Assessment of western North Pacific tropical cyclone genesis in the AI models

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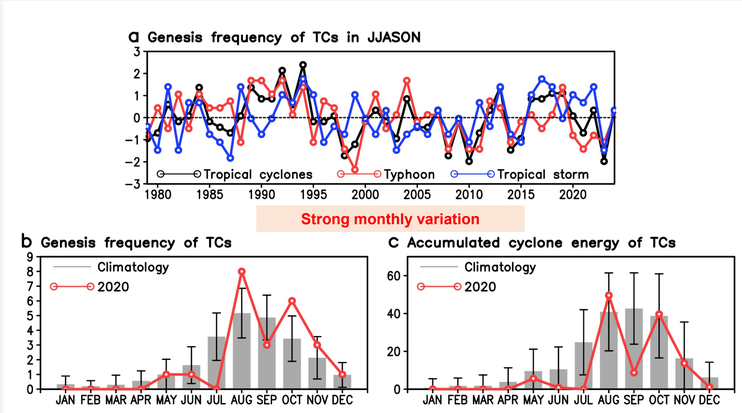
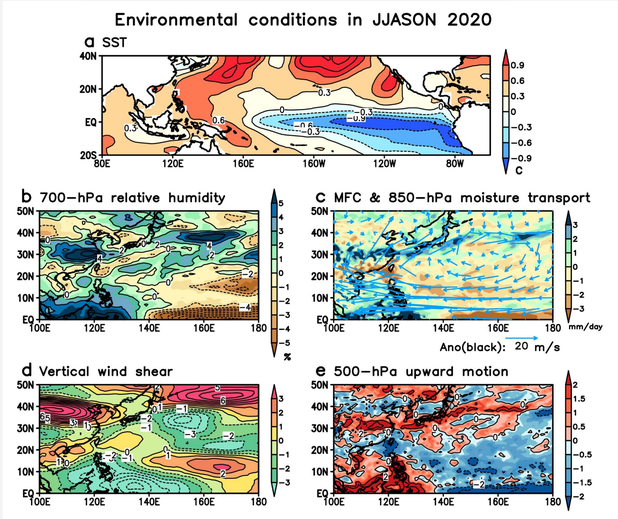
1. Introduction

- In recent years, advances in AI-based weather prediction models have led to notable improvements in forecasting major meteorological variables traditionally simulated by dynamical models. A particularly remarkable enhancement has been observed in the prediction of tropical cyclone (TC) tracks, which are strongly influenced by the surrounding environmental flows. Liu et al., (2024) comparing TC track forecasts from state-of-the-art AI systems—Pangu-Weather, FourCastNet, GraphCast, FuXi, and FengWu—suggested that improved representation of large-scale environmental flows significantly contributes to enhanced TC track prediction.
- Compared to the ECMWF's IFS, a conventional dynamical model, AI-based models appear to correct environmental steering flows more rapidly, resulting in earlier improvements in track forecasts. Despite these advances, AI models still tend to underestimate TC intensity and associated precipitation. Thus, a comprehensive evaluation of not only track, intensity, and rainfall, but also genesis skill, is essential. TC genesis in the western North Pacific (WNP) is strongly linked to the variability of the WNP subtropical high and the monsoonal flows.
- To address this, we adopt the Okubo–Weiss Zeta Parameter (OWZP) TC tracking method (Tory et al., 2013a,b) to assess the 2020 WNP TC genesis performance using AI models—GraphCast and Pangu-Weather—trained on 0.25° ERA5 reanalysis data provided by WeatherBench2. The performance in reproducing TC genesis in the AI models initialized with both ERA5 reanalysis and IFS analysis data, will be further evaluated against the International Best Track Archive for Climate Stewardship (IBTrACS).



- The year 2020 was historically notable as no TC formed in July, likely due to strong warming over the equatorial Indian Ocean, while TC genesis was active in August and October. The absence of tropical cyclone formation in July 2020, which is the first time in available historical records, was attributed to the tropical Indian Ocean warming (Wang et al., 2021).

La Nina and Indian ocean warming in 2020



2. Data and Method

Data

- Best track dataset : IBTrACS v4r01 (Knapp et al., 2010)
- Environmental datasets: ERA5 reanalysis (Hersbach et al., 2020), ERSSTv5
- Model datasets:

WeatherBench 2 (Rasp et al, 2020, 2024)

Dynamic model	AI models			
IFS HRES (ECMWF)	Pangu-Weather (Bi et al., 2023)	Pangu-Weather (operational)	GraphCast (Lam et al., 2023)	GraphCast (operational)

TC Tracking method: OWZP tracking scheme

(Tory et al., 2013a,b; Raavi and Walsh, 2020; Yeasmin et al., 2021)

The OWZ parameter is defined as follows:

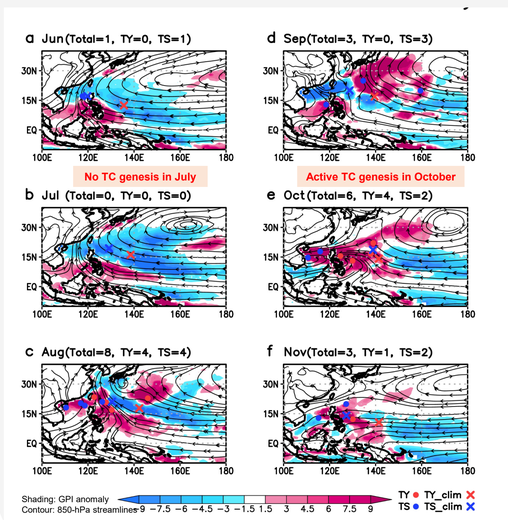
$$\mathrm{OWZ} = \max(\mathrm{OW}_{\mathrm{norm}}, 0) \times (\zeta + f) \times \mathrm{sign}(f)$$

$\mathrm{Ow}_{\mathrm{norm}}$: the normalized Okubo-Weiss parameter, ζ the relative vorticity, f the planetary vorticity, ζ + f the absolute vorticity

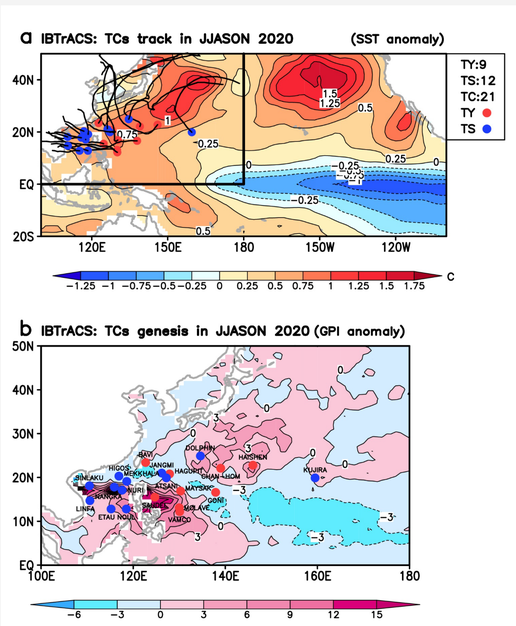
Parameters	Initial	Core
OWZ850	$50\times10^{-6}s^{-1}$	$60\times10^{-6}s^{-1}$
OWZ500	$40\times10^{-6}s^{-1}$	$50\times10^{-6}s^{-1}$
RH975	70%	85%
RH700	50%	70%
VWS	$25\ m\ s^{-1}$	$12.5\ m\ s^{-1}$
SH950	$10\ g\ kg^{-1}$	$14\ g\ kg^{-1}$

3. Observation

850-hPa streamline and anomalous GPI in 2020



- Genesis potential index (GPI) (Murakami and Wang, 2010)

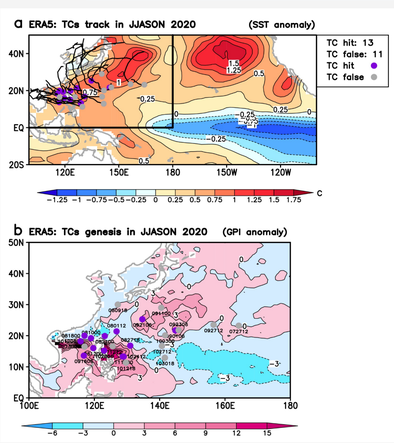


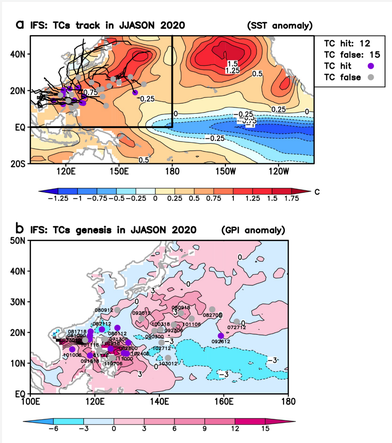
2020 tropical cyclones list (June–November)

Genesis time (UTC)	Name	Lon	Lat	MSW (kt)	ACE (kt^2)	Translation speed ($m\ s^{-1}$)
2020061212	NURI	117.60	17.10	40	8100	5.80
2020080100	SINLAKU*	110.50	18.10	40	8950	4.90
2020080106	HAGUPIT	127.90	20.80	70	39500	5.50
2020080818	JANGMI*	126.20	21.00	45	15350	13.70
2020081000	MEKKHALA	118.60	19.10	50	9375	6.70
2020081800	HIGOS	116.90	20.30	55	12400	5.70
2020082200	BAVI	122.70	23.40	85	95900	4.60
2020082806	MAYSAK	130.30	16.90	95	137725	5.50
2020083112	HAISHEN	146.00	22.80	105	176800	6.00
2020091518	NOUL	118.50	12.80	45	19775	7.00
2020092100	DOLPHIN	134.60	24.90	60	33775	4.70
2020092618	KUJIRA*	159.50	19.90	60	33775	9.40
2020100500	CHAN-HOM	139.00	22.10	70	82225	3.90
2020101018	LINFA*	110.60	14.70	45	4475	5.00
2020101206	NANGKA	115.90	17.80	45	15350	5.90
2020102000	SAUDEL	124.70	15.50	65	59225	4.10
2020102406	MOLAVE	130.00	13.10	90	85875	6.80
2020102818	GONI	137.90	16.60	120	148850	4.60
2020110218	ATSANI*	127.20	19.90	50	37425	3.70
2020110818	ETAU*	115.20	12.80	45	10500	5.40
2020110912	VAMCO	130.10	12.20	85	89125	5.40

- * is the missing alarm in both reanalysis and analysis

4. Detected TCs

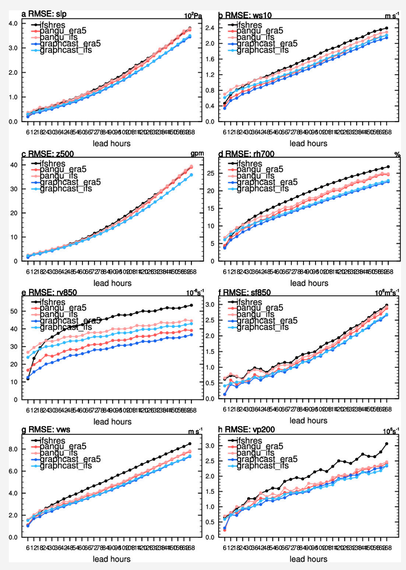




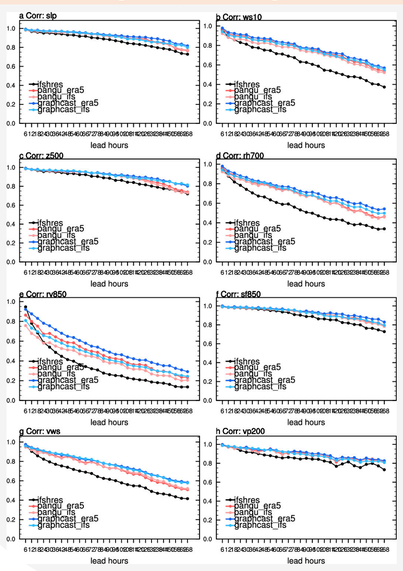
ERA5	Genesis time (UTC)	Lon	Lat	Alarm	Distance(km)
1	2020061200	119.7	16.0	Hit(NURI)	240.82 km
2	2020071212	125.6	16.6	False	
3	2020072712	164.2	23.2	False	
4	2020073006	117.0	16.5	False	
5	2020080112	126.8	21.4	Hit(HAGUPIT)	128.87 km
6	2020080918	127.2	30.0	False	
7	2020081000	119.0	19.2	Hit(MEKKHALA)	18.77 km
8	2020081800	117.0	20.0	Hit(HIGOS)	218.89 km
9	2020082100	123.2	19.9	Hit(BAVI)	218.89 km
10	2020082718	131.0	16.8	Hit(MAYSAK)	78.19 km
11	2020090106	144.8	21.7	Hit(HAISHEN)	167.20 km
12	2020091100	140.5	29.0	False	
13	2020091606	116.8	13.6	Hit(NOUL)	193.54 km
14	2020092106	134.7	25.3	Hit(DOLPHIN)	33.19 km
15	2020092306	145.8	21.8	False	
16	2020092712	156.5	23.5	False (KUJIRA)	499.12 km
17	2020100300	141.7	20.1	False (CHAN-HOM) too early	345.70 km
18	2020101206	115.8	18.2	Hit(NANGKA)	22.36 km
19	2020101218	129.7	11.3	False	
20	2020102006	123.0	15.2	Hit(SAUDEL)	190.00 km
21	2020102412	128.7	13.3	Hit(MOLAVE)	145.28 km
22	2020102712	140.7	16.7	False (GONI) too early	311.55 km
23	2020103018	141.6	12.9	False	
24	2020111000	129.0	13.3	Hit(VAMCO)	145.04 km

5. Model performance

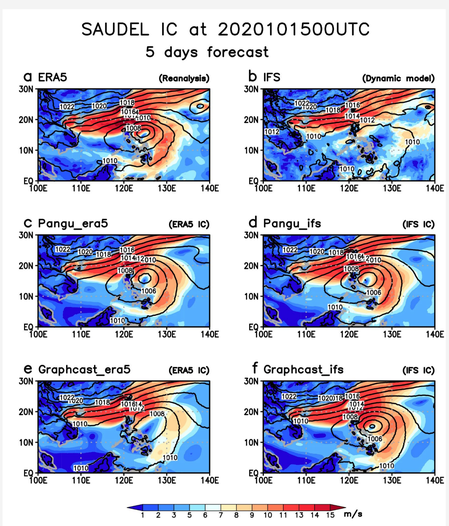
Performance over the globe in October

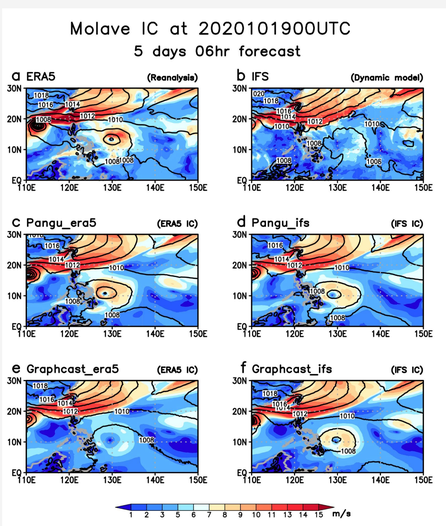


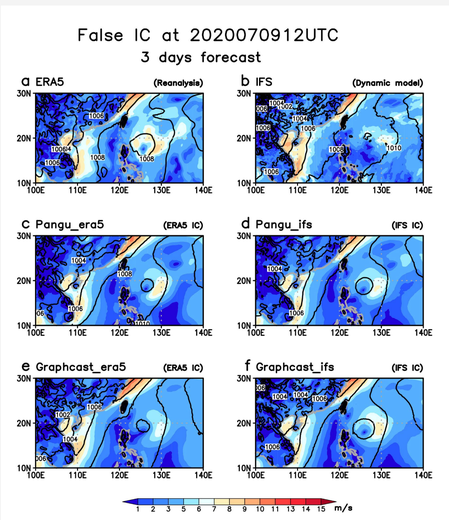
Performance over the TC main formation region in the WNP [5-30N, 100-180E] in October

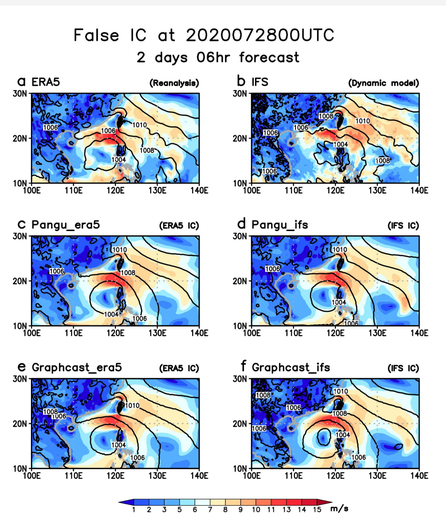


- Recent advances in AI-based weather forecast models outperform the dynamical model (IFS) in predicting the WNP TC genesis.
- Compared to AI models, the performance of IFS for environmental variables related to TC genesis such as vertical wind shear, 850-hPa relative vorticity, and 700-hPa relative humidity reduces more rapidly over time.









10-m wind speed (shading) and sea level pressure (contour)

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