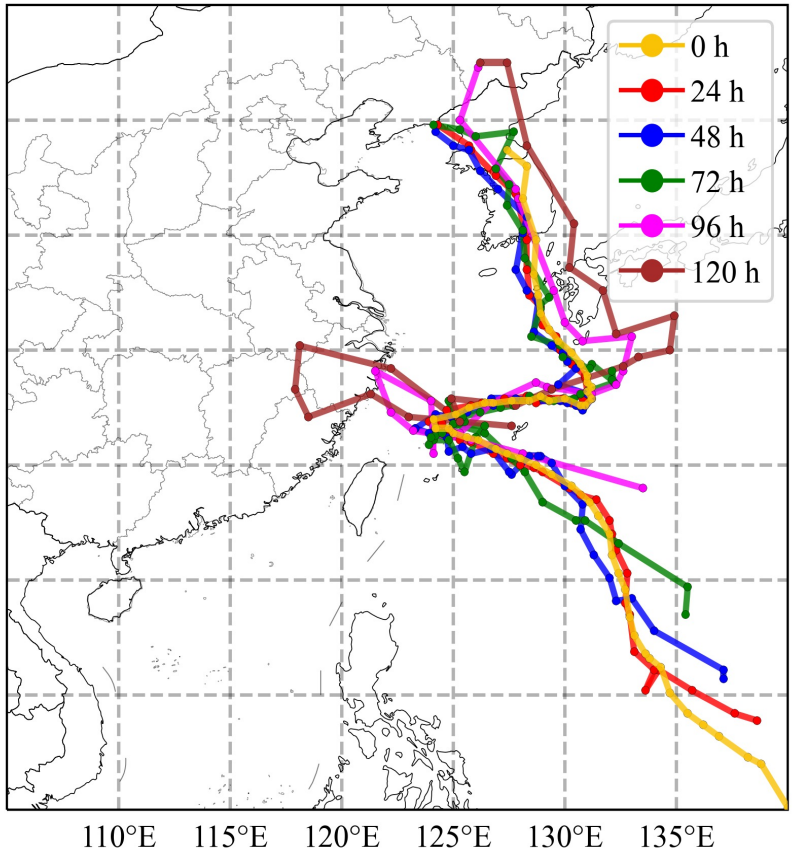


* Data provided by Shanghai Typhoon Institute of China Meteorological Administration

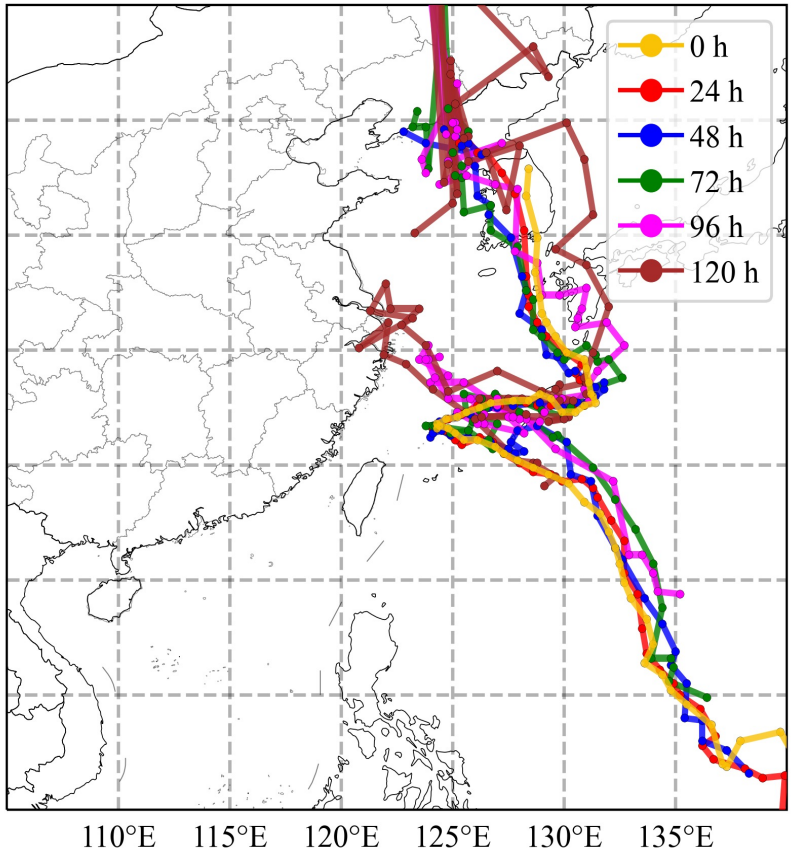
Operational Tropical Cyclone Prediction

Operational Khanun track prediciton analysis for ECMWF-IFS, NCEP-GFS, and FengWu

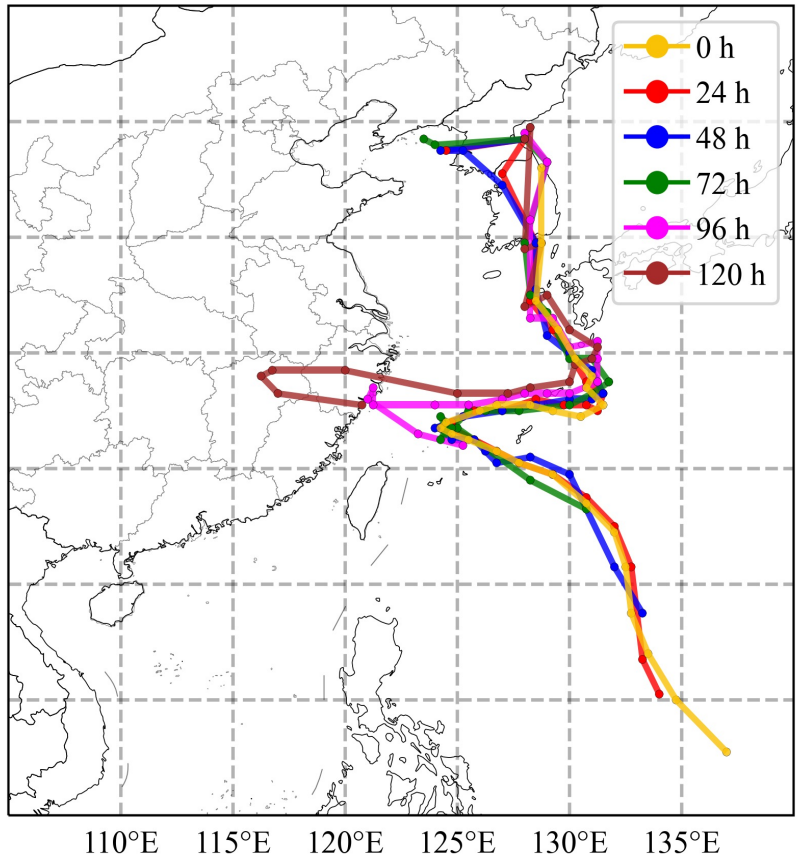
ECMWF-IFS
Forecast Track Map
Khanun(2306)



NCEP-GFS
Forecast Track Map
Khanun(2306)



FengWu
Forecast Track Map
Khanun(2306)

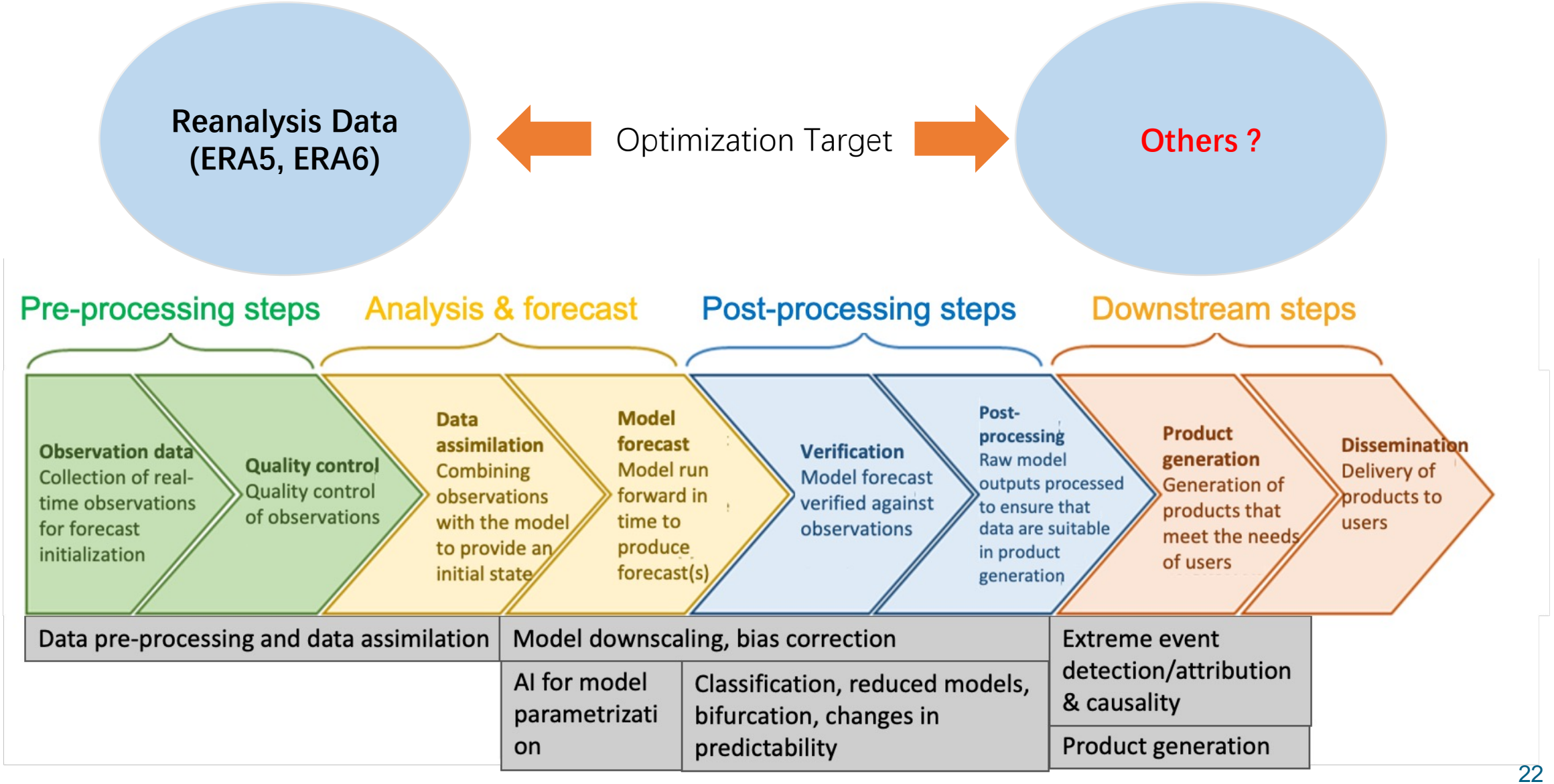


* Figures provided by Shanghai Typhoon Institute of China Meteorological Administration

Future Works

- **Direct upgrade**
  - Higher spatiotemporal resolution
  - More variables
- **Shorter and longer forecasting**
  - Short-term precipitation – especially extreme precipitation
  - Sub-seasonal forecasting
- **Better methods to decrease the error accumulation**
  - Physics constrains?
- **Explanation**
  - Open the black box

Future Works



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Thanks

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