



A Hybrid model of CMA-TRAMS and Pangu-Weather: framework and application

**Guangzhou Institute of Tropical and Marine Meteorology/
Guangdong Provincial Key Laboratory of Regional Numerical Weather
Prediction, CMA**



Outline



Introduction



Framework of hybrid model



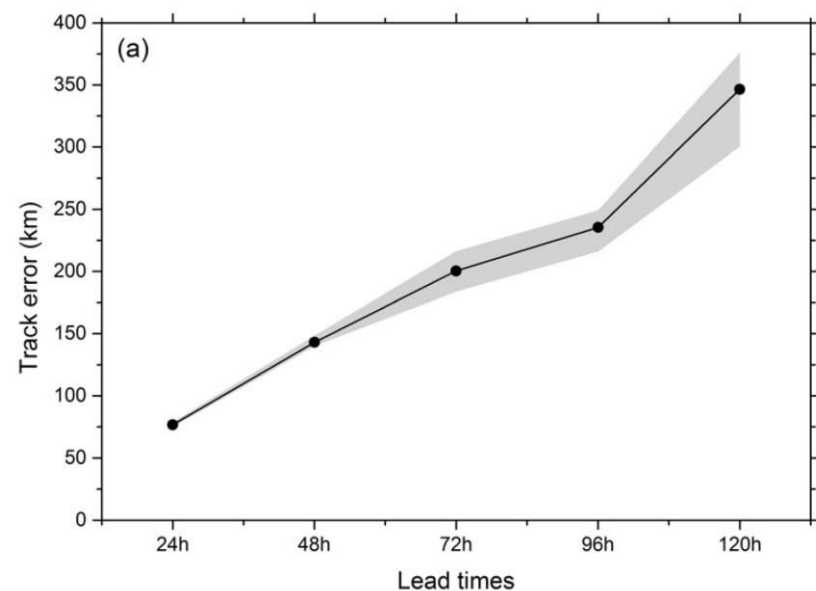
Experimental results



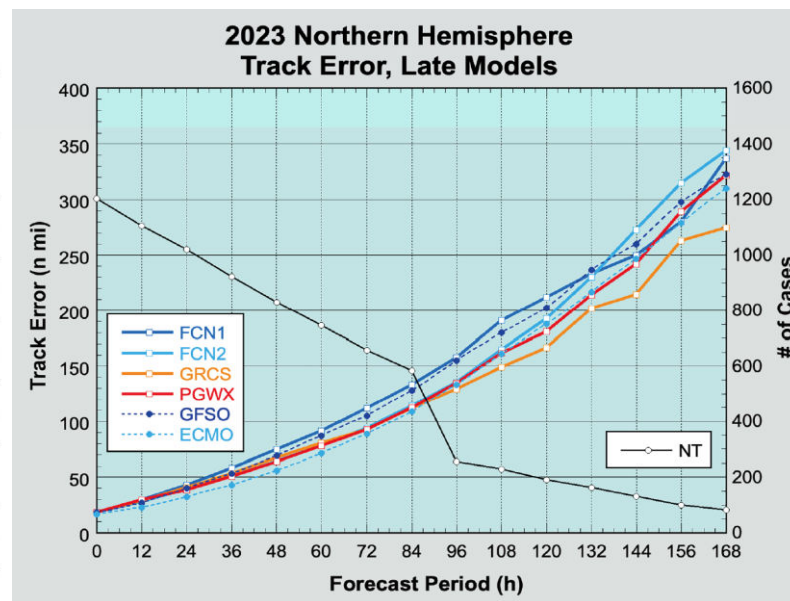
Application and plans

Introduction

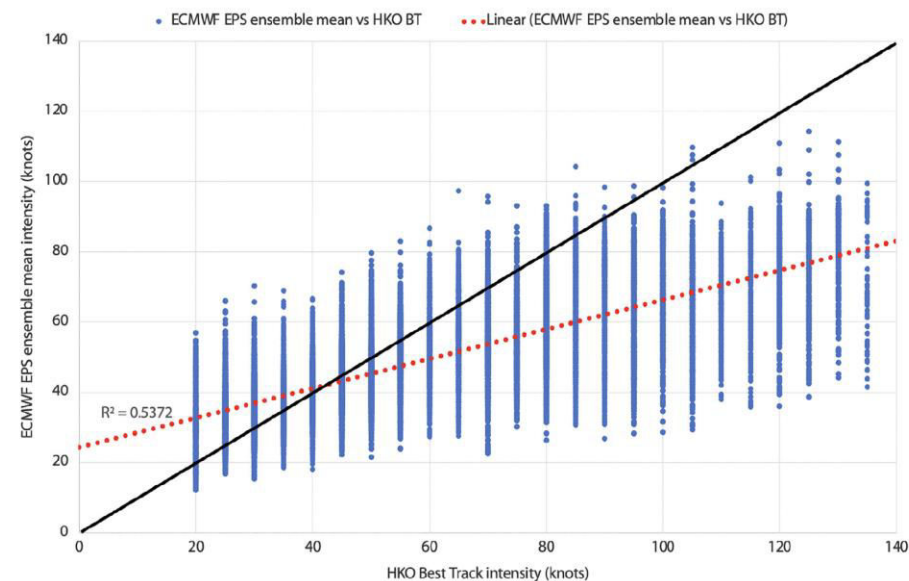
- Forecasting techniques based on numerical weather prediction (NWP) models have become the most important tools in weather forecasting.
- NWP models are still poor in the TC track forecasting at longer lead times and in the TC intensity forecasting for stronger cases (especially RI).



Annual mean PEs for track of the CMA official forecast guidance in 2022 (Yu et al. 2024)



Mean track errors for the late versions of the AIWP, GFS, and ECMWF models, for cases from May to November 2023 (DeMaria et al. 2025)



ECMWF EPS mean versus HKO BT intensity for TCs over the western North Pacific from 2016 to 2019 (Chan et al. 2021)

Introduction

CMA-TRAMS is a regional NWP model, which is developed by GITMM, CMA based on the GRAPES model.

Resolution: 0.09°, 65 vertical layers

Region: 70~161°E, 0~51°N

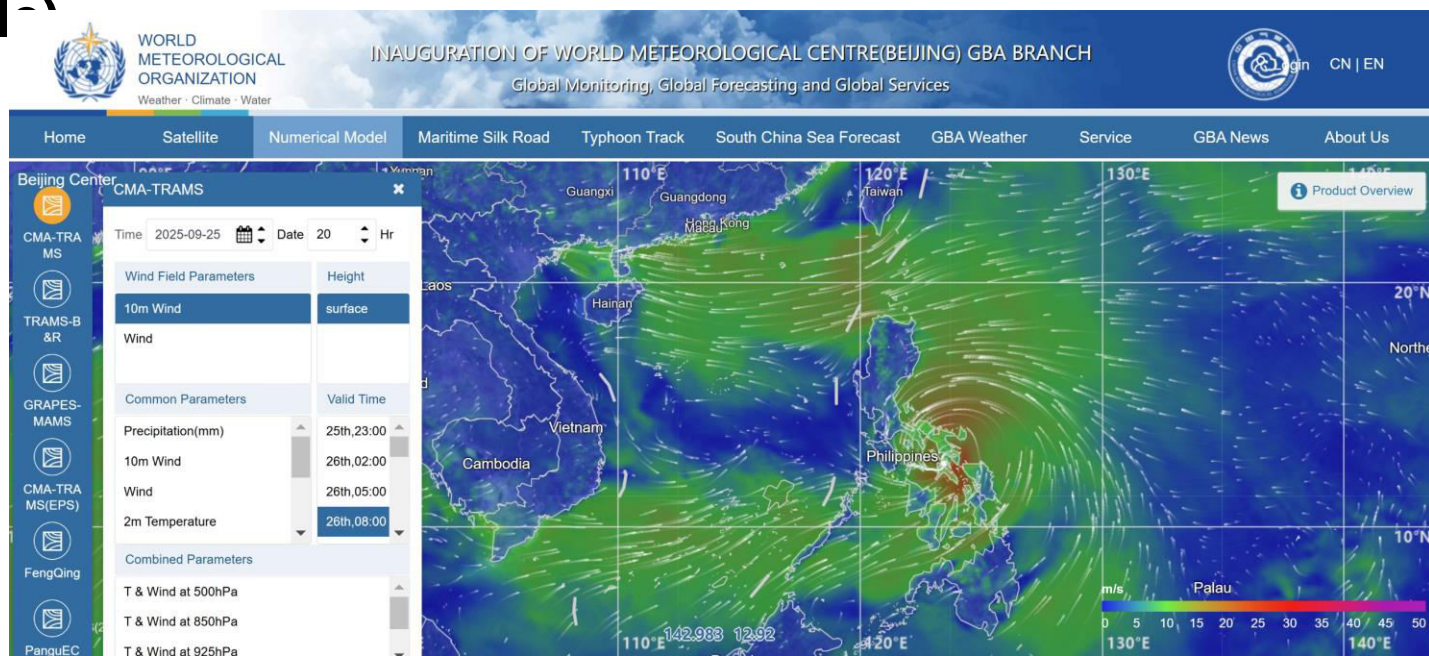
Initialization: (Cloud Analysis) Nudging + Land surface analysis

Init Time: 00/12z, T+168hrs FCS; 06/18z, T+72hrs FCS
(Deterministic)

00/12z, T+120hrs FCS (Ensemble)

Products:

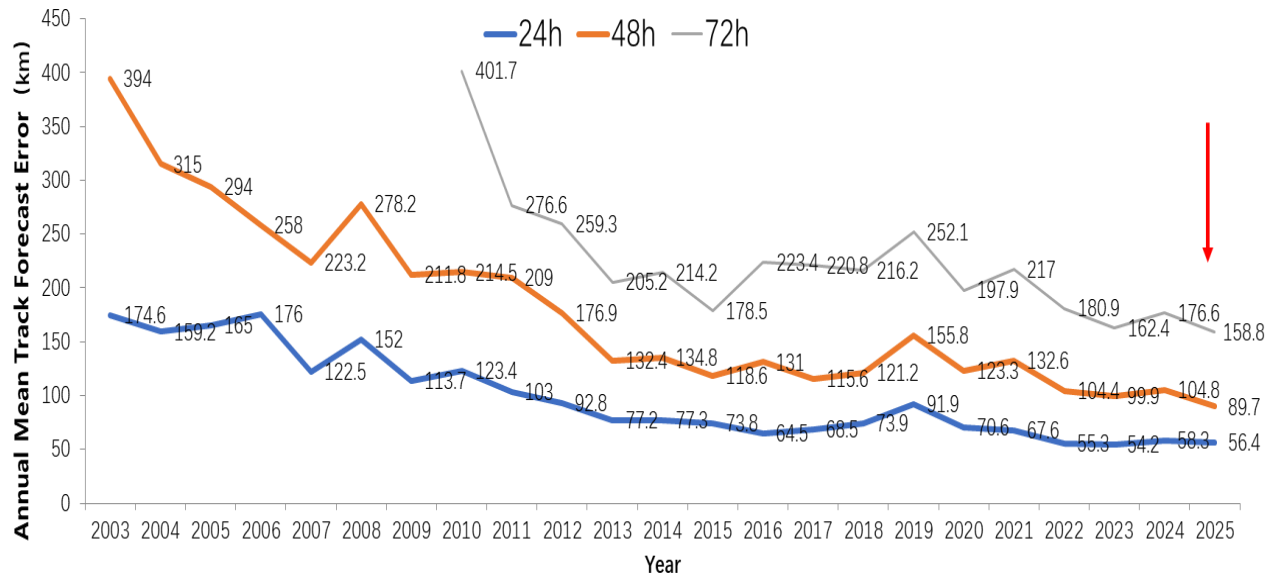
- TC track and intensity;
- Upper-air meteorological variables;
- Surface variables (e.g., precipitation)



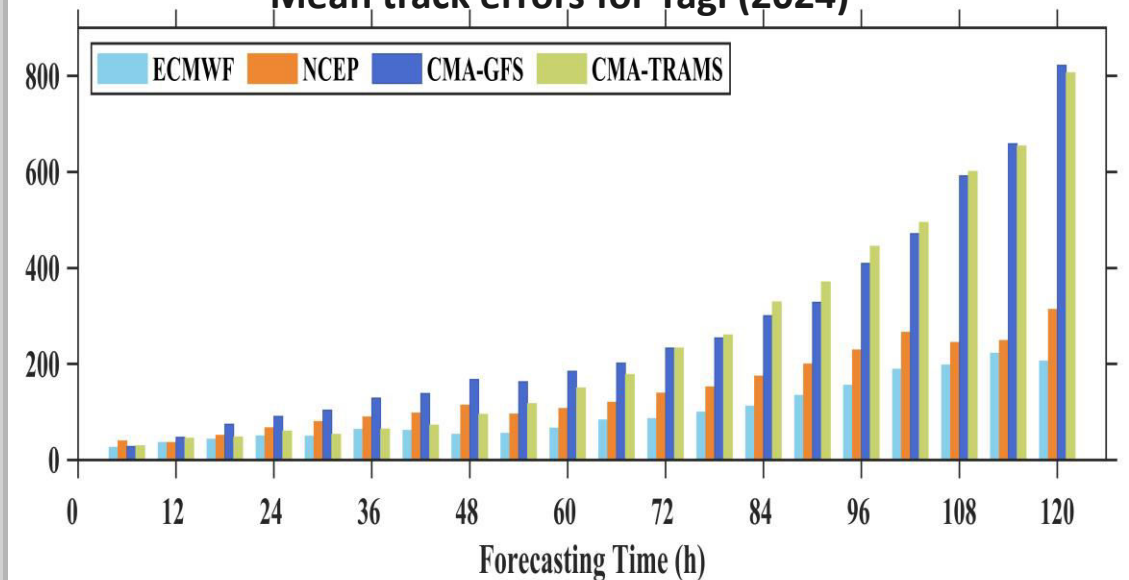
Introduction

- Although the performance of CMA-TRAMS in TC track forecasting has generally been improved year by year, it is still poor in the longer-term forecasting of TC track for some TC cases.

CMA-TRAMS Annual Mean Track Forecast Error (km)

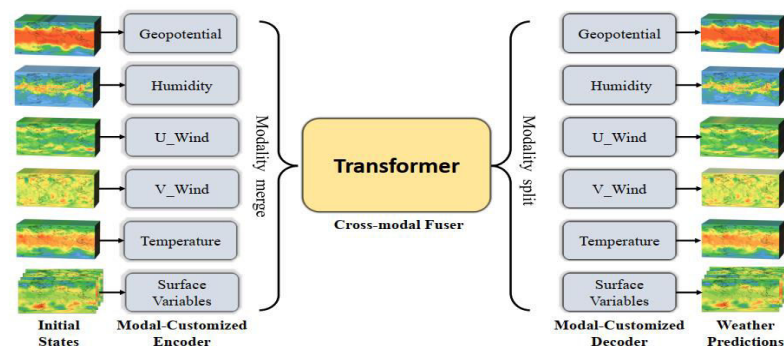


Mean track errors for Yagi (2024)

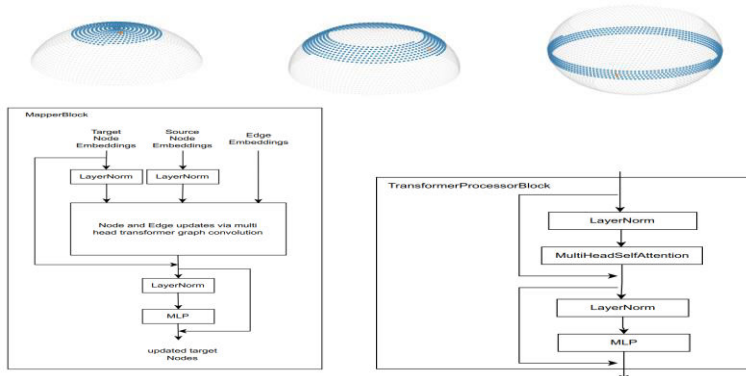


Introduction

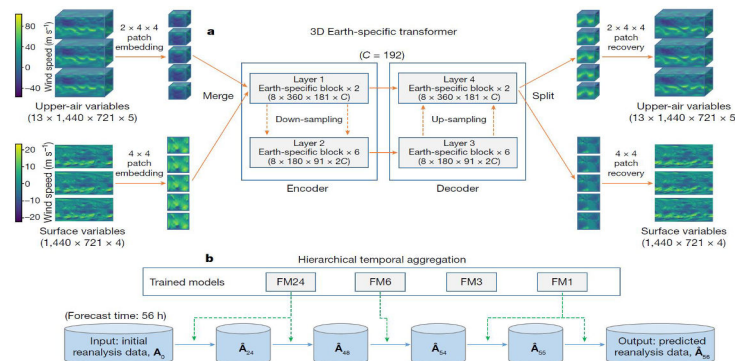
Artificial intelligence (AI) technology is rapidly advancing, with data-driven weather forecasting models (such as Pangu, Fuxi, Fengwu, AIFS, and GraphCast) gradually evolving



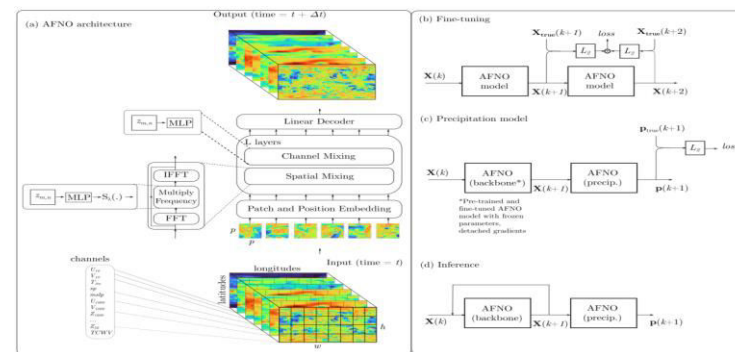
Fengwu (K. Chen et al., 2022)



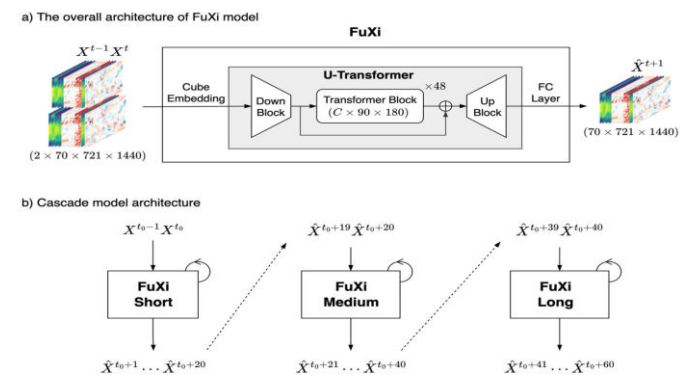
AIFS (Lang et al., 2024)



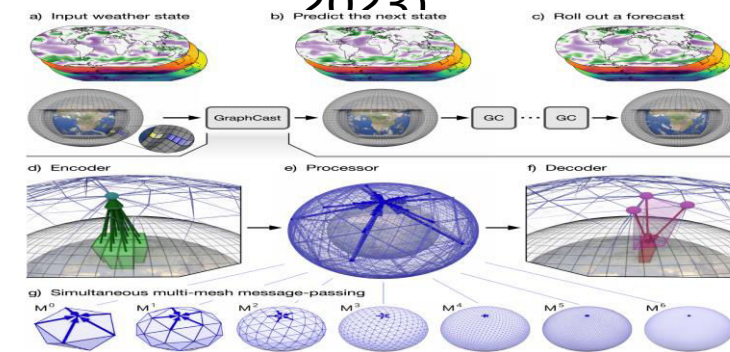
Pangu (Bi et al., 2023)



FourCastNet (Pathak et al., 2022)



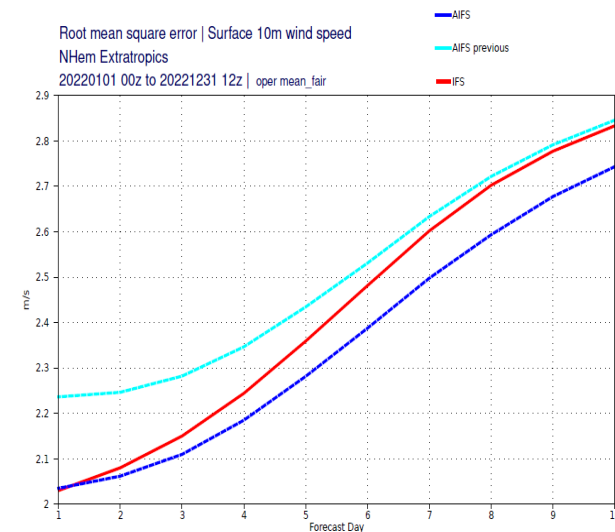
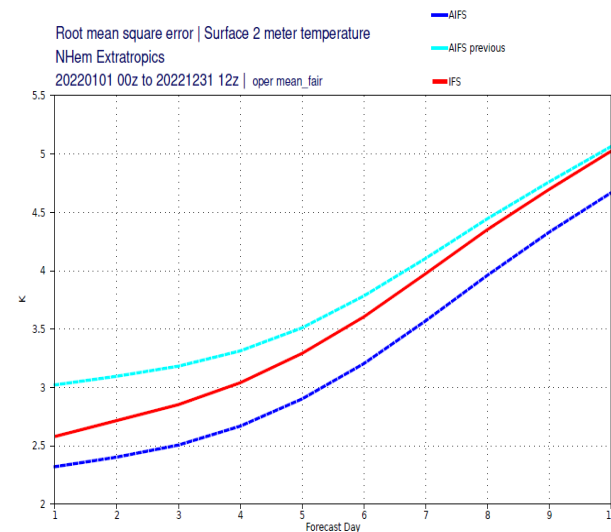
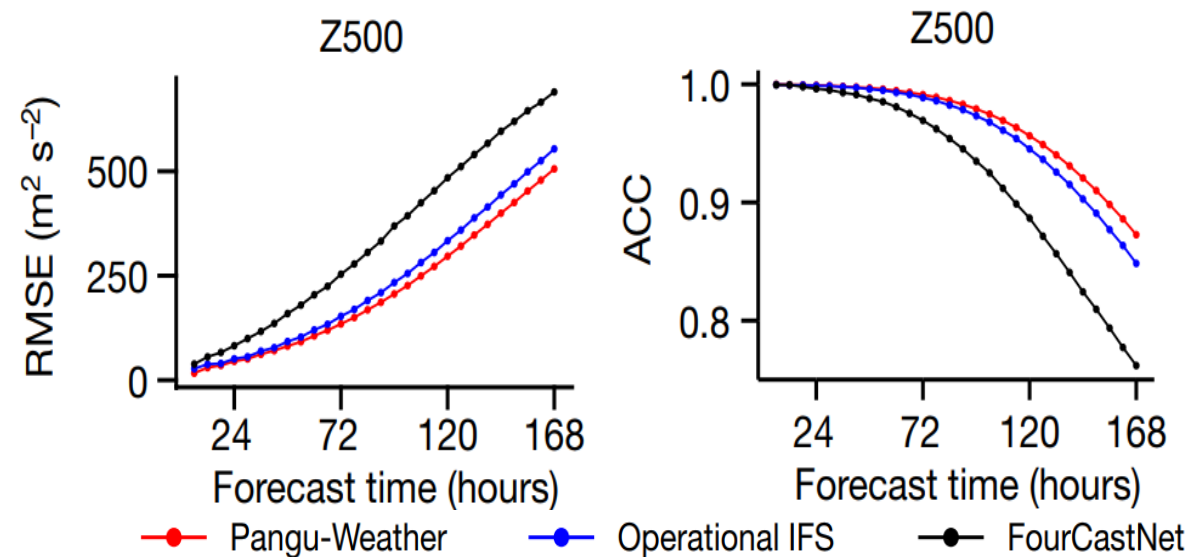
FuXi (L. Chen et al., 2022)



GraphCast (Lam et al., 2023)

Introduction

Compared with some operational global models (such as ECMWF IFS), AI-based weather models exhibit comparable or even superior forecasting skills in the spatial-temporal evolution of large-scale meteorological variables at higher levels.

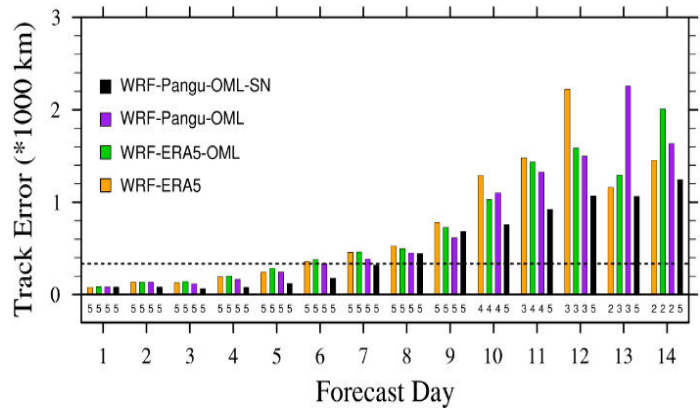
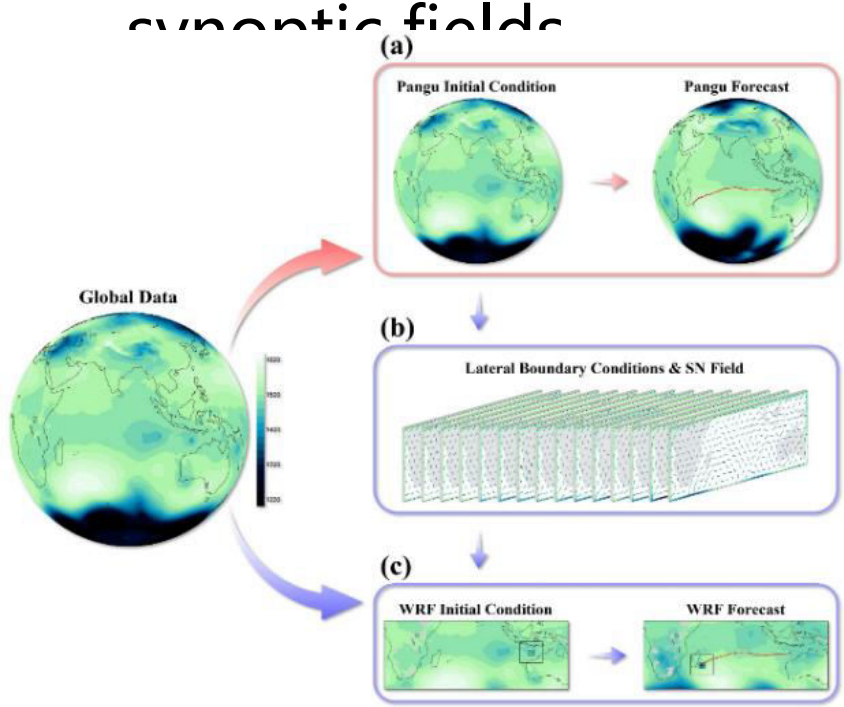


Pangu-Weather produces higher accuracy than the operational IFS and FourCastNet in deterministic forecasts on the ERA5 data (Bi et al. 2023).

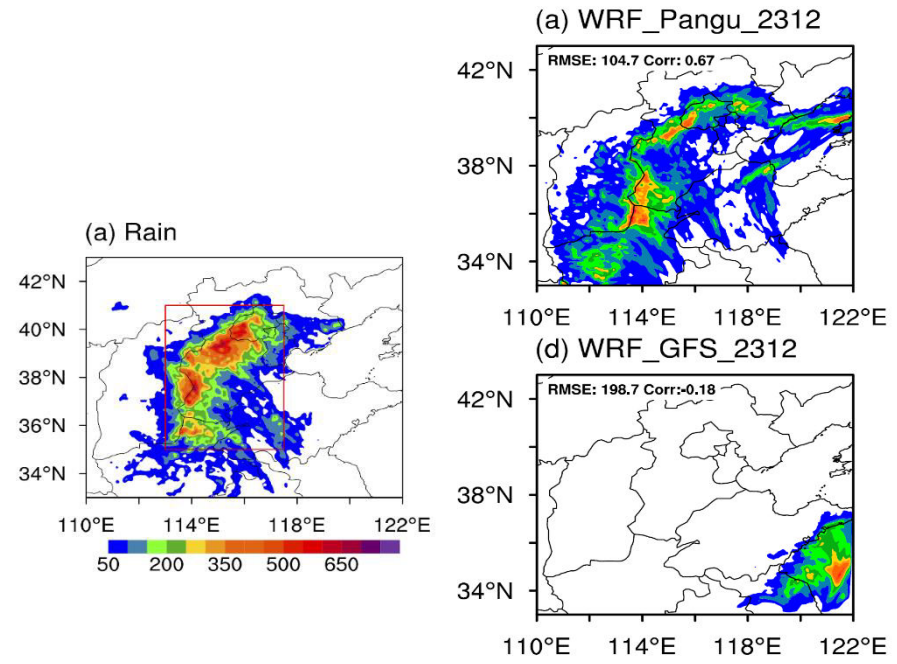
AIFS shows smaller RMSE than the operational IFS in deterministic forecasts (Lang et al. 2024).

Introduction

- The forecast performance of regional NWP models is closely related to the forecasts of large-scale synoptic fields from the global NWP models.
- Using AI-based weather models (e.g., Pangu) as the driving fields for the regional NWP models can leverage the advantages in forecasting large-scale synoptic fields



Downscaling and nudging improves TC track forecasting
(Liu et al. 2024).



Using forecasts of Pangu weather Model as the driving fields of WRF improves the forecasts of heavy rainfall (Xu et al. 2024).

Flowchart of the Integration of Pangu weather Model and regional NWP Model (Liu et al. 2024).



Outline



Introduction



Framework of hybrid model



Experimental results



Application and plans

NWP and AI-based models

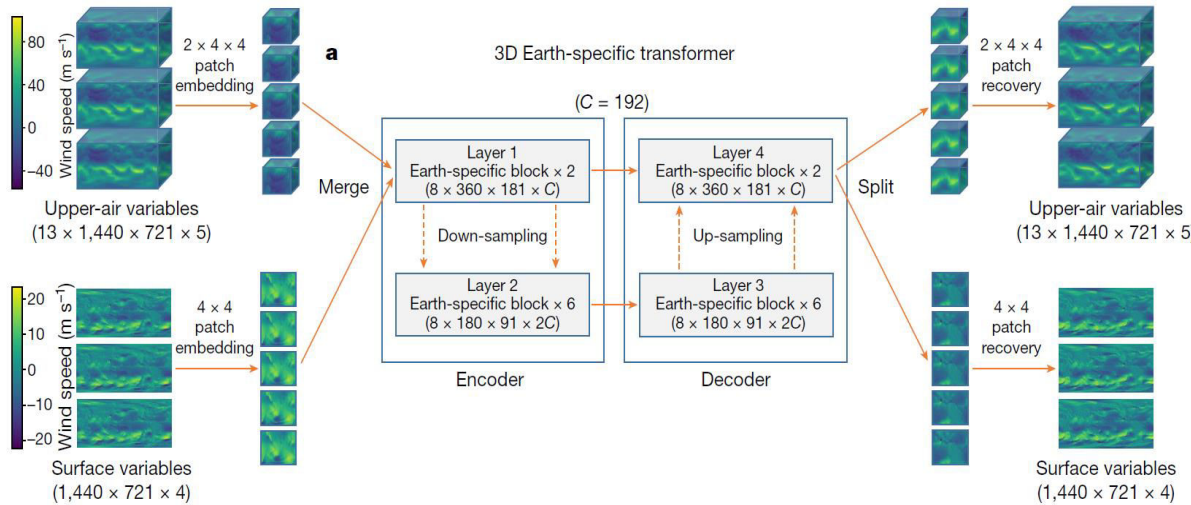
Regional **NWP** model: **CMA-TRAMS**

AI-based weather model: **Pangu**

IC/LBCs: The analyses and forecasts of ECMWF IFS with the horizontal resolutions of $0.1^{\circ} \times 0.1^{\circ}$ are used as the driving fields for Pangu and CMA-TRAMS.

CONFIG	CMA-TRAMS
Dyn frame	Fully Compressive, Non-hydrostatic, Predictor-Corrector Method For SISL, 3D Reference Atmosphere Scheme, Terrain Following Coordinate with Charney-philip Staggering, Lon-lat Grid with Arrakawa-C Stagerring
Microphysics	WSM6
PBL	MRF
LAND	SMS + CoLM
Cumulus	Deep convection: scale-aware NSAS; Shallow convection: CSC

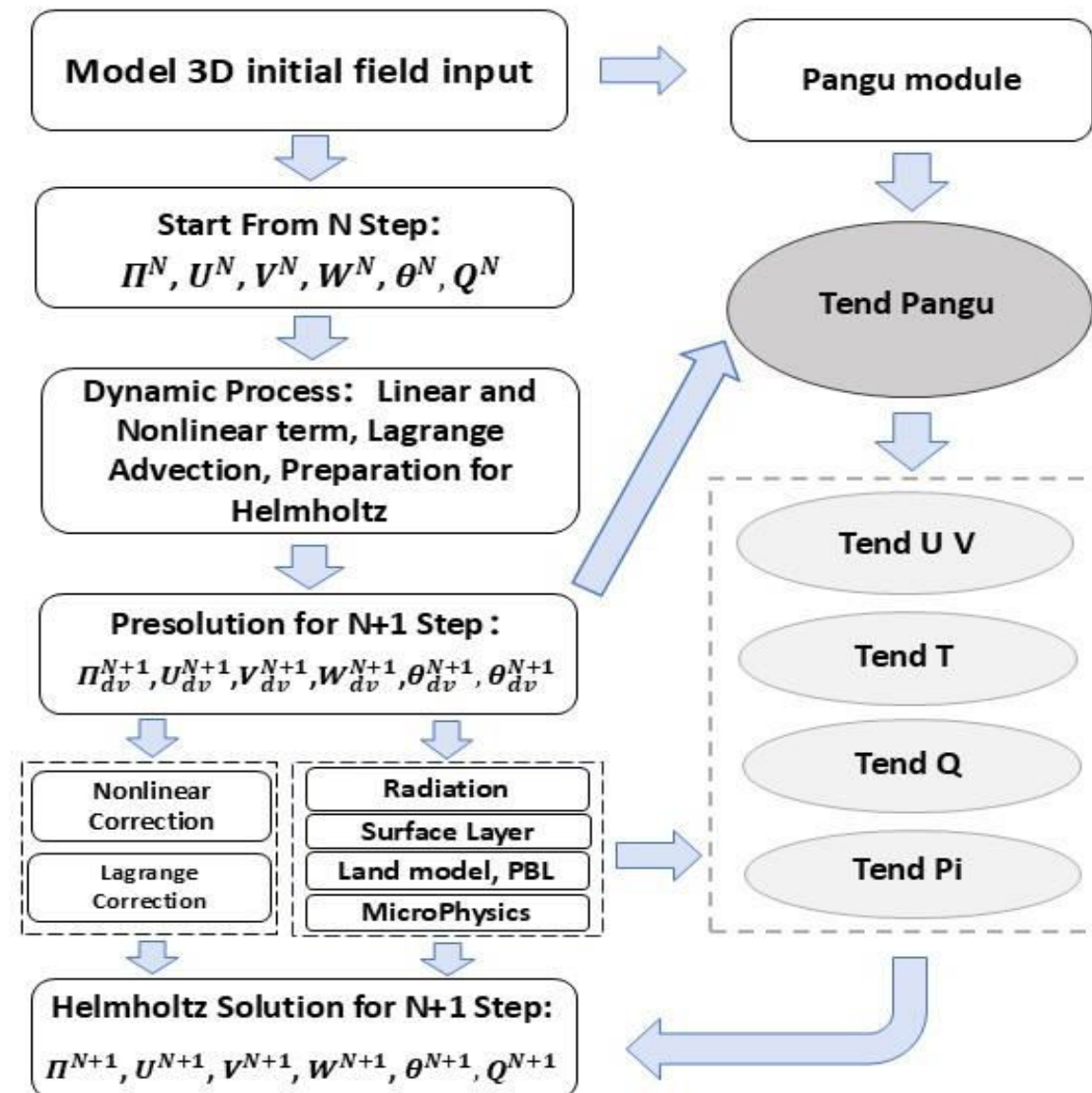
CMA-TRAMS (Chen et al., 2021)



Pangu (Bi et al., 2023)

Framework of the hybrid model

- During the integration process of CMA-TRAMS, the forecast variables (e.g., U, V, T) with precision advantages from Pangu model are used in the online correction to reduce the model errors of CMA-TRAMS.
- Similar to the parametrized tendency of physical processes, Pangu model generates tendency of forecast variables, which is used in the Helmholtz Solution.





Framework of the hybrid model

Time integral equation:

$$A^{n+1} = A_*^n + \Delta t [\alpha_\varepsilon (L_A + N_A)^{n+1} + \beta_\varepsilon (L_A + N_A)_*^n] + \Delta t \alpha_p S_A^{n+1} + \Delta t \beta_p S_*^n$$

Lagrange upstream
point

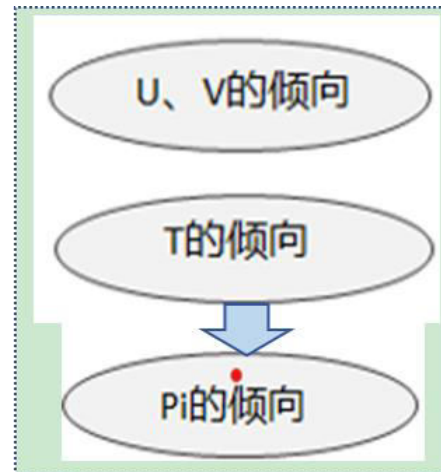
Linear
term

Nonlinear
term

Parametrized
tendency of physical
processes

=> Time integral equation:

$$\begin{cases} \bar{W}^{n+1} = \Delta t [\alpha_\varepsilon (L_{\bar{W}})^{n+1}] + \bar{W}_0 \\ \theta^{n+1} = \Delta t [\alpha_\varepsilon (L_\theta)^{n+1}] + \theta_0 \\ \pi^{n+1} = \Delta t [\alpha_\varepsilon (L_\pi)^{n+1}] + \pi_0 \end{cases}$$



Tendency
from Pangu
model



Outline



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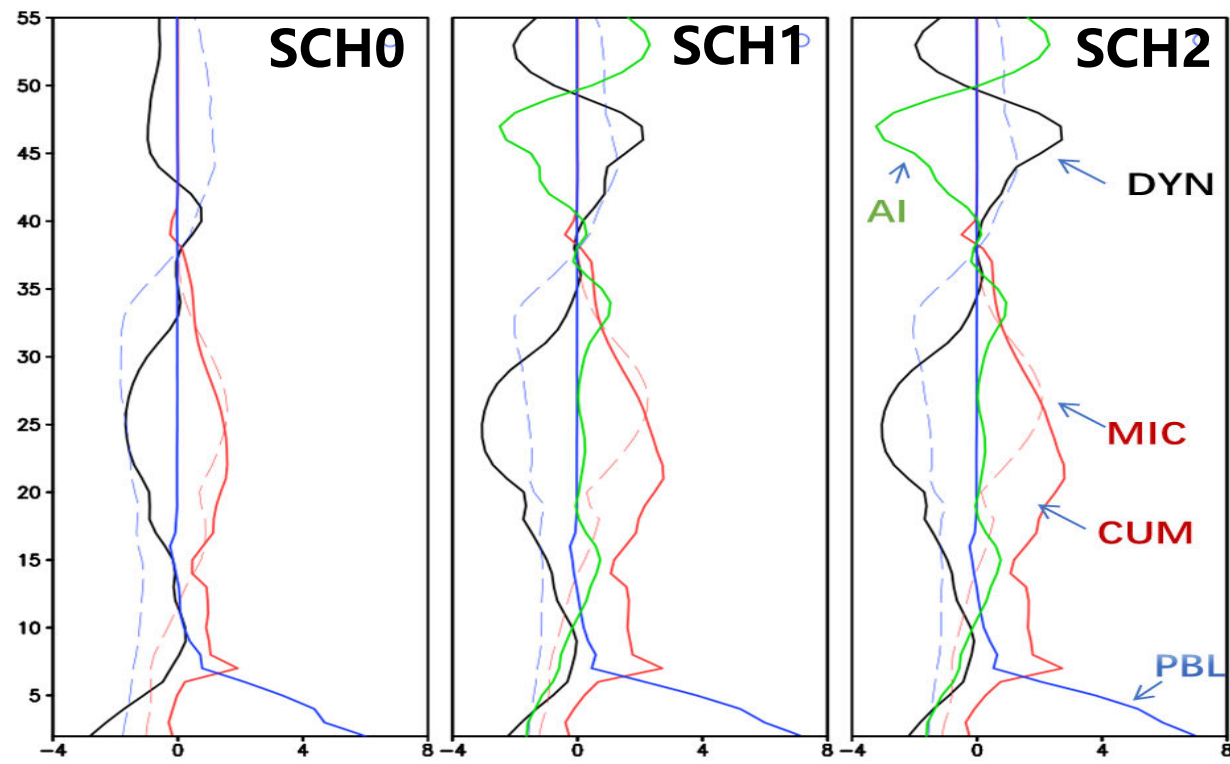


Application and plans

Experimental results

- Comparative experiments (May-Oct 2025) show the impacts of introducing the tendency from Pangu on the tendencies from both the dynamic process and the parametrized physical processes (Cumulus, Microphysics, PBL).

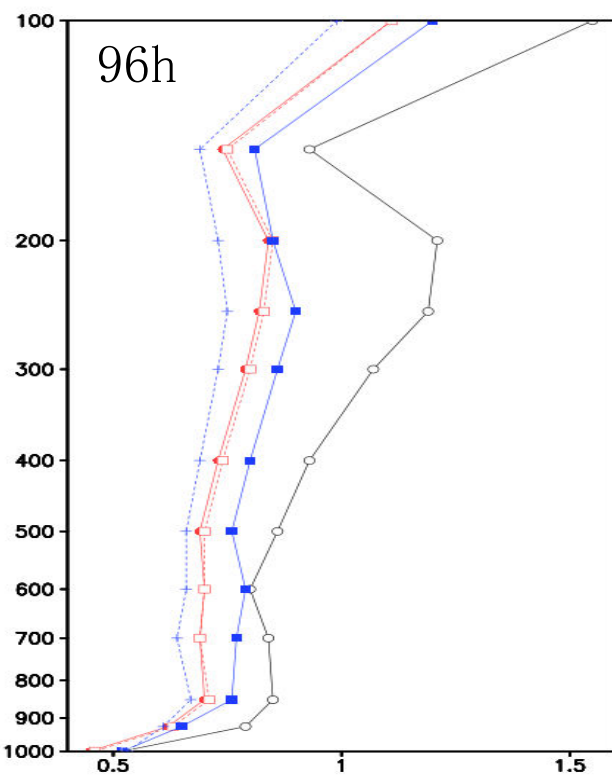
Exp	Hybird scheme
SCH0	No hybrid
SCH1	Hybrid with T tendency from Pangu
SCH2	Hybrid with T, U, V tendencies from Pangu



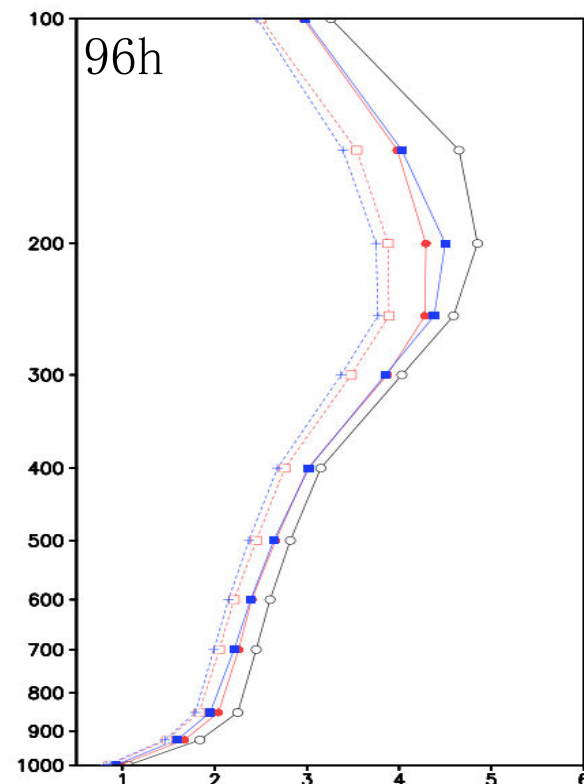
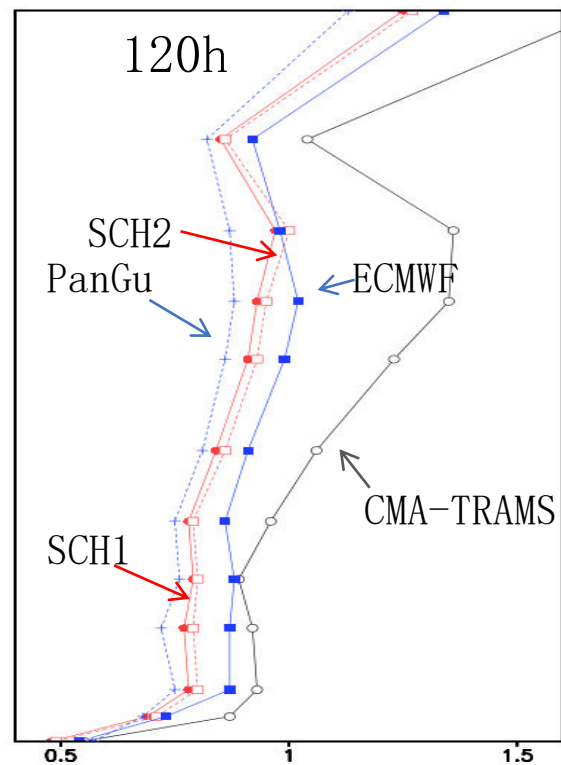
72-96-h Tendency of T from various processes for Podul (2025)

Experimental results

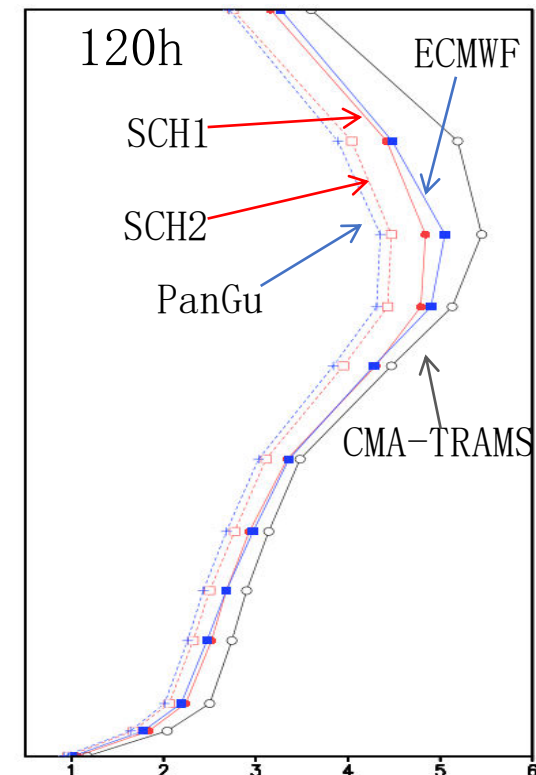
- Introducing the tendency from Pangu (especially all of T, U, and V) reduces the forecast errors of T and wind beyond 72 h.



MAE of T from various models

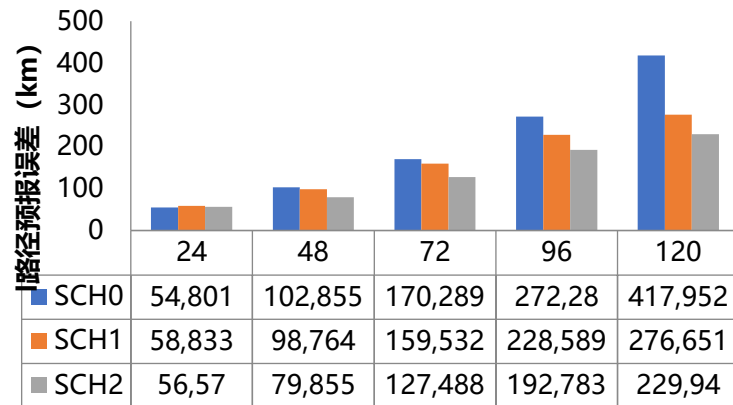


MAE of Wind speed from various models

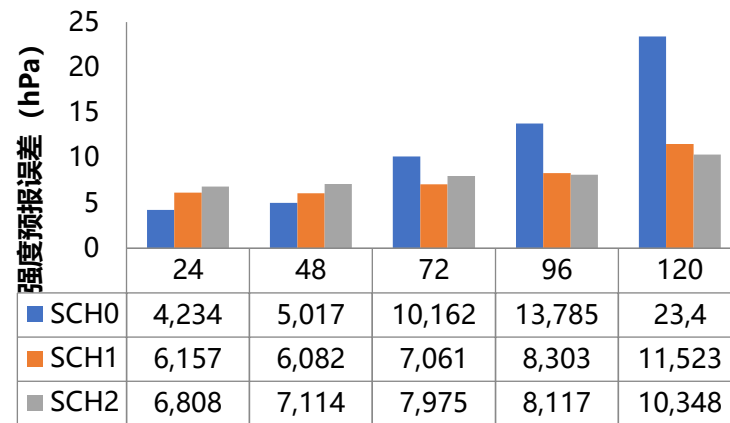


Experimental results

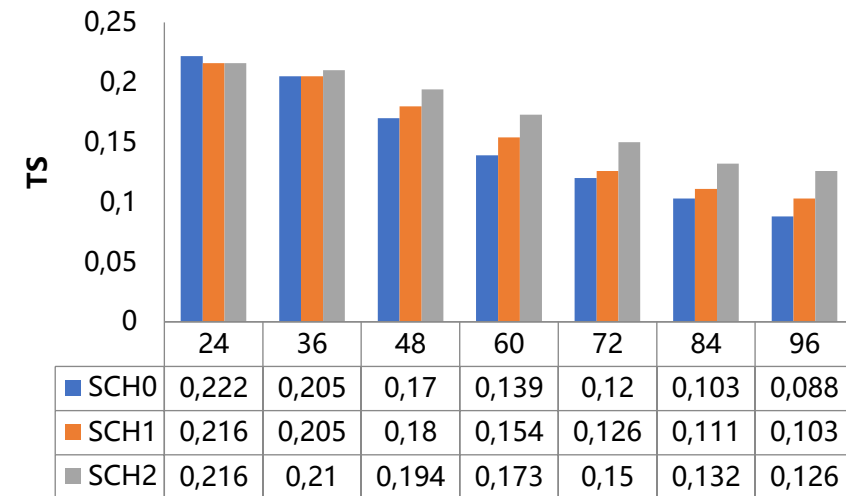
- Introducing the tendency from Pangu (especially all of T, U, and V) reduces the errors for both TC track and intensity forecasting beyond 72 h and improves the heavy rainfall forecasting beyond 48 h.



MAE of Track from various experiments



MAE of Intensity from various experiments

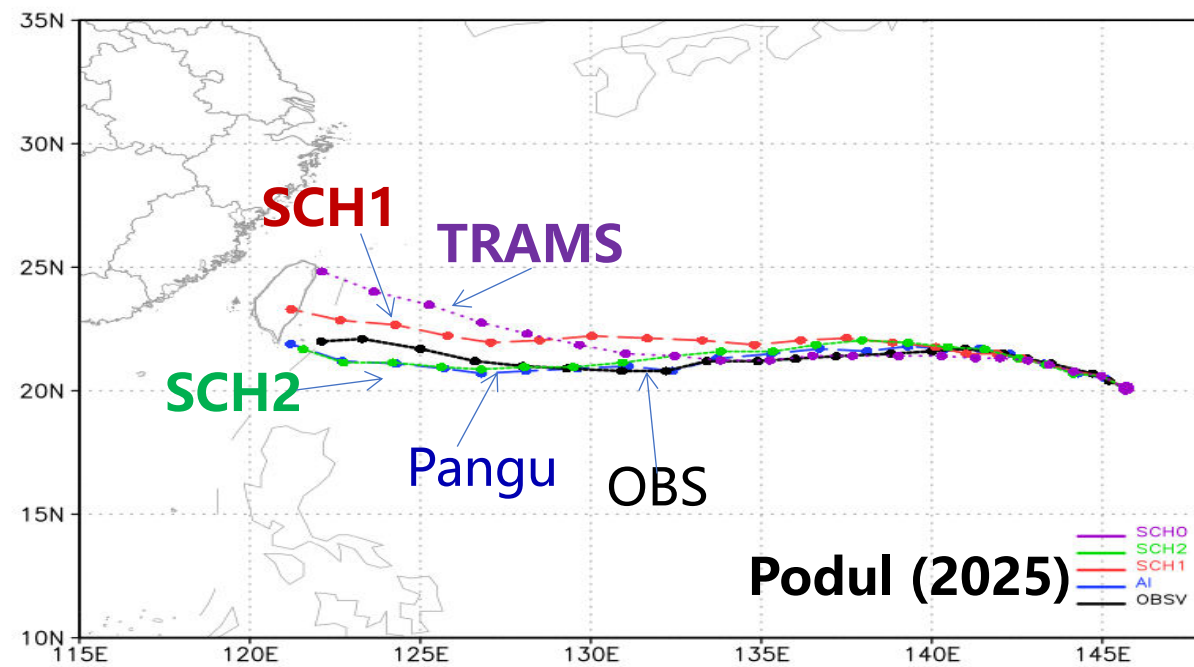
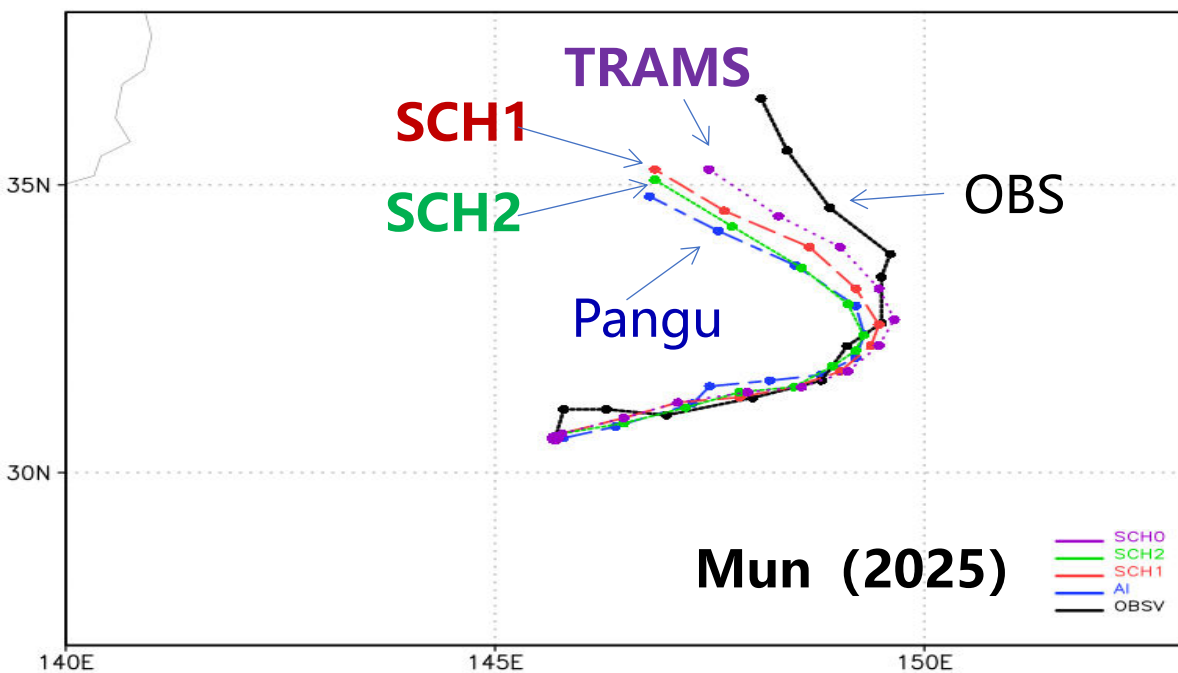


TS for 24-h accumulated rainfall above 50 mm from various experiments



Experimental results

- Introducing the tendency from Pangu (especially all of T, U, and V) can significantly improve TC track forecasting at longer valid times if Pangu model has better performance than CMA-TRAMS.





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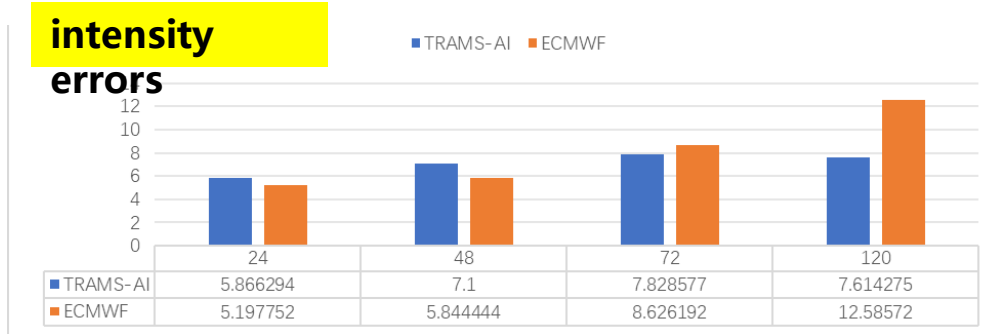
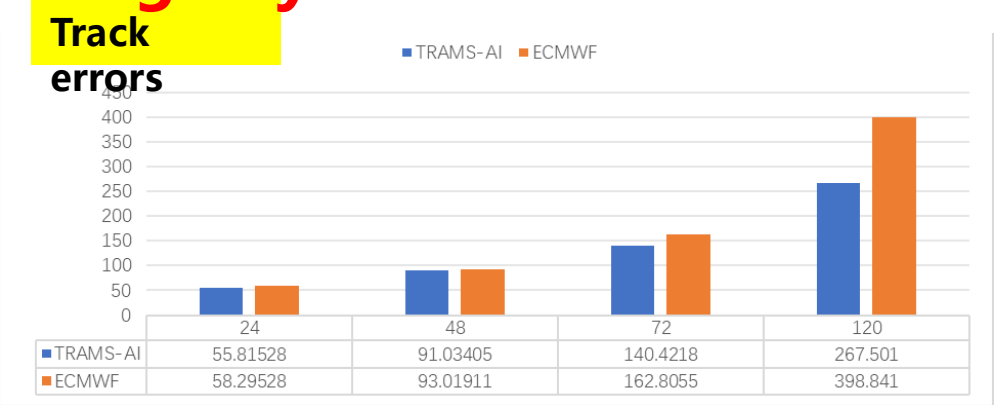
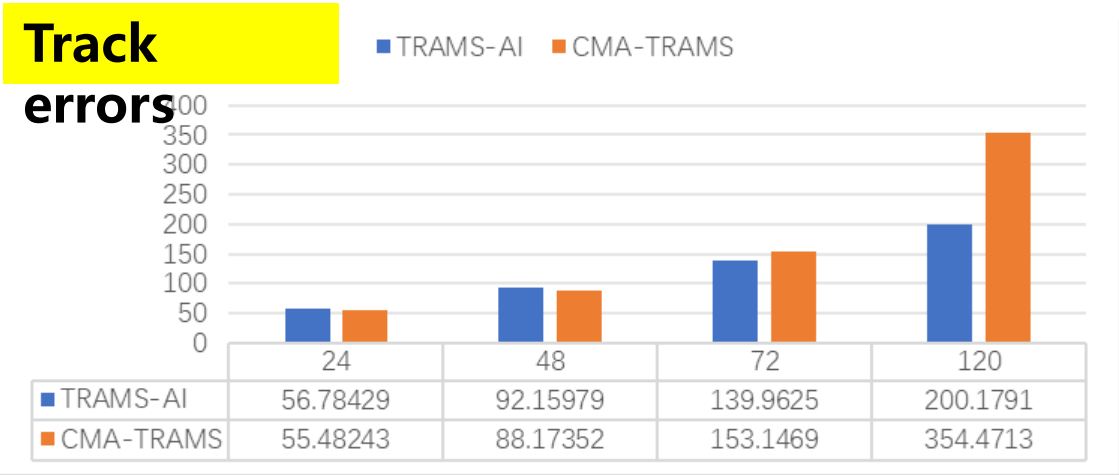
The pre-operational run

- The hybrid model (namely TRAMS-AI) of CMA-TRAMS and Pangu-weather has been in the pre-operational run since late May 2025.

Configuration: introducing the tendency of T from Pangu

Verification: TC cases in Jun-Sep 2025

Advantages: TC track and intensity forecasting beyond 72 h





Issues need further works

- Although the hybrid model shows some **advantages** in the **long-term** forecasting, it may **degrade** the **short-term** forecasting (especially in **intensity**).
- The forecast performance of hybrid model is **closely related to the Pangu forecasting** (especially introducing all of T, U, V).



Future planning

- I. Further experiments ***comparing SCH1 (only T tendency) with SCH2 (all of T, U, V tendency)*** in TC forecasting to select the better configuration of hybrid model.
- II. Improving the ***framework of hybrid model*** for further improvements.
- III. More experiments covering ***more TC cases***.



THANK YOU!