ASSESSMENT AND VERIFICATION OF ARTIFICIAL INTELLIGENCE MODELS ON TROPICAL CYCLONE FORESCASTING IN 2023

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BACKGROUND

FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators

A Preprint

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Abstract

FourCastNet, short for *Four*ier Fore*Cast*ing Neural *Net*work, is a global data-driven weather forecasting model that provides accurate short to medium-range global predictions at $0.25°$ resolution. FourCastNet accurately forecasts high-resolution, fast-timescale variables such as the surface wind speed, precipitation, and atmospheric water vapor. It has important implications for planning wind energy resources, predicting extreme weather events such as tropical cyclones, extra-tropical cyclones, and atmospheric rivers. FourCastNet matches the forecasting accuracy of the ECMWF Integrated Forecasting System (IFS), a state-of-the-art Numerical Weather Prediction (NWP) model, at short lead times for large-scale variables, while outperforming IFS for small-scale variables, including precipitation. FourCastNet generates a week-long forecast in less than 2 seconds, orders of magnitude faster than IFS. The speed of FourCastNet enables the creation of rapid and inexpensive large-ensemble forecasts with thousands of ensemble-members for improving probabilistic forecasting. We discuss how data-driven deep learning models such as FourCastNet are a valuable addition to the meteorology toolkit to aid and augment NWP models.

Keywords Numerical Weather Prediction · Deep Learning · Adaptive Fourier Neural Operator · Transformer

FourCastNet (NVIDIA)

Pangu-Weather: A 3D High-Resolution System for Fast and Accurate Global Weather Forecast

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Abstract—In this paper, we present Pangu-Weather, a deep learning based system for fast and accurate global weather forecast. For this purpose, we establish a data-driven environment by downloading 43 years of hourly global weather data from the 5th generation of ECMWF reanalysis (ERA5) data and train a few deep neural networks with about 256 million parameters in total. The spatial resolution of forecast is $0.25° \times 0.25°$, comparable to the ECMWF Integrated Forecast Systems (IFS). More importantly, for the first time, an AI-based method outperforms state-of-the-art numerical weather prediction (NWP) methods in terms of accuracy (latitude-weighted RMSE and ACC) of all factors (*e.g.*, geopotential, specific humidity, wind speed, temperature, *etc.*) and in all time ranges (from one hour to one week). There are two key strategies to improve the prediction accuracy: (i) designing a 3D Earth Specific Transformer (3DEST) architecture that formulates the height (pressure level) information into cubic data, and (ii) applying a hierarchical temporal aggregation algorithm to alleviate cumulative forecast errors. In deterministic forecast, Pangu-Weather shows great advantages for short to medium-range forecast (*i.e.*, forecast time ranges from one hour to one week). Pangu-Weather supports a wide range of downstream forecast scenarios, including extreme weather forecast (*e.g.*, tropical cyclone tracking) and large-member ensemble forecast in real-time. Pangu-Weather not only ends the debate on whether AI-based methods can surpass conventional NWP methods, but also reveals novel directions for improving deep learning weather forecast systems.

Index Terms—Numerical Weather Prediction, Deep Learning, Medium-range Weather Forecast.

1 Introduction

Weather forecast is one of the most important scenarios of scientific computing. It offers the ability of predicting future weather changes, especially the occurrence of extreme weather events (*e.g.*, floods, droughts, hurricanes, *etc.*), which has large values to the society (*e.g.*, daily activity, agriculture, energy production, transportation, industry, *etc.*). In the past decade, with the bloom of high-performance computational device, the community has witnessed a rapid development in the research field of numerical weather prediction (NWP) [1]. Conventional NWP methods mostly follow a simulation-based paradigm which formulates the physical rules of atmospheric states into partial differentiable equations (PDEs) and solves them using numerical simulations [2], [3], [4]. Due to the high complexity of solving PDEs, these NWP methods are often very slow, *e.g.*, with a spatial resolution of $0.25° \times 0.25°$, a single simulation procedure for 10-day forecast can take hours of computation using hundreds of nodes in a supercomputer [5]. This largely reduces the timeliness in daily weather forecast and the number of ensemble members that can be used for probabilistic weather forecast. In addition, conventional NWP algorithms largely rely on the parametric numerical models, but these models, albeit being very complex [1], are often considered inadequate [6], [7], *e.g.*, errors will be introduced by parameterization of unresolved processes.

To address the above issues, a promising direction lies in data-driven weather forecast with AI, in particular, deep learning[1]. The methodology is to use a deep neural network to capture the relationship between the input (observed data) and output (target data to be predicted). On specialized computational device (*e.g.*, GPUs), AI-based methods run very fast and easily achieve a tradeoff between model complexity, prediction resolution, and prediction accuracy [9], [10], [11], [12], [13], [14], [15]. As a recent example, FourCastNet [14] increased the spatial resolution to $0.25° \times 0.25°$, comparable to the ECMWF Integrated Forecast Systems (IFS), yet it takes only 7 seconds on four GPUs for making a 100-member, 24-hour forecast, which is orders of magnitudes faster than the conventional NWP methods. However, the forecast accuracy of FourCastNet is still below satisfaction, *e.g.*, the RMSE of 5-day Z500 forecast using a single model and a 100-member ensemble are 484.5 and 462.5, respectively, which are much worse than 333.7 reported by operational IFS of ECMWF [16]. In [8], researchers conjectured that 'a number of fundamental breakthroughs are needed' before AI-based methods can beat NWP.

The breakthrough comes much earlier than they thought. In this paper, we present Pangu-Weather, a powerful AI-based weather forecast system that, **for the first time**, surpasses existing NWP methods (and, of course, AI-based methods) in terms of prediction accuracy of all factors. The test is performed on the 5th generation of ECMWF reanalysis (ERA5) data. We download 43 years (1979–2021) of global weather data, among which we use the 1979–2017 data for training, the 2019 data for validation, and the 2018,

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1. Throughout this paper, we will use 'conventional NWP' or simply 'NWP' to refer to the numerical simulation methods, and use 'AI-based' or 'deep learning based' to specify data-driven forecast systems. We understand that, verbally, AI-based methods also belong to NWP, but we follow the convention [8] to use these terms.

Pangu-Weather (Huawei)

GraphCast: Learning skillful medium-range global weather forecasting

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[*]equal contribution, [1]DeepMind, [2]Google

We introduce a machine-learning (ML)-based weather simulator—called "GraphCast"—which outperforms the most accurate deterministic operational medium-range weather forecasting system in the world, as well as all previous ML baselines. GraphCast is an autoregressive model, based on graph neural networks and a novel high-resolution multi-scale mesh representation, which we trained on historical weather data from the European Centre for Medium-Range Weather Forecasts (ECMWF)'s ERA5 reanalysis archive. It can make 10-day forecasts, at 6-hour time intervals, of five surface variables and six atmospheric variables, each at 37 vertical pressure levels, on a 0.25° latitude-longitude grid, which corresponds to roughly 25×25 kilometer resolution at the equator. Our results show GraphCast is more accurate than ECMWF's deterministic operational forecasting system, HRES, on 90.0% of the 2760 variable and lead time combinations we evaluated. GraphCast also outperforms the most accurate previous ML-based weather forecasting model on 99.2% of the 252 targets it reported. GraphCast can generate a 10-day forecast (35 gigabytes of data) in under 60 seconds on Cloud TPU v4 hardware. Unlike traditional forecasting methods, ML-based forecasting scales well with data: by training on bigger, higher quality, and more recent data, the skill of the forecasts can improve. Together these results represent a key step forward in complementing and improving weather modeling with ML, open new opportunities for fast, accurate forecasting, and help realize the promise of ML-based simulation in the physical sciences.

Keywords: Weather forecasting, ECMWF, ERA5, HRES, learning simulation, graph neural networks

1. Introduction

Every day, people factor in the upcoming weather when they plan what they do, from deciding which jacket to wear, to deciding whether to flee a hurricane. When these decisions involve anticipating the weather over the next ten days, people rely on "medium-range" weather forecasts, which are provided up to four times a day by weather bureaus, such as the European Centre for Medium-Range Weather Forecasts (ECMWF), the US's National Oceanic and Atmospheric Administration, and the UK Met Office. Here we show that weather forecasting based on machine learning (ML) can rival the approaches these bureaus have traditionally used.

Medium-range weather forecasts are generated by simulations run on large high-performance computing (HPC) clusters, and involve two main components. The first component is "data assimilation", which is the process of inferring and tracking the weather, based on recent and past observations from satellites, weather stations, ships, etc. The resulting output of data assimilation is an estimate of the most recent sequence of weather states, termed "analysis". The second is a forecast model, traditionally based on "numerical weather prediction" (NWP), which predicts the future temporal evolution of variables that represent the state of the weather. These two components are closely

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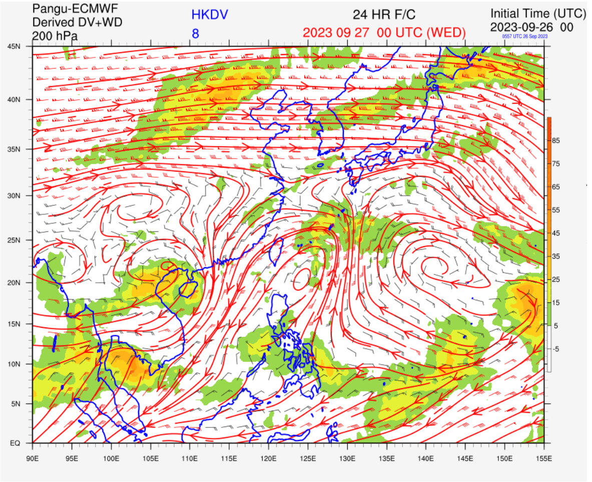
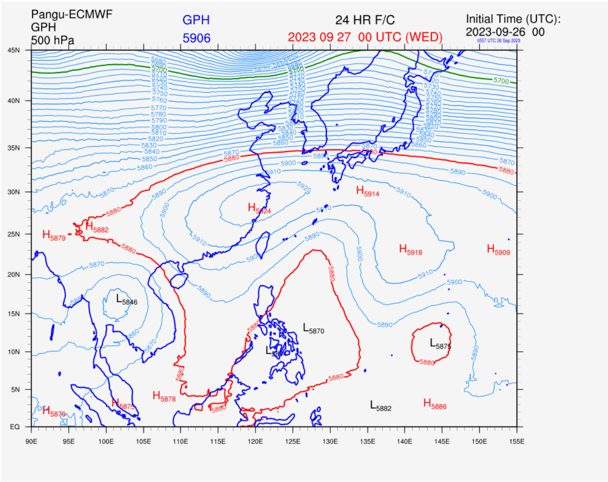
GraphCast (DeepMind/Google)

BACKGROUND

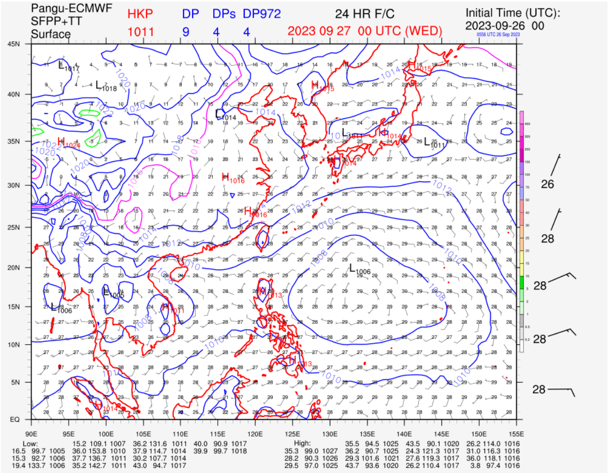
- In the past one or two years, breakthroughs have been made in using big data and artificial intelligence (AI) models to generate medium-range weather forecasts. Several academic articles indicate that the forecasting skill of AI models could match or exceed those of traditional global numerical weather prediction (NWP) models.
- Purely data-driven weather forecast models do not necessarily guarantee physical consistency of forecast results. Can these machine learning-based models give physically consistent and meteorologically meaningful forecasts?
- AI models may output highly optimized predictions or maybe similar to post-processing products from traditional models. For longer-term forecasts, the prediction of AI models tends to become smoother, similar to the ensemble average of ensemble forecasts.
- Based on the latest development of AI models, this presentation introduces the real-time operation of AI models tested by HKO, as well as the evaluation and verification of AI models in tropical cyclone (TC) forecasting.

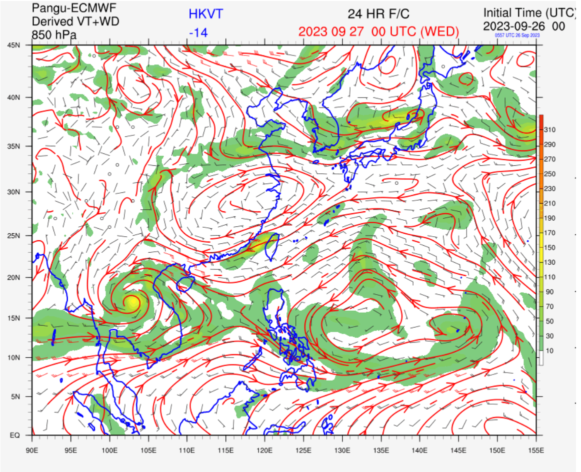
STARTING FROM MID-2023, HKO BEGAN INTERNAL TRIALS OF REAL-TIME OPERATION OF ARTIFICIAL INTELLIGENCE MODELS SUCH AS "PANGU WEATHER" AND "FENGWU" TO ASSIST IN FORECASTING OPERATIONS.

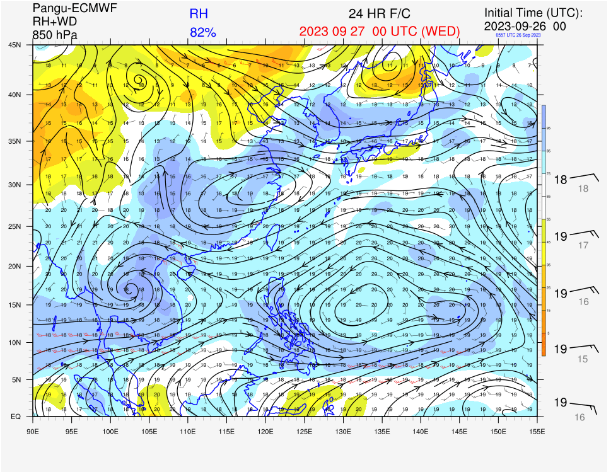




- The initial conditions of the AI models were based on the operational analysis of traditional global NWPs, respectively from DWD, ECCC, ECMWF, NCEP and MeteoFrance.







- The outputs based on AI models are visually quite similar to those of traditional models.

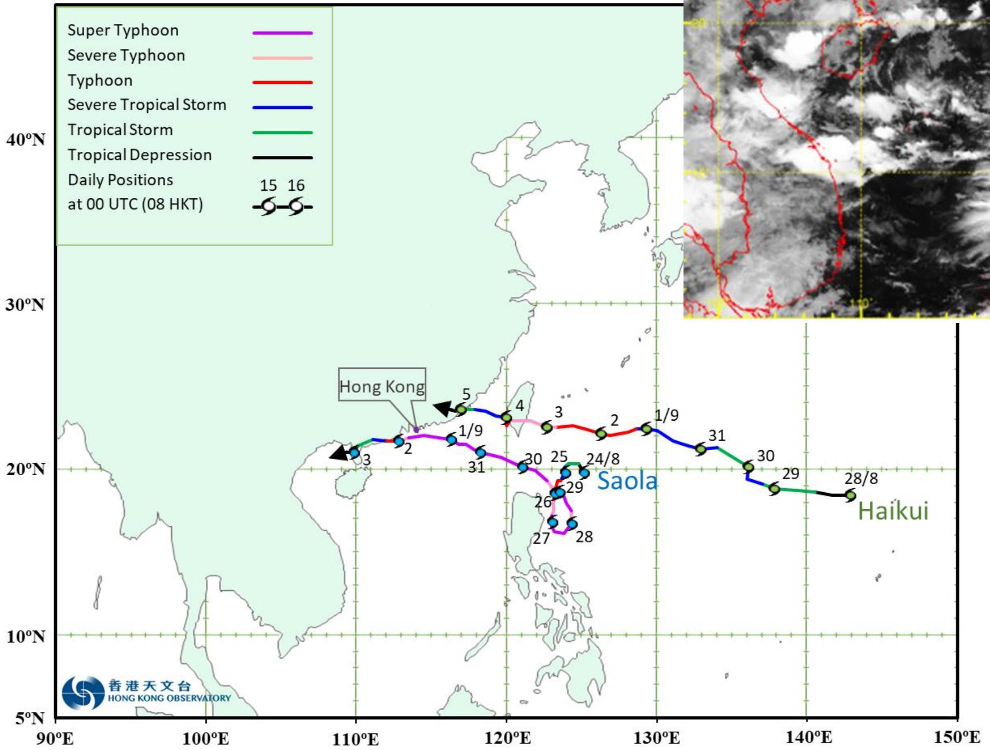
- Bi, K.; Xie, L.; Zhang, H.; Chen, X.; Gu, X.; Tian, Q. Accurate medium-range global weather forecasting with 3D neural networks. Nature 2023, 619, 533–538.
- Chen, K.; Han, T.; Gong, J.; Bai, L.; Ling, F.; Luo, J.-J.; Chen, X.; Ma, L.; Zhang, T.; Su, R.; et al. FengWu: Pushing the Skillful Global Medium-range Weather Forecast beyond 10 Days Lead. arXiv 2023.

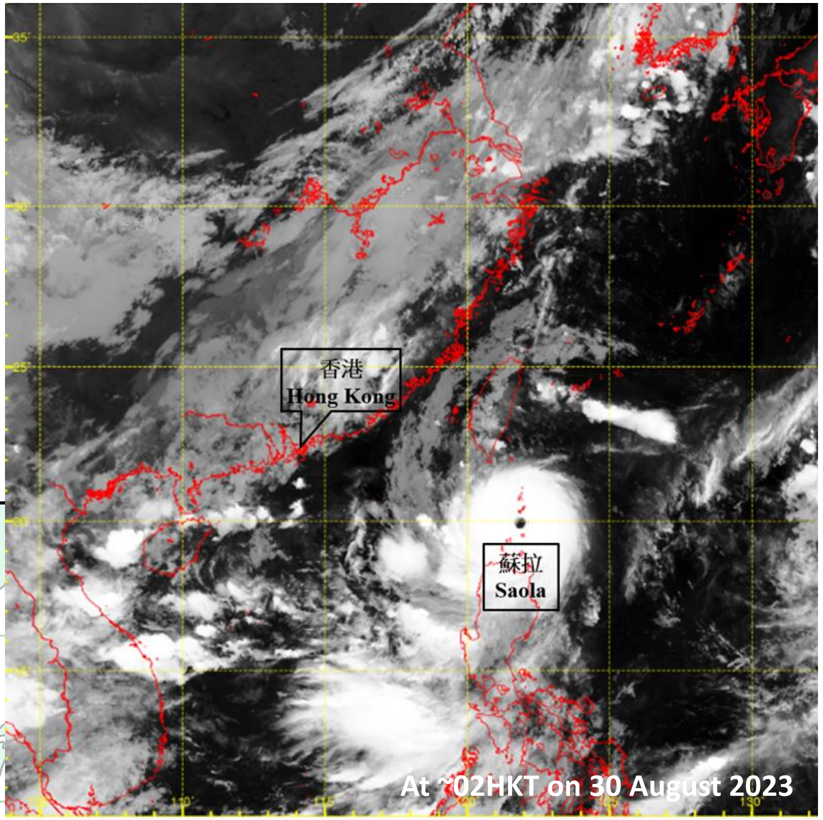
CASE STUDY

SUPER TYPHOON SAOLA (2309)

- September 2023 was an eventful month in Hong Kong with the ferocious strike by Super Typhoon Saola on 1 – 2 September and the phenomenal rainstorm on 7 – 8 September.
- Saola necessitated the issuance of the Hurricane Signal No. 10 again since Super Typhoon Mangkhut hitting Hong Kong in 2018.
- Saola entered the South China Sea later on 30 August while maintaining an estimated maximum sustained wind of 230 km/h near its centre, making it the second strongest tropical cyclone in the South China Sea since the Observatory's records began in 1950.

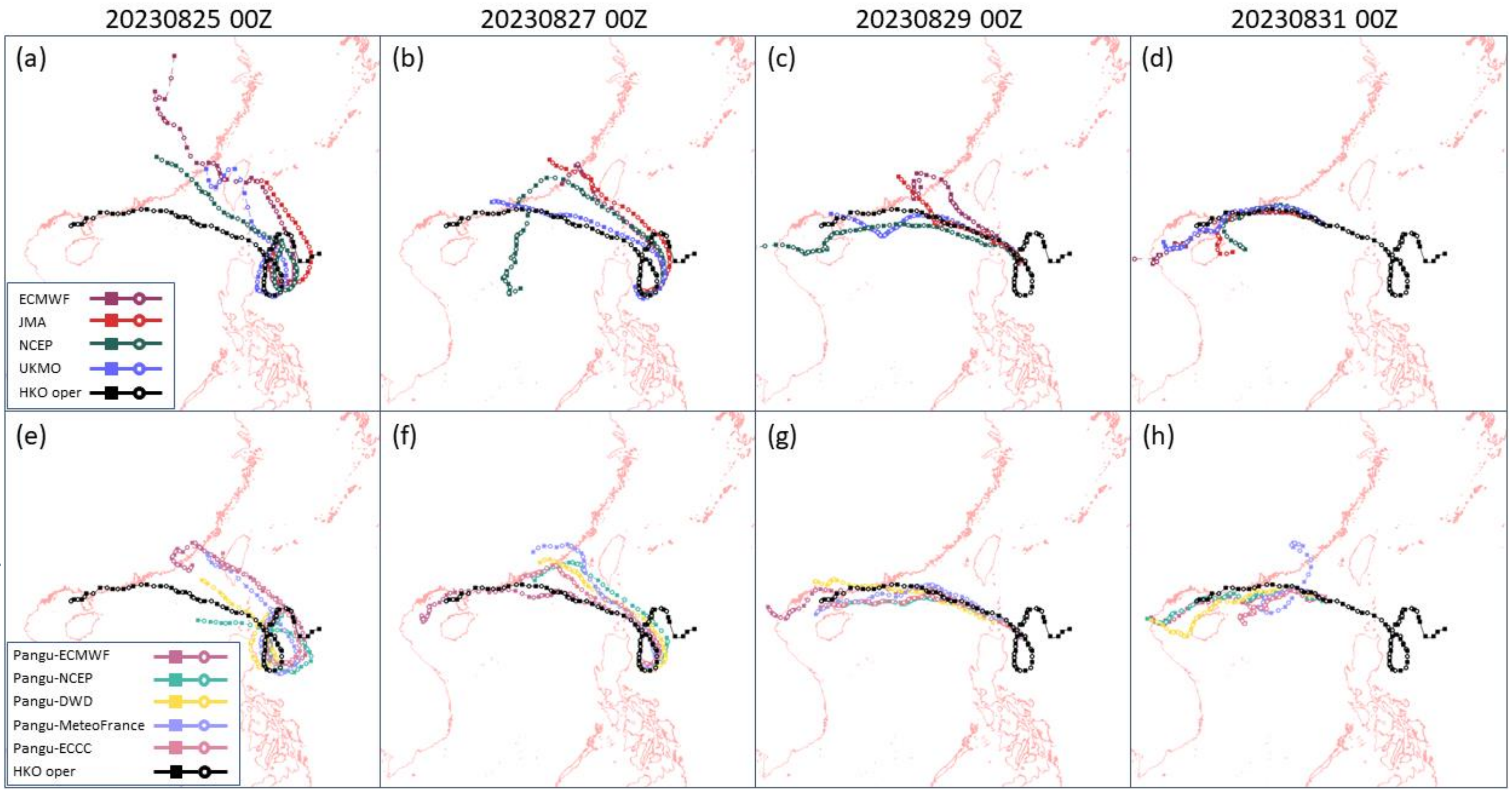

On the morning of 1 September





Traditional NWP models

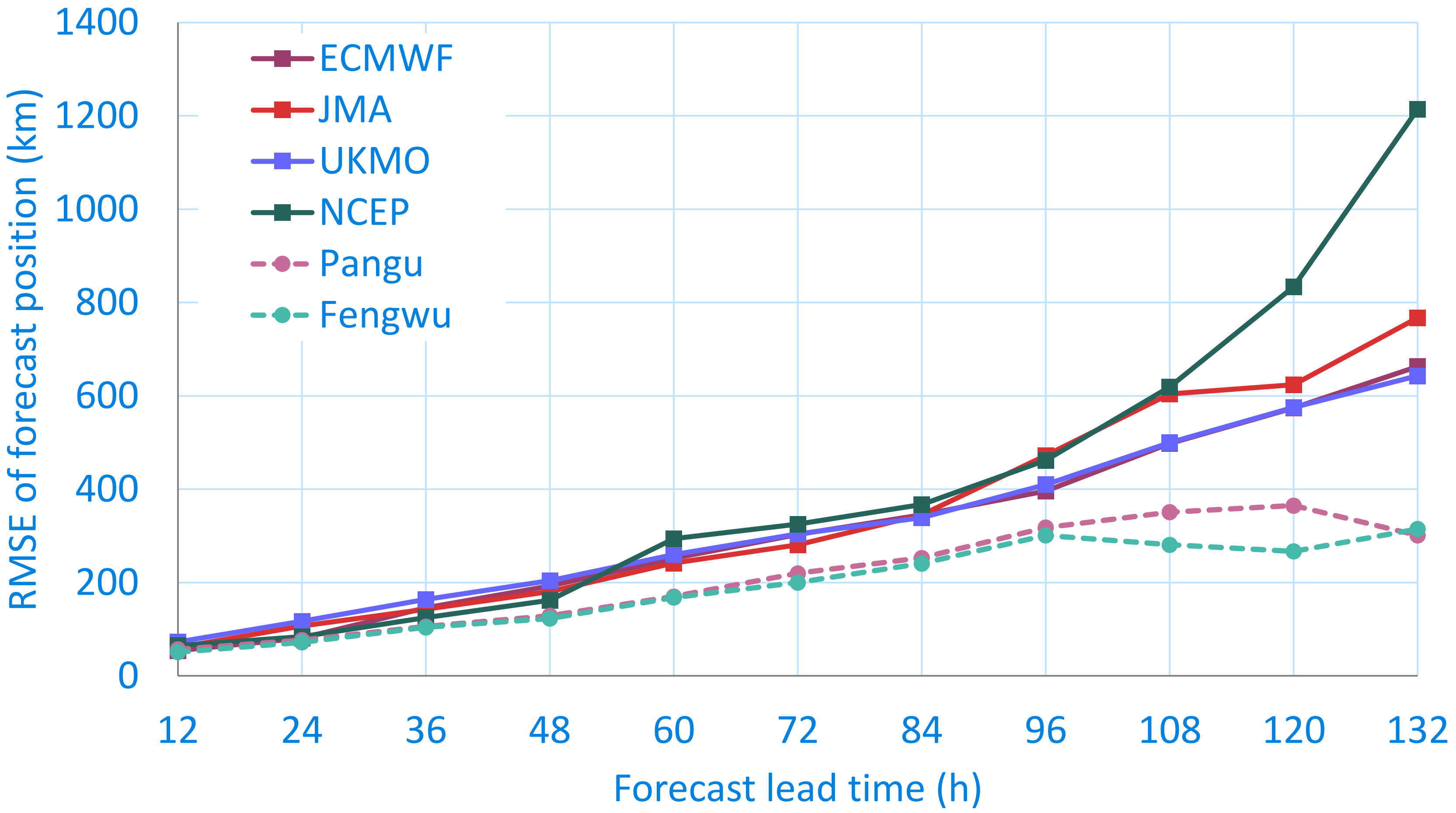
Pangu-Weather



- Some earlier "Pangu" forecasts suggested that Saola would move across the northeastern part of the South China Sea.
- As of the forecasts initialized at 00UTC on 29 Aug, the "Pangu" models converged earlier than traditional models, although the forecasts were slightly southwards.
- However, for the run initialized at 00UTC on 31 Aug, the "Pangu" models once again diverged, and the short-term forecast errors were larger than those of the traditional models.

Chan, P.W.; He, Y.H.; Lui, Y.S. Super Typhoon Saola (2309) affecting Hong Kong in September 2023–Forecasting Aspect. Preprints 2023, 2023091634. https://doi.org/10.20944/preprints202309.1634.v1

TROPICAL CYCLONE TRACK FORECAST ERRORS



The data include the following TCs in 2023: Saola (2309), Haikui (2311), Kirogi (2312), Yun-yeung (2313), a tropical depression in the central South China Sea (Sep 2023), Koinu (2314) , Bolaven (2315), Sanba (2316).

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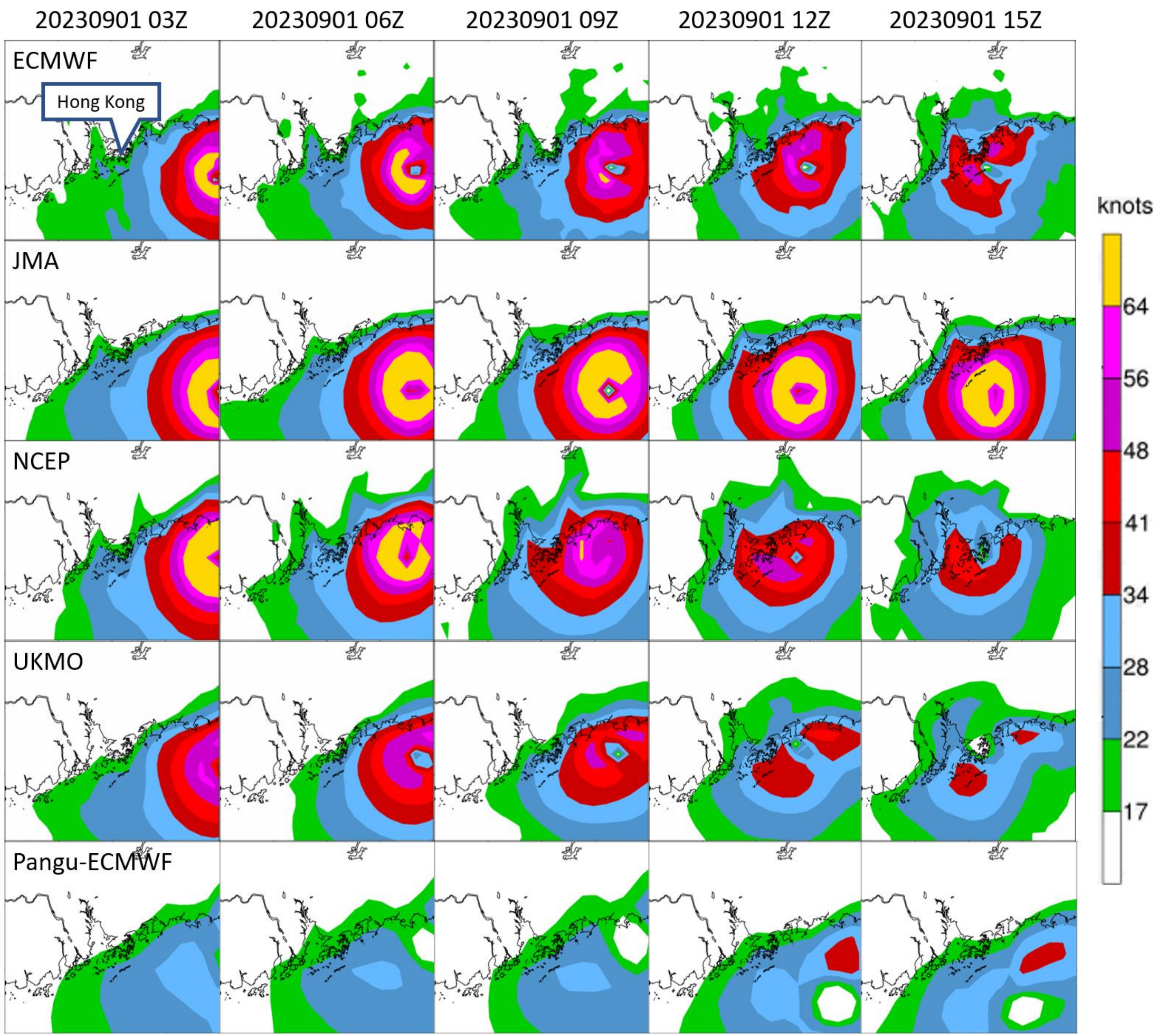
CASE STUDY

SUPER TYPHOON SAOLA (2309)

- The panel on the right shows the 10-meter wind speed predicted by the model as Saola approached Hong Kong, with the hurricane shown in yellow, based on short-term forecast initialized at 12UTC on 31 Aug.
- Many places in Hong Kong, including Waglan Island, Cheung Chau, Green Island, Stanley, Ngong Ping and Tate's Cairn, have been affected by the hurricane force winds.
- The wind forecast output by the "Pangu" model was significantly weaker and failed to capture the wind structure of Saola.



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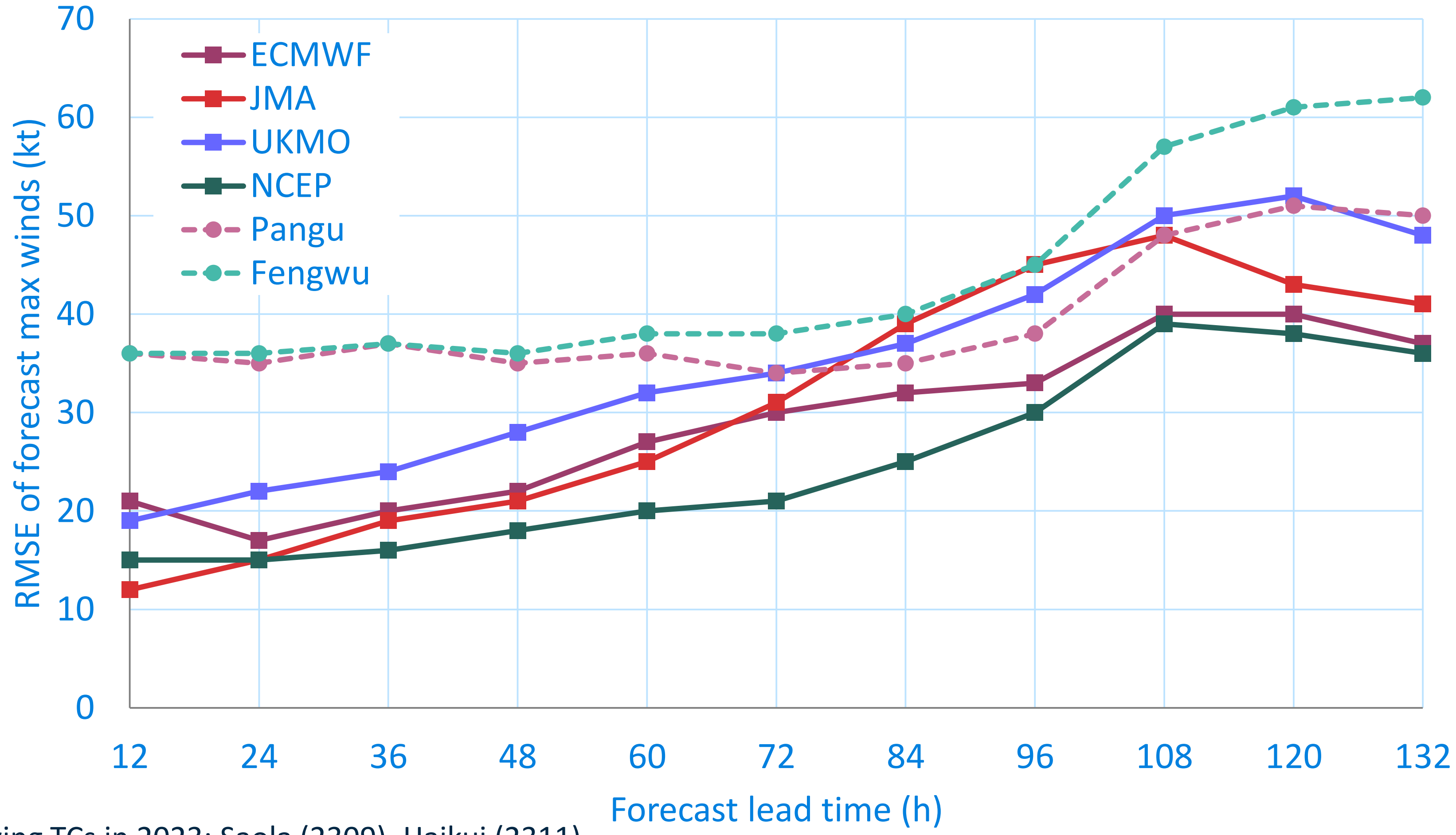
TROPICAL CYCLONE INTENSITY FORECAST ERRORS



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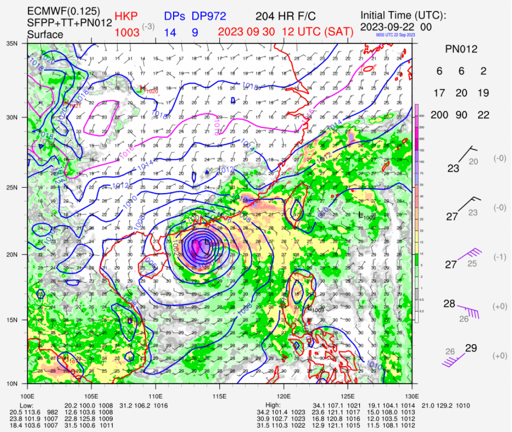
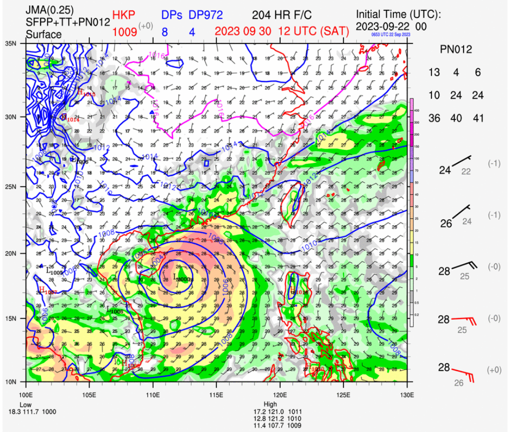
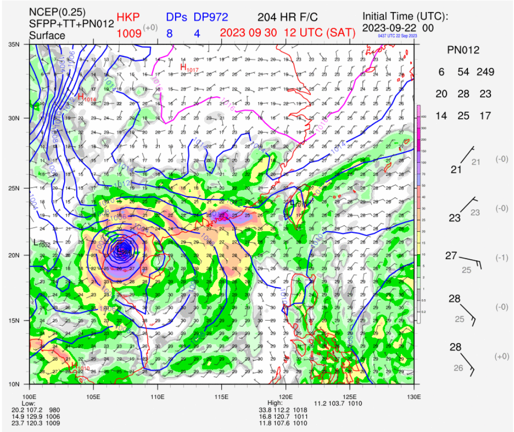
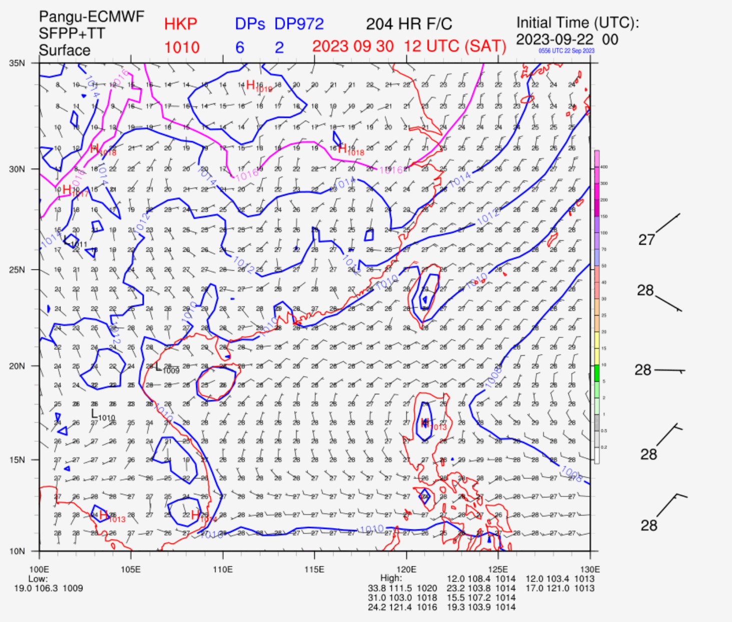
CASE STUDY ： CYCLOGENESIS

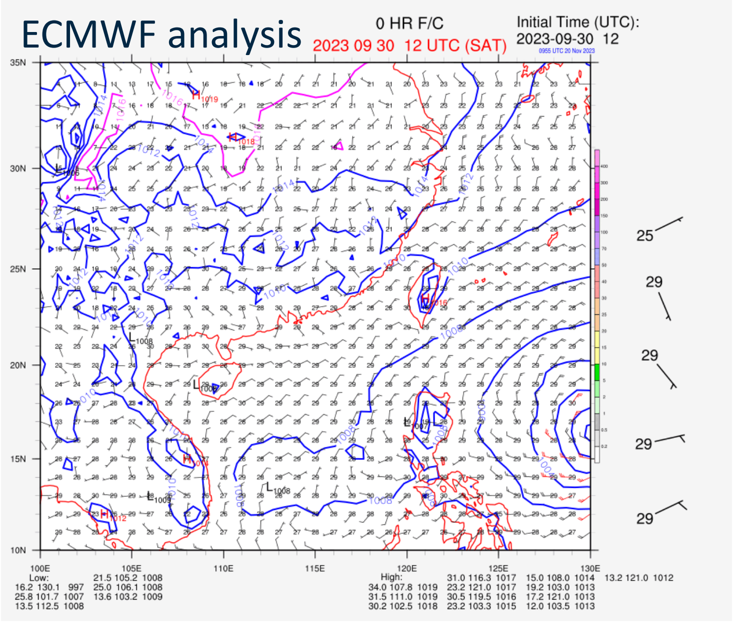
- According to early predictions from major traditional NWP models, a potential TC would form during the Mid-Autumn Festival (29-30 Sep 2023) and affect the northern part of the South China Sea.
- At last, predictions of TC genesis came to nothing.
- The AI model correctly predicted no TC formation.











Summary and Outlook

- In the past one or two years, a new generation of AI models has shown great promise in weather forecasting, especially TC forecasting.
- Although AI models have an edge over traditional NWPs in TC track forecast, TC intensity prediction remains a big challenge.
- Current AI models fail to output key variables such as precipitation, and the spatiotemporal resolution of the output products is still relatively rough.
- Further research and collaboration in exploring the utilization of AI models together with traditional NWP models could improve TC forecasting and early warning capabilities as well as support more effectively TC operational decisions.

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