Global tropical cyclone size and intensity reconstruction dataset for 1959–2022 based on IBTrACS and ERA5 data

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Abstract. Tropical cyclones (TCs) are powerful weather systems that can cause extreme disasters. ~~We extensively utilize The~~ ~~t~~The International Best Track Archive for Climate Stewardship (IBTrACS) dataset provides the ~~extensively accessed~~widely used data ~~has been~~are~~is used extensively~~ to estimate TC climatology. However, it has low data coverage, lacking intensity and outer size data for more than half of all recorded storms, and is therefore insufficient as a reference for researchers and decision makers. To fill this data gap, we reconstruct~~ed~~ a long-term TC dataset by integrating IBTrACS and European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA5) data. This reconstructed~~new~~ dataset covers the period 1959–2022, with 3 h temporal resolution. Compared to the IBTrACS dataset, it contains approximately 3–4 times more data points per characteristic. We establish~~ed~~ machine learning models to estimate the maximum sustained wind speed (V_{max}) and radius ~~to~~ of maximum wind~~ speed~~ (R_{max}) in six basins for which TCs ~~were~~ are generated, using ERA5-derived 10 m azimuthal ~~median~~ mean azimuthal wind profiles as input, with V_{max} and R_{max} data from the IBTrACS dataset used as learning target~~training~~ data. Furthermore, we employ ~~An~~ an empirical wind–pressure relationship and six wind profile models~~ were are employed~~ to estimate the minimum central pressure (P_{min}) and outer size of the TCs, respectively. Overall, this high-resolution TC reconstruction dataset demonstrates~~d~~ global consistency with observations, exhibiting mean biases of <1% for V_{max} and 3% for R_{max} and P_{min} in almost all basins. The ~~new~~ dataset is publicly available from https://doi.org/10.5281/zenodo.13919874 ~~10.5281/zenodo.12740372~~ (Xu et al., 2024) and substantial~~significantly~~ly advances our understanding of TC climatology, thereby facilitating risk assessments and defenses against TC-related disasters.

1. Introduction

Tropical cyclones (TCs) are powerful~~formidable~~ weather systems accompanied by gale winds, ~~torrential~~ heavy rainstorms, substantial~~significant~~ waves, and ~~devastating~~ severe storm surges, which cause extensive damage in affected regions (Gray, 1968). During the 2003-2022 period, the global average of ~~tropical cyclone~~TCs ~~was~~is 104 annually, resulting in estimated annual economic losses of 95.6 billion US dollars and affecting ~~over~~more than 3.2 million individuals ~~people~~ ~~During the past two decades, TCs have resulted in an average annual economic loss of 29 billion~~ US ~~dollars, affecting more than 22 million individuals~~ (~~Guha-Sapir~~CRED, ~~2017~~2023; Geiger et al., 2018). Given the considerable scale and frequency of TC-related disasters, a comprehensive understanding of TC climatology is essential for effective risk assessment, emergency planning, and community resilience enhancement.

TCs are typically characterized according to their intensity, size, location, and translation speed (Weber et al., 2014). Many studies have reported increasing TC intensity at both the basin and global scales under global warming (e.g., Webster et al., 2006; Gualdi et al., 2008; Wu et al., 2022). Vincent et al. (2014) ~~detect~~detectsed~~ed~~ a 30% increase in high-intensity TCs at the global scale. Mei and Xie (2016) ~~demonstrat~~demonstrated~~ed~~ a significant correlation between TC intensification and increasing sea surface temperatures (SSTs) in East and Southeast Asia. In addition, Walsh et al. (2016) observes~~d~~ significant increasing trends in TC intensity ~~have beene observed~~ in the Atlantic basin over the past few decades ~~(Walsh et al., 2016)~~. However, assessments of the response of TC intensity to climate change are subject to uncertainty, partly due to the challenging and costly process of collecting observational data (Gualdi et al., 2008; Knutson et al., 2019). Furthermore, the size of TCs may~~movement of TCs may be~~ significantly influence~~d~~ ~~by~~ their ~~size~~ movement (Liu and Chan, 1999), further contributing to their destructive potential (Xu et al., 2020). Similarly, a significant increase in TC size ~~was~~ is~~is~~was ~~reported to be~~ proportional to surface latent heat flux under warmer air and ocean temperatures (Hill and Lackmann, 2009; Radu et al., 2014). Xu et al. (2020) demonstrates~~d~~ that TC size increases with ocean warming, based on idealized experiments. Sun et al. (2013, 2014) ~~discover~~discovers~~ed~~ that TC size increases significantly as SST increases through a modeling analysis. However, the conclusions of these case studies are necessarily limited, and the relationships between TC size and climatology factors remain unclear due to the lack of historical records (Xu et al., 2020).

The International Best Track Archive for Climate Stewardship (IBTrACS) dataset is one of the most commonly used sources for TC data; it contains location, intensity, and size data for all known tropical and subtropical cyclones at a resolution of 3 h (Knapp et al., 2010).~~ In t~~This dataset utilizes~~,~~ maximum sustained wind speed (V_{max}) and minimum central pressure (P_{min}) ~~are used~~ to quantify TC intensity (Simpson, 1974; Chavas et al., 2017; Casas et al., 2023). Among the several metrics that ~~have been~~ are defined to measure TC size, one of the most widely recognized is the radius of~~to~~ maximum wind~~ speed~~ (R_{max}, Chavas et al., 2015; Ren et al., 2022). Radial distances from the cyclone center to locations where sustained wind speeds of 34, 50 and 64 knots (~17, 26, and 33 m/s) are observed near the ~~on~~ surface, i.e., R_{34}, R_{50}, and R_{64}, are also widely used metrics to estimate TC size (Pérez-Alarcón et al., ~~2023~~2021). However, reliable TC size and intensity estimates are available only from 1988 onwards (Demuth et al., 2006), and post-storm analyses of wind radii, including R_{34}, R_{50}, and R_{64}, ~~did do not~~have only commenced ~~until~~ since 2004 (Gori et al., 2023). Furthermore, more than half of all recorded storms lack intensity and size data, often with only location data provided even during periods when post-storm analyses ~~were arewere~~are conducted. Thus, constructing a TC climatology is an arduous task due to low data coverage.

Previous researches have extensively~~widely~~ used ~~Machine~~ machine learning ~~has beenis widely used~~ to reconstruct TC datasets. Yang et al. (2022) divided~~sd~~ hurricane wind fields into symmetric and asymmetric components, and proposes~~d~~ a downscaling model based on the XGBoost software library to reconstruct TC structure; however, V_{max} and R_{max} ~~were arewere~~are the model input variables. Zhuo and Tan (2023) applied~~syied~~ deep learning algorithms to estimate reliable TC sizes over the western North Pacific during 1981–2017, based on a homogeneous satellite database. Li et al. (2024) proposed~~sd~~ a transfer learning-based generative adversarial network framework to derive TC wind fields from synthetic aperture radar images. Eusebi et al. (2024) demonstrated~~sd~~ that a physics-informed neural network can produce accurate reconstructions of TC wind and pressure fields by assimilating observations in a computationally efficient manner. Nevertheless, the datasets used in these studies ~~were we~~a~~a~~re generally limited to several cases or specific regions of interest, and some are not publicly available.

By contrast, reanalysis datasets such as the fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis 5 (ERA5) dataset (Hersbach et al., 2020), the 55-year Japanese Reanalysis (Kobayashi et al., 2015), and US National Centers for Environmental Prediction and National Centre for Atmospheric Research Reanalysis products (Kistler et al., 2001), which combine past observations and model results through data assimilation, have unique advantages in terms of data availability and spatiotemporal coverage. Schenkel et al. (2017) evaluate~~d~~s whether reanalysis dataset can be used to derive a long-term TC size dataset utiliz~~ us~~ing QuikSCAT ~~D~~data. Zick and Matyas (2016) explore~~d~~ the impact of satellite-derived precipitation over ocean on TC in the North American Regional Reanalysis. Gori et al. (2023) ~~utilize~~use~~d~~s ERA5 reanalysis data to estimate the TC outer size, and ~~a physics-based TC ~~wind model to estimate the radius of maximum wind. Thompson et al. (2024) construct~~ed~~s ~~details the creation of ~~a tropical cyclone (TC) size dataset using the NCEP/NCAR Reanalysis I dataset for landfalling TCs along the United States coastline from 1948 to 2022. Previous studies have ~~have~~ suggested~~ed~~ that ERA5 products are among the most promising reanalysis data sources in terms of representing TC outer size and structure, due to their relatively fine horizontal grid spacing (Bian et al., 2021; Pérez-Alarcón et al., ~~2023~~2021; Dulac et al., 2024). Yeasmin et al. (2023) demonstrate~~d~~s that t~~T~~he reconstruction of TC proxies using ERA5 ~~data has been~~are ~~demonstrated to be~~wasis a viable approach~~ (Yeasmin et al., 2023)~~. Nevertheless, due to horizontal resolution limits and conservative physics parameterizations, reanalysis products have exhibited large underestimation and overestimation of TC V_{max} and R_{max} values, respectively (Hatsushika et al., 2006; Schenkel and Hart, 2012). Thus, despite the substantial body of research reconstructing the outer sizes and proxies of TCs using ERA5 data (Bian et al., 2021; Gori et al., 2023; Pérez-Alarcón et al., ~~2023~~2021), studies that have employed ~~this data~~it to derive~~ based on its it to derive ~~relatively accurate TC intensity data are lacking.

In this study, we exploit~~ed~~ the advantages of the IBTrACS and ERA5 datasets to generate a reconstructed~~new~~ TC dataset containing all characteristics of TCs. Given the high degree of accuracy demonstrated by the ERA5 data in capturing TC structures, we employ~~ed~~ ERA5-derived azimuthal ~~median~~ mean azimuthal wind profiles in conjunction with a machine learning model to reduce the bias observed in the V_{max} and R_{max} of TCs between the ERA5 and IBTrACS datasets. In addition, we model~~ed~~ six TC radial wind profiles to compute R_{34}, R_{50}, and R_{64}. The resulting long-term TC reconstruction dataset covering the period 1959–2022 is anticipated to facilitate future TC climatology research. The generated dataset is approximately 3–4 times larger than the IBTrACS dataset in terms of the number of records per characteristic.

In the subsequent sections, we describe the IBTrACS and ERA5 datasets and the methodology used to create the novel TC reconstruction dataset. We report and discuss t~~T~~he findings ~~are reported and discussed~~ in comparison with IBTrACS data according to a comprehensive set of statistical metrics. Finally, we consider the potential applications of the reconstructed TC dataset.

2. Data

2.1 IBTrACS data

We obtain ~~Data~~ data on TC tracks, intensity, and size ~~were are obtained~~ from the IBTrACS (version 4r01 in netCDF format), which is a unified dataset containing track estimates for all TC basins with a 3 h temporal resolution, based on data produced by tropical warning centers. As the TC R_{max} data from all main TC basins ~~were~~ are accessible from U.S. agencies (the National Oceanic and Atmospheric Administration's ~~(NOAA)~~ National Hurricane Center ~~(NHC)~~ for the North Atlantic and east Pacific and the military's Joint Typhoon Warning Center ~~(JTWC)~~ for the remainder of the globe), we employ~~ed~~ these data and ~~excluded~~ exclude the irregular time steps. We use a~~A~~ll TC events in all basins ~~were are used~~, except for those over the South Atlantic, where TC generation is insufficient. A comprehensive overview of the recorded TC characteristics is presented in Table 1. The IBTrACS dataset encompasses a total of 7,552 TCs on a global scale, spanning the period 1959–2022, corresponding to 423,296 individual time points. However, IBTrACS dataset only ~~record~~records 125,477 V_{max}, 142,430 P_{min}, and 94,415 R_{max} values ~~were are recorded~~. TC tracks and V_{max} data extracted from the IBTrACS dataset are presented in Fig. 1.

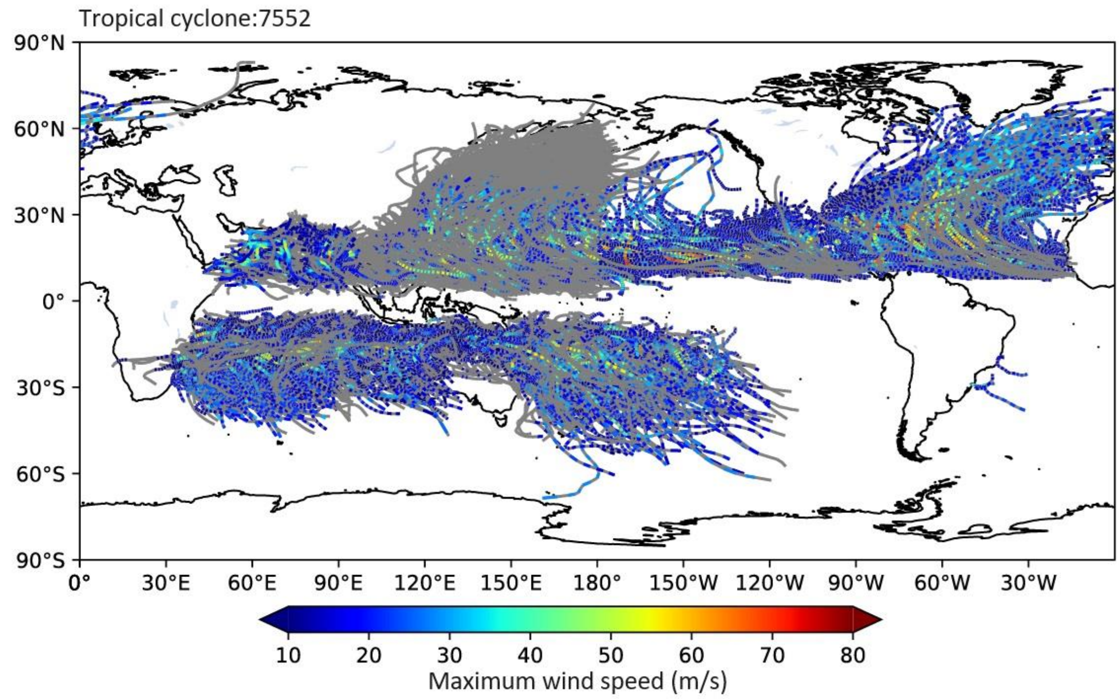

Figure 1: Overview of the tracks and 10-m maximum wind speeds of tropical cyclones in IBTrACS dataset. Grey lines represent the unrecorded wind speeds.

Table 1: Basic information on the number of recorded tropical cyclone characteristics from 1959 to 2022 recorded in IBTrACS.

Basin	Time point	V_{max}	P_{min}	R_{max}	R_{34}	R_{50}	R_{64}
Western Pacific	152362	26604	61018	28715	19340	10641	7149
North Atlantic	55679	28310	21409	18161	14961	7630	4212
North Indian	24101	5481	5476	4281	2354	1029	614
South Indian	86790	23935	24468	16367	10697	5108	2977
South Pacific	45189	12322	12467	7169	4827	2577	1521
Eastern Pacific	59175	28825	17592	19722	12283	6482	3986
Global	423296	125477	142430	94415	64462	33467	20459

2.2 ERA5 data

ERA5 is the latest ECMWF reanalysis, following a decade of developments in model physics, core dynamics, and data assimilation (Hersbach et al., 2020). We utilize~~d~~ the main ERA5 dataset for the period 1959–2022 to estimate the track, intensity, and size of each TC. The spatial resolution of the ERA5 dataset is 0.25° × 0.25°, with a temporal resolution of 3 h, aligning with that of the IBTrACS dataset. We exclude p~~P~~re-1959 ERA5 back-extension data~~ were are not adopted~~, as some TCs in these data ~~exhibite~~exhibit~~d~~ unrealistically high levels of tension (Bell, 2021). Notably, despite the higher uncertainty associated with TC intensity data derived from ERA5 for the pre-satellite time period (1959–1978), comparisons of TC intensity pre- and post-1979 reveal~~ed~~ similar climatological distributions for both TC groups in all basins (Fig. S1). We employ~~ed~~ 10 m surface meridional and latitudinal wind speeds to obtain 10 m azimuthal–mean azimuthal wind profiles for TCs. We utilize t~~T~~he sea level pressure (SLP) ~~was is utilized~~ to provide environmental pressure data for computing the TC central pressure. We derive the p~~P~~arameters including the SLP; relative vorticity at 700, 850, and 925 hPa; and geopotential height at 700 and 850 hPa ~~were are derived~~ from the ERA5 data to identify TC centers.

3. Methodology

3.1 TC center identification and azimuthal wind profile estimation

We identify TC centers in the ERA5 data, ~~were are identified~~ based on the method of Schenkel et al. (2017). We initially ascertain ~~tThe~~the position of each TC within the reanalysis grid ~~was is initially ascertained~~ utilizing the IBTrACS position as a first guess. To remove uncertainties associated with TC centers in the reanalysis data, we obtain the ~~centroids~~ centers of six reanalysis variables (SLP; relative vorticity at 700, 850, and 925 hPa; and geopotential height at 700 and 850 hPa) by calculating~~computing~~ the ~~center-of-mass~~centroids~~maximum~~ of positive relative vorticity values and ~~minimum of~~negative ~~values of~~ other variables values over the grid near the first guess position (±2°) using ~~p~~Python ~~v3.10.7~~. Subsequently, we average ~~Then~~ the centers~~centroids~~ ~~was are averaged over the grid near the first guess position~~ to adjust the position of the estimated reanalysis TC center.

We estimate a~~A~~zimuthal wind profiles based on the ERA5 data~~, were are estimated~~ as described by Chavas and Vigh (2014). First, we subtract estimated environment wind fields, which ~~were~~ are calculated as 0.55 of the TC translation vectors rotated 20° counterclockwise (Lin and Chavas, 2012) ~~, were are subtracted~~ from the meridional and latitudinal wind speeds. We determine TC translation vectors ~~were are determined~~ according to the TC positions at the next and current time points in the IBTrACS data. Next, we interpolate the 10 m surface meridional and latitudinal wind fields ~~were are interpolated~~ to a TC-centered polar coordinate. In contrast to the method of Chavas and Vigh, we ~~did~~ do not exclude grid points over land to obtain the TC intensity after landfall. Then, we employ the parameter $\mathcal{X}$, defined as the normalized average magnitude of all vectors from the TC center to each grid point included at a specified radius (Chavas and Vigh, 2014) ~~was is employed~~ to remove asymmetrical radial bins by excluding radial bins with $\mathcal{X} > 0.5$. Finally, we calculate the TC 10 m azimuthal–mean azimuthal wind profiles ~~were are calculated~~ as changes in wind speed with distance from the TC center, with grid points spaced at 10 km intervals. We obtain t~~T~~he ERA5-derived TC V_{max} (V_{max_ERA5}) and R_{max} (R_{max_ERA5}) ~~were are obtained~~ from the wind profiles.

3.2 Machine learning model for reconstructing TC V_{max} and R_{max} from ERA5 data

As shown in Fig. 2, there ~~were~~ are discernible biases in all six TC basins between the ERA5- and IBTrACS-derived V_{max} and R_{max} values. The biases of V_{max} ~~were~~ are less dependent on the basin, suggesting the systematic underestimation of V_{max}

by the ERA5 data, partly due to the lower P_{min} and the underestimation of the TC wind-pressure relation described in ERA5 (Magnusson et al., 2021)~~.~~. ~~Besides~~Moreover, convective-scale processes substantially influence V_{max}~~—~~, which ~~—is significantly substantially influenced by convective-scale processes that are not~~cannot be adequately represented in global models, leading to an inherent tendency for underestimation~~ is largely dependent on convective-scale (O(1 km)) processes that are not resolved in the global models, and it is therefore expected to be regularly underestimated~~. To further demonstrate the performance of ERA5-derived data, we select the Saffir-Simpson categories as the uniform scale for all the basins, and analyze the differences between ERA5-derived and observed data across various wind speed ranges, following the methods in previous researches (Wright, 2019; Bloemendaal et al., 2022; Mo et al., 2023)~~.~~. In contrast, biases ~~were~~ are more pronounced for larger V_{max} values, with underestimation detected for wind speeds exceeding 20 and 30 m/s for Saffir–Simpson categories 1–2 and 3–5, respectively, in all six basins. Notably, this bias even exceeds~~ed~~ 40 m/s for Saffir–Simpson categories 3–5 in the East Pacific basin. In addition, ERA5-derived results overestimate~~d~~ R_{max} by >15 km in all basins, and by >80 km in the West Pacific (WP) basin. The large biases produced by ERA5 motivate~~d~~ us to establish a reconstructed~~new~~ TC dataset that is more consistent with observations.

~~Previous studies have indicated that despite the discrepancymodesty of ERA5-derived TC intensity data, the ERA5 dataset accurately depicts TC structural alterations (Bian et al., 2021). Therefore, we used the TC 10 m azimuthal-mean azimuthal wind speed at radial distances from 0 to 1000 km, at 10 km intervals, as a parameter to estimate V_{max} in each basin. The parameters also included the TC translation speed, given that the IBTrACS V_{max} data (V_{max_IB}) represent a combination of the environmental and TC wind fields. After testing s-A series ofSeveral machine learning models were tested withinusing python v3.10.7, including ann random forest (RF) algorithms, artificial neural network (ANN), convolutional neural network, support vector regressor, and multivariate linear regression (Table 2 and 3)multilayer perceptron regression. For a detailed account of the hyperparameter selections for each model, please refer to the supplementary materials. ls., Although the ANN-derived R_{max} Rmax obtained by ANN exhibitsed a stronger correlations with observations, the root mean square error (RMSE) of $V_{max}$the Rmax and R_{max} derivobtained by RF~~

with observations wereis considerably smaller than thoseat obtainedderived by other models.and random forest (RF) algorithms, we found thatTherefoWre,We found that RF provided the most robust predictions. For a comprehensivedetailed account of the hyperparameter calibrationdeterminationselections process and a comparative analysis of the model performance offor each machine learning models, please refer to the supplementary materials.A detailed description of the determination of the expressionhyperparameters and comparison of the performance for the function Feach model can be found in the Supplementary materials. Therefore, as evidenced by higher correlations and smaller root mean square error RMSEs (RMSE) values in most basins. Accordingly,Therefore,and ann RF regressor was developed to predict reconstructed V_{max} (V_{max_RC}), as follows:

$$V_{max\_RC} = RF(V_0, V_{10}, V_{20}, \ldots, V_{1000}, V_{TS}) \qquad (1)$$

where RF and V_{TS} are the RF regressor and TC translation speed, respectively, and $V_0, V_{10}, V_{20}, \ldots, V_{1000}$ refer to the 10 m azimuthal mean azimuthal wind speeds at radial distances from 0 to 1000 km.

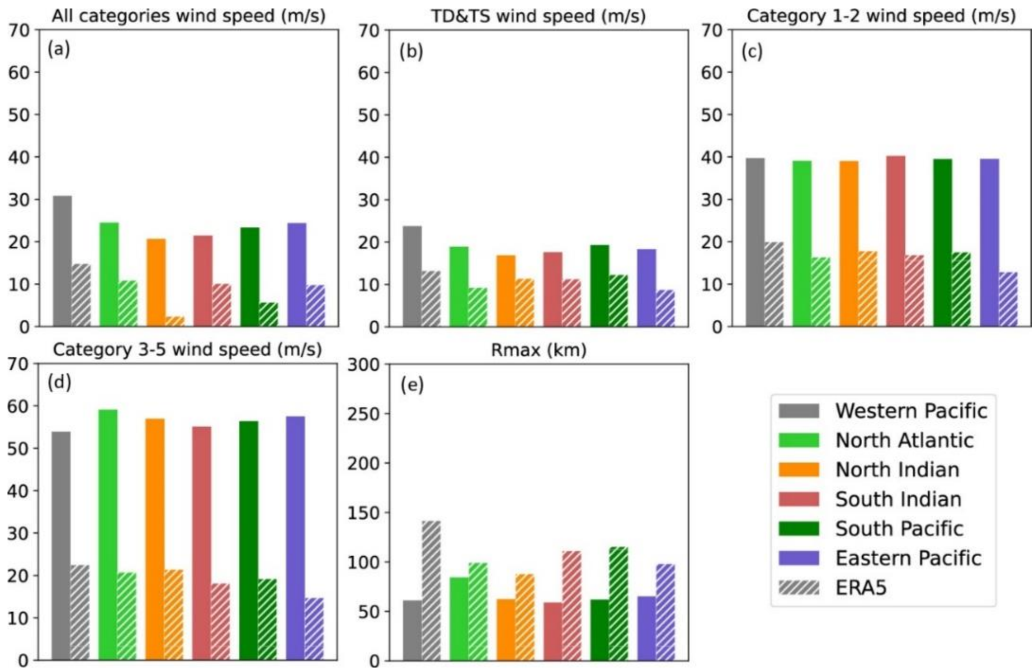

Figure 2: Bar charts for comparing the mean value of the 10-m maximum wind speeds and the radii to maximum winds. Each of the colors indicates a different basin. Solid and dashed bars represent IBTrACS and ERA5-derived data.

Despite the discrepancy in TC intensity, Bian et al. (2021) demonstrates that ERA-5 accurately depicts TC structural alterations. Previous studies have indicated that despite the discrepancy of ERA5-derived TC intensity data, the ERA5 dataset accurately depicts TC structural alterations (Bian et al., 2021). Therefore, we used the TC 10 m azimuthal–mean azimuthal wind speed at radial distances from 0 to 1000 km, at 10 km intervals, as a parameter to estimate V_{max} in each basin. The parameters also included~~d~~ the TC translation speed, given that the IBTrACS V_{max} data (V_{max_IB}) represent a combination of the environmental and TC wind fields. We optimize ~~aA series of~~the machine learning models~~ wereare optimized~~ by Randomized Search Cross-Validation with ~~adopting~~ mean square error~~RandomizedSearchCVtested~~ as the loss function using ~~p~~Python~~ v3.10.7,~~. The models includ~~ing~~e ~~an~~a random forest (RF) algorithm, artificial neural network (ANN), convolutional neural network, support vector regressor, and multivariate linear regression (Table 2). In the above-mentioned models, we incorporate data for the entire period (1959–2022) ~~were incorporated~~ into the model training process. We randomly divide ~~tT~~the dataset, made up of the input array and learning target,~~ wasis randomly divided~~ into two subsets, with 75% allocated for training and the remaining 25% for ~~validation~~testing, following the methods of previous studies (e.g., Breiman, 2001; Guo et al., 2024). ~~Training data for the entire period (1959–2022) were incorporated into the model training process. To optimize the model's' performance, we opted for the MSE as the loss function.~~ For a detailed account of the hyperparameter selections for each model, please refer to the Text S1 in supplementary materials. We f~~ound~~ind that RF provided the most robust predictions, as evidenced by higher ~~Pearson~~ correlation~~ coefficients~~s and smaller root mean square error (RMSE) values in most basins. ~~To further assess the accuracy of the RF model, we define the error rate as the absolute relative errors between the predicted and observed V_{max} in the test data, normalized by the observations. The error rates are 0.13, 0.15, 0.22, 0.15, 0.1920, and 0.18, 0.22, 0.17 for the Western Pacific (WP), North Atlantic (NA), Eastern Pacific (EP), North Indian (NI), South Indian (SI) and South Pacific (SP)Western PacificWP, North Atlantic, Eastern Pacific, North Indian, South Indian, and South Pacific and Eastern Pacific basins, respectively. NA~~Accordingly, we develop an RF regressor~~ wasis developed~~ to predict reconstructed V_{max} (V_{max_RC}), as follows:

$$V_{max\_RC} = RF(V_0, V_{10}, V_{20}, \ldots, V_{1000}, V_{TS}) \qquad (1)$$

where RF and V_{TS} are the RF regressor and TC translation speed, respectively, and $V_0, V_{10}, V_{20}, \ldots, V_{1000}$ refer to the 10 m azimuthal –mean azimuthal wind speeds at radial distances from 0 to 1000 km. To further assess the accuracy of the RF model, we define~~ the~~ the error rate of the ~~random forest~~RF on the training data~~error rate~~ as the absolute relative errors between the predicted and observed V_{max} ~~inon the testtraining data~~, normalized by the observations. The error rates are 0.1~~3~~1, 0.1~~56, 0.22~~, 0.1~~5~~09, 0.~~20~~19, ~~and~~ 0.1~~8~~6 and 0.2~~2~~0 for the ~~Western Pacific (~~WP~~)~~, North Atlantic (NA), ~~Eastern Pacific (EP),~~ North Indian (NI), South Indian (SI), ~~and~~ South Pacific (SP) Eastern Pacific (EP) and basins, respectively.

Table 2. Basic information on the comparison of the ~~data derived from~~ different model-deriveds with ~~the~~ observed ~~ation dataevaluation indices for~~ V_{max} in Western Pacific (WP), North Atlantic (NA)~~, Eastern Pacific (EP)~~, North Indian (NI), South Indian (SI) ~~and~~ South Pacific (SP) and Eastern Pacific (EP). CE, ~~PpearsonPearson c~~correlation coefficients; RMSE, root mean square error. RF, random forecast; ANN, artificial neural network; CNN, convolutional neural network; SVR, support vector regressor; MLR, multivariate linear regression.

	WP	NA	NI	SP	SI	EP
RF_{CE}	0.98	0.99	0.99	0.99	0.98	0.99
ANN_{CE}	0.98	0.99	0.99	0.98	0.99	0.97
CNN_{CE}	0.97	0.99	0.98	0.97	0.98	0.97
SVR_{CE}	0.99	0.99	0.98	0.99	0.99	0.99
MLR_{CE}	0.97	0.98	0.98	0.97	0.97	0.96
RF_{RMSE} (m/s)	2.60	4.09	1.33	3.73	3.25	5.05
ANN_{RMSE} (m/s)	5.09	5.31	1.65	3.87	4.37	10.05
CNN_{RMSE} (m/s)	5.92	8.39	2.43	7.18	7.30	11.2
SVR_{RMSE} (m/s)	3.99	6.70	2.18	4.87	5.03	9.08
MLR_{RMSE} (m/s)	7.33	9.34	2.28	7.42	7.45	12.49

Similarly, we use variation in radial distance with azimuthal wind speed ~~was is used~~ to estimate R_{max} in the six basins. ~~After~~ We also test ~~testing ssS~~several machine learning models ~~wereare also tested~~ (Table 3)~~.~~, Although the ANN-derived R_{max} exhibit~~ed~~ stronger correlations with observations, the ~~root mean square error (~~RMSE~~)~~ values of R_{max} derived by RF with observations ~~were~~are considerably smaller than that derived by other models. Therefore, we also utilize the RF regressor ~~was is utilized~~ to predict the reconstructed R_{max} (R_{max_RC}), as follows:

$$R_{max\_RC} = RF(R_0, R_{0.01}, R_{0.02}, \ldots, R_1) \quad (2)$$

where $R_0, R_{0.01}, R_{0.02}, \ldots, R_1$ represent the radial distances at which normalized wind speeds range from 0 to 1, at an interval of 0.01. In the RF models, the error rates are 0.~~13221~~19, 0.~~152671~~3, ~~0.228,~~ 0.1~~56~~4, 0.~~2~~1~~091 and~~, 0.1~~87~~5 and 0.2~~81~~3 for the ~~Western Pacific~~WP, N~~orth Atlantic~~A~~, Eastern Pacific~~P, N~~orth Indian~~I, S~~outh Indian~~I ~~and~~, S~~outh Pacific~~P and EP basins, respectively. We further evaluate ~~T~~t~~he dataset, made up of the input array and learning target, was randomly divided into two subsets, with 75% allocated for training and the remaining 25% for validation, following the methods of previous studies (e.g.,~~

~~Breiman, 2001; Guo et al., 2024). Training data for the entire period (1959–2022) were incorporated into the model training process.~~ ~~When optimizing the random forecast model for regression tasks, we utilize Randomized Search Cross-Validation (RandomizedSearchCV) to systematically explore a wide range of hyperparameters. Specifically, we define hyperparameter distributions that encompass a range of values for the number of trees in the forest (100 to 300), maximum depth of the tree (10 to 30), maximum number of features (1 to 7), minimum number of samples (2 to 10), minimum number of samples (2 to 20), and maximum number of leaf nodes (800 to 1200). With 500 iterations and 5-fold cross-validation, we search for the optimal hyperparameter combination that minimizes the mean squared error, which is a common choice for regression problems due to its ability to penalize large errors. Leveraging parallel computing, we efficiently fit the model to the training data and obtain the best-performing estimator.In the RF models, hyperparameters including the maximum tree depth, minimum leaf samples, minimum sample splits, and maximum leaf nodes were determined by randomized searches.~~ ~~The dataset, made up of the input array and learning target, was randomly divided into two subsets, with 75% allocated for training and the remaining 25% for validation, following the methods of previous studies (e.g., Breiman, 2001; Guo et al., 2024). Training data for the entire period (1959–2022) were incorporated into the model training process.~~ m~~M~~odel performance ~~was~~ is further ~~evaluated~~ by comparing the model-derived and observed V_{max} and R_{max} on the testing dataset in ~~the~~ Section 4~~following sections,~~ using a comprehensive set of statistical metrics, including mean error, mean ~~of the~~ absolute error (MAE), ~~root mean square error (~~RMSE~~)~~, and Pearson correlation coefficients. We evaluate t~~T~~he statistical significance of Pearson correlation coefficients ~~is evaluated~~ through the application of a t-test.~~viathrough the use of a t-test.~~

Table 3. Similar to Table 2, but for R_{max}~~.~~.

	WP	NA	NI	SP	SI	EP
RF_{CE}	0.93	0.96	0.96	0.91	0.96	0.93
ANN_{CE}	0.96	0.97	0.93	0.97	0.96	0.94
CNN_{CE}	0.95	0.96	0.95	0.97	0.94	0.96
SVR_{CE}	0.06	0.21	0.26	0.25	0.01	0.07
MLR_{CE}	0.90	0.93	0.98	0.98	0.96	0.84
RF_{RMSE} (km)	20.80	31.47	10.48	15.11	16.51	24.75
ANN_{RMSE} (km)	31.96	46.74	16.62	21.06	23.22	41.14
CNN_{RMSE} (km)	34.93	52.89	22.04	20.97	25.69	44.07
SVR_{RMSE} (km)	43.53	72.43	28.26	29.05	30.99	51.15

MLR_{RMSE} (km)	37.65	57.82	21.93	23.35	27.22	44.16

3.3 Empirical wind speed–pressure relationship for determining P_{min}

We model t~~T~~he conversion between V_{max} and P_{min} at a given time point during a TC ~~was is modeled~~ using the empirical wind–pressure relationship (Atkinson and Holliday, 1977; Harper, 2002), as follows:

$$V_{max} = a(P_{env} - P_{min})^b \tag{3}$$

where P_{env} is the environmental pressure obtained from the mean SLP for the TC center location 1–10 days earlier based on the ERA5 data, following the method of Bloemendaal et al. (2020); we estimate a and b ~~are were estimated~~ in each basin using a nonlinear least squares approach, based on V_{max} and the corresponding P_{min} of the IBTrACS dataset. V_{max_RC} ~~was~~ is input into the fitted Eq. (3) to obtain the reconstructed P_{min} (P_{min_RC}).

3.4 TC radial wind profile models for computing R_{34}, R_{50}, and R_{64}

Previous studies have developed TC radial wind profile models for estimating TC structures (e.g., Pérez-Alarcón et al., 2021). After obtaining the reconstructed V_{max} and R_{max}, we utilize six widely used wind field models (Holland, 1980; DeMaria, 1987; Willoughby et al., 2006; Emanuel and Rotunno, 2011; Frisius and Scgönemann, 2013; Chavas et al., 2015)~~, were~~ are ~~used~~ to estimate the reconstructed TC R_{34}, R_{50}, and R_{64} (R_{34_RC}, R_{50_RC}, and R_{64_RC}). For a detailed description of the wind profile models~~hyperparameter selections for each model~~, please refer to the Text S~~1~~2 in supplementary materials.

We evaluate the performance of each profile model by comparing R_{34}, R_{50}, and R_{64} estimates with those recorded in the IBTrACS dataset. Subsequently, w~~We~~e ~~select~~select the~~The~~ optimal model ~~is selected~~ to generate reconstructed R_{34}, R_{50}, and R_{64}, as described in detail in Section 4.

~~The wind profile model proposed by Holland (1980) was formulated as follows:~~

$$V(r) = V_{max}\sqrt{\left(\frac{R_{max}}{r}\right)^{b} e^{1-\left(\frac{r}{R_{max}}\right)^{-b}}} \tag{4}$$

~~where V is the wind speed at distance r from the TC center, and b = 2, according to Kowaleski and Evans (2016).~~

~~The model developed by DeMaria (1987) was formulated as follows:~~

$$V(r) = V_{max}\left(\frac{R_{max}}{r}\right) e^{\frac{\frac{1}{c}-\frac{1}{c}\left(\frac{r}{R_{max}}\right)^{c}}{d}} \tag{5}$$

~~where c = 0.63 and d = 1, following Kowaleski and Evans (2016).~~

~~The model proposed by Willoughby et al. (2006; hereinafter, W06) was formulated as follows:~~

$$V(r) = \begin{cases} V_{max}\left(\frac{r}{R_{max}}\right)^{n}, & 0 \le r \le R_1 \\ V_i(1-w) + V_0 w, & R_1 \le r \le R_2 \\ V_{max} e^{-\frac{r-R_{max}}{X_1}}, & R_2 \le r \end{cases} \tag{6}$$

~~where V_i and V_0 are the tangential wind components in the eye and beyond the transition zone, respectively, and w, X_1, and n are the weight function, exponential decay length in the outer vortex, and power law exponent within the eye, respectively.~~

~~The model proposed by Emanuel and Rotunno (2011) was formulated as follows:~~

$$V(r) = \frac{2r(R_{max}V_{max}+0.5fR_{max}^2)}{R_{max}^2+r^2} - \frac{fr}{2} \quad (7)$$

~~where f is the Coriolis parameter.~~

~~The model developed by Frisius and Scgönemann (2013) was formulated as follows:~~

$$V(r) = V_{max}\frac{r}{R_{max}}\left[\frac{2(\frac{R_{max}}{r})^2}{2-(\frac{C_H}{C_d})[1-(\frac{r}{R_{max}})^2]}\right]^{\frac{1}{2}-\frac{C_H}{C_d}} - \frac{fr}{2} \quad (8)$$

~~where C_H and C_D are the surface enthalpy transfer and drag coefficients, respectively, and $\frac{C_H}{C_d} = 1$, according to Frisius and Scgönemann (2013).~~

~~The model proposed by Chavas et al. (2015; hereinafter, CLE15) was formulated as follows:~~

$$(\frac{M_{inner}}{M_m})^{2-\frac{C_k}{C_d}} = \frac{2(\frac{r}{R_{max}})^2}{2-(\frac{C_k}{C_d})+(\frac{C_k}{C_d})(\frac{r}{R_{max}})^2} \quad (9)$$

$$\frac{\partial M_{outer}}{\partial r} = \frac{C_d(rV)^2}{0.001(r_0{}^2-r^2)}$$

~~where M_{inner}, M_{outer}, and M_m are the angular moment of the inner and outer wind regimes and at R_{max}, respectively; and C_k and C_d are the exchange surface enthalpy and momentum coefficients, respectively.~~

~~The performance of each profile model was~~ is evaluated ~~by comparing R_{34}, R_{50}, and R_{64} estimates with those recorded in the IBTrACS dataset. The optimal model was~~ is ~~selected to generate reconstructed R_{34}, R_{50}, and R_{64}, as described in detail in Section 4.~~

3.5 Flowchart for optimal wind profile model selection

After identifying the TC center, we use~~d~~ an RF approach to estimate V_{max} and R_{max} based on the ERA5-derived TC 10 m azimuthal ~~–~~mean azimuthal wind profiles. We evaluate model performance by comparing the model-derived and observed V_{max} and R_{max} on the testing dataset, using a comprehensive set of statistical metrics.~~,~~ Next, we estimate the parameters of the empirical wind–pressure relationship ~~were are estimated~~, and compute TC P_{min} values ~~were are computed~~. Finally, we derive the TC R_{34}, R_{50}, and R_{64} ~~were are derived~~ by selecting the optimal wind profile model from among the six widely used models. The overall methodology is illustrated in Fig. 3.

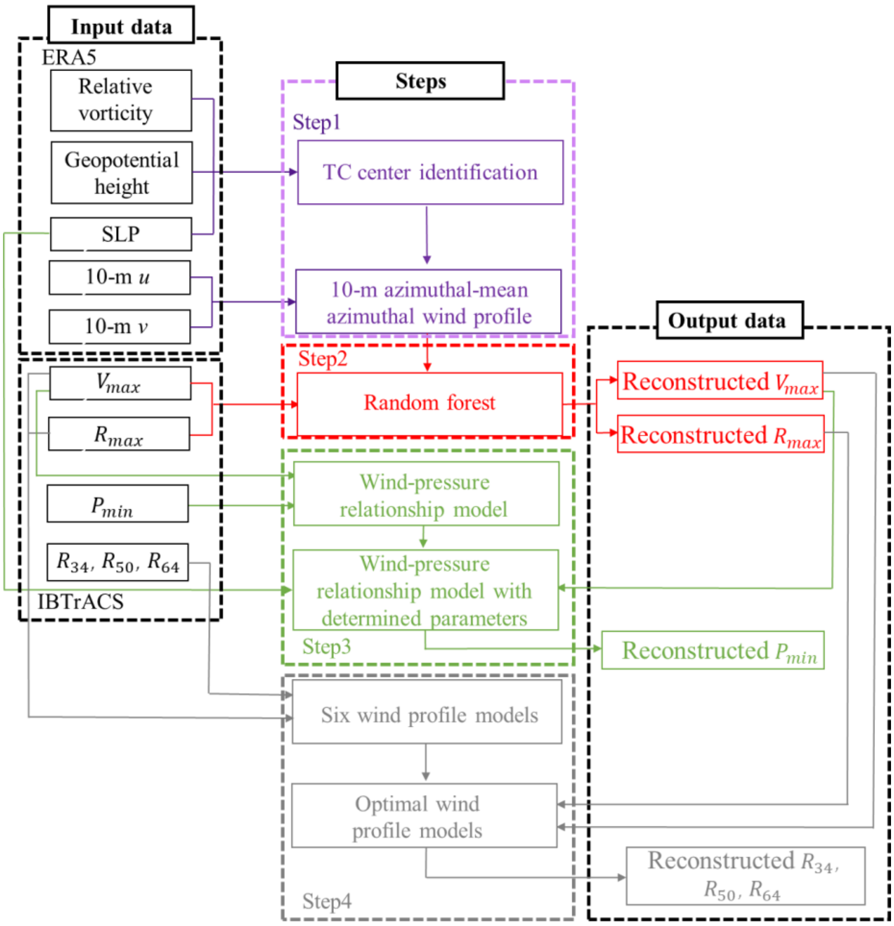

Figure 3: Flowchart with the tropical cyclone center identification and wind profiles extracted from ERA5 (Step 1; in purple), the 10-m maximum wind speeds and radii to maximum winds estimated by random forest model (Step 2; in red), the minimum central pressure estimated by empirical wind-pressure relationship (Step 3; in green), and the out size estimated by wind profile models (Step 4; in grey).

4. Results and Discussion

We evaluate t~~T~~he accuracy of the V_{max_RC} model results ~~was is evaluated~~ according to various statistical metrics based on the testing datasets (Fig. 4), as prescribed by Breiman (2001). The V_{max_RC} data ~~were~~ are strongly correlated with observations, with correlation coefficients exceeding 0.98 for all six basins. The RMSE values for the WP, NA, NI, SI, SP and EP~~West Pacific, North Atlantic, North and South Indian Ocean, and South and East Pacific~~ basins ~~were~~ are 2.60, 4.09, 1.33, 3.25, 3.73, and 5.05 m/s, respectively. Compared to V_{max_ERA5}, the reconstruction ~~provide~~provides~~d~~ a reduction in the ~~mean absolute bias~~MAE of over 10 m/s in most basins, with a further reduction of 19.62 m/s in the East Pacific basin, as described in detail in Table ~~2~~4. The model ~~was~~ is more effective at reducing biases between ERA5-derived results and observations for larger V_{max} values. Furthermore, given the high influence of ENSO on TC intensity (Chu, 2024), we ~~also~~ evaluate the accuracy of V_{max_RC} ~~was is evaluated~~ for moderate to strong El Niño and La Niña years (Fig. S2 and S3). We also observed a~~A~~ high degree of correlation coefficients (>0.97) and low RMSE values (<5m/s) ~~were are observed~~ between V_{max_RC} and V_{max} in all six basins during ENSO years. These metrics ~~clearly~~ demonstrate the ~~superior~~ better accuracy of V_{max_RC} and its reduced bias compared to V_{max_ERA5}.

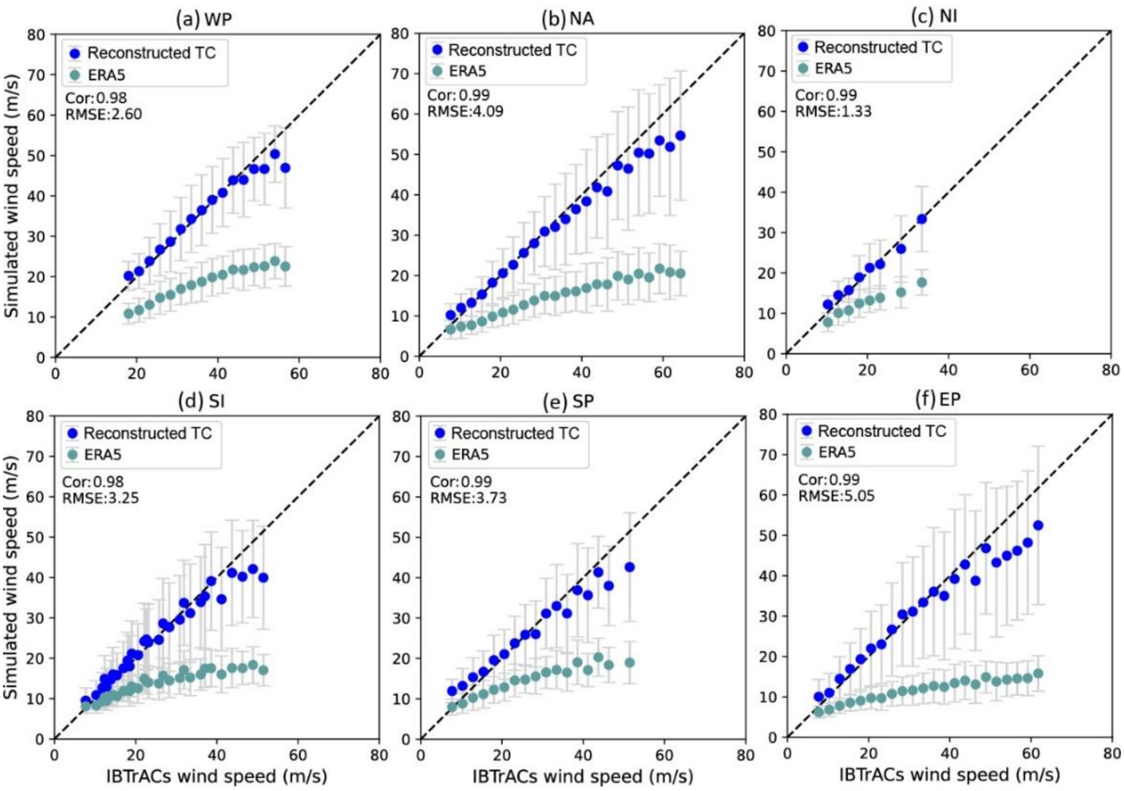

Figure 4: Comparison between value-averaged maximum wind speeds (V_{max}) from ERA5-derived and reconstructed (ERA5 + Random forest) data and IBTrACS maximum wind speeds for tropical cyclones in (a) Western Pacific, (b) North Atlantic, (c) North Indian, (d) South Indian, (e) South Pacific and (f) Eastern Pacific basins. Grey lines represent the error bar, given as one standard deviation from the mean. The values with sample sizes less than 30 in IBTrACS ~~were~~ are excluded.

Table ~~2~~4: Basic information on the comparison of the ERA-5-derived and reconstructed ~~data~~ with ~~the~~ observation~~ed~~ ~~data evaluation indices for~~ V_{max}. ME, mean errors; MAE, mean ~~of the~~ absolute ~~bias~~error; RMSE, root mean square error; CE, correlation coefficients.

	ME (m/s)	MAE (m/s)	RMSE (m/s)	CE
$\mathrm{Global}_{\mathrm{ERA5}}$	16.73	16.80	21.70	0.92
$\mathrm{Global}_{\mathrm{Reconstructed}}$	2.82	2.83	4.34	0.99
$\mathrm{WP}_{\mathrm{ERA5}}$	18.93	18.93	20.54	0.97
$\mathrm{WP}_{\mathrm{Reconstructed}}$	0.56	1.63	2.60	0.98
$\mathrm{NA}_{\mathrm{ERA5}}$	21.03	21.03	24.46	0.98
$\mathrm{NA}_{\mathrm{Reconstructed}}$	2.38	2.82	4.09	0.99
$\mathrm{NI}_{\mathrm{ERA5}}$	7.74	7.74	8.96	0.98
$\mathrm{NI}_{\mathrm{Reconstructed}}$	-0.25	1.11	1.33	0.99
$\mathrm{SI}_{\mathrm{ERA5}}$	12.39	12.41	15.61	0.93
$\mathrm{SI}_{\mathrm{Reconstructed}}$	0.71	2.17	3.25	0.98
$\mathrm{SP}_{\mathrm{ERA5}}$	13.71	13.73	16.67	0.96
$\mathrm{SP}_{\mathrm{Reconstructed}}$	1.19	2.70	3.73	0.99
$\mathrm{EP}_{\mathrm{ERA5}}$	23.09	23.09	26.86	0.97
$\mathrm{EP}_{\mathrm{Reconstructed}}$	2.36	3.47	5.05	0.99

We similarly evaluate~~d~~ the accuracy of $R_{max\ \_RC}$ for the six basins based on the testing datasets (Fig. 5). Correlation coefficients between $R_{max\ \_RC}$ and R_{max} recorded in IBTrACS (R_{max_IB}) exceed~~ed~~ 0.9, indicating strong correlation between the reconstructed results and observations. Moreover, the RMSEs for the ~~West Pacific~~WP, N~~orth Atlantic~~A, ~~North~~ NI~~and South Indian Ocean~~, SI, ~~and South~~ SP and E~~ast Pacific~~P basins ~~were~~ are 20.80, 31.47 10.48, 16.51, 15.11, and 24.75 km, respectively. Importantly, $R_{max\ \_ERA5}$ exhibits~~ed~~ a large deviation from observations, exceeding 300 km at very low R_{max_IB} values. Therefore, for clarity, the $R_{max\ \_ERA5}$ data are not shown with the reconstructed TC results in Fig. 5. The ~~mean of the absolute bias error (~~MAE~~W)~~ ~~exhibit~~exhibits~~ed~~ a reduction of 39.57 km on a global scale, with a further reduction of over 59.37 km in the ~~South Indian Ocean~~SI basin, as described in detail in Table ~~3~~5. It is noteworthy that the error bars are larger for the N~~orth Atlantic~~A and E~~ast Pacific~~P basins in comparison to the other basins. This may be attributed to the low correlations between R_{max} in IBTrACS and in ERA5 (NA: 0.37; EP: -0.02). ~~–~~Although the $R_{max\ \_RC}$ data slightly overestimate~~d~~ observations at low R_{max_IB} values and underestimated observations at high R_{max_IB} values, they greatly reduce~~d~~ biases compared to the $R_{max\ \_ERA5}$ data, and thus produced ~~superior~~ better predictions for all six basins.

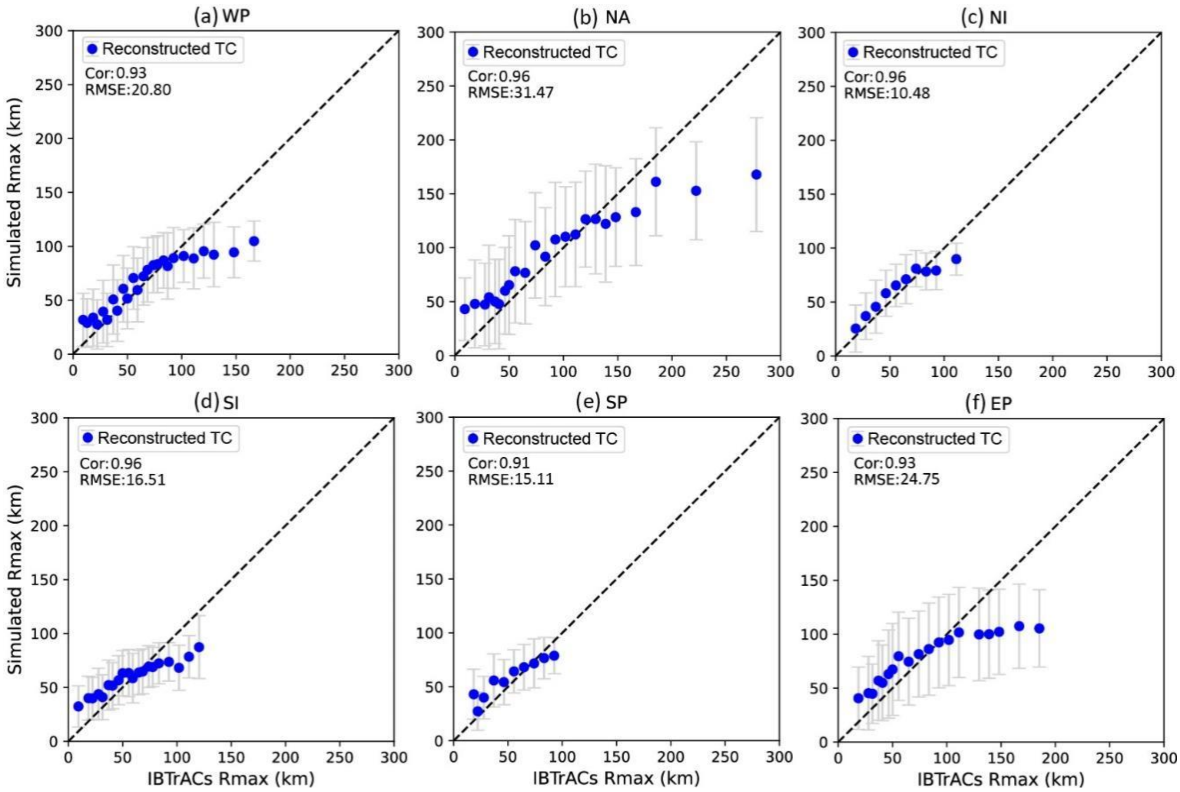

Figure 5. Similar to Figure 4, but for radii to maximum winds (R_{max}).

Table ~~3~~5: Similar to Table ~~2~~4, but for R_{max}.

	ME (km)	MAE (km)	RMSE (km)	CE
$\text{Global}_{\text{ERA5}}$	-41.64	55.49~~15.92~~	67.66	0.44
$\text{Global}_{\text{Reconstructed}}$	1.37	~~55.49~~15.92	22.19	0.94
WP_{ERA5}	-56.43	58.31	69.86	0.75
$\text{WP}_{\text{Reconstructed}}$	1.32	14.93	20.80	0.93
NA_{ERA5}	-7.79	54.25	64.59	0.37
$\text{NA}_{\text{Reconstructed}}$	4.05	21.44	31.47	0.96
NI_{ERA5}	-28.95	29.39	33.75	0.96
$\text{NI}_{\text{Reconstructed}}$	-2.30	9.65	10.48	0.96
SI_{ERA5}	-73.40	73.48	88.39	0.74
$\text{SI}_{\text{Reconstructed}}$	-1.50	14.11	16.51	0.96
SP_{ERA5}	-52.42	52.99	61.95	0.90
$\text{SP}_{\text{Reconstructed}}$	-3.21	12.09	15.11	0.91
EP_{ERA5}	-24.31	47.83	56.59	-0.02
$\text{EP}_{\text{Reconstructed}}$	6.91	18.83	24.75	0.93

We compute

P_{min_RC} ~~was is computed~~ based on an empirical wind–pressure relationship. We employ V_{max_IB} and the corresponding P_{min} recorded in IBTrACS (P_{min_IB}) ~~were are also employed~~ in the reconstruction, and we obtain P_{env} ~~was is obtained~~ from the ERA5 dataset, following the method of Bloemendaal et al. (2020). We estimate r~~R~~elated parameters ~~were are estimated~~ through nonlinear fitting; the results are shown in Fig. 6. For the WP, NA, NI, SI, SP and EP~~West Pacific, North Atlantic, North and South Indian Ocean, and South and East Pacific~~ basins, we use~~d~~ *a* values of 0.118, 0.051, 0.259, 0.184, 0.325, and 0.073 and *b* values of 1.67, 1.692, 1.402, 1.507, 1.371, and 1.651, respectively, in Eq. (3).

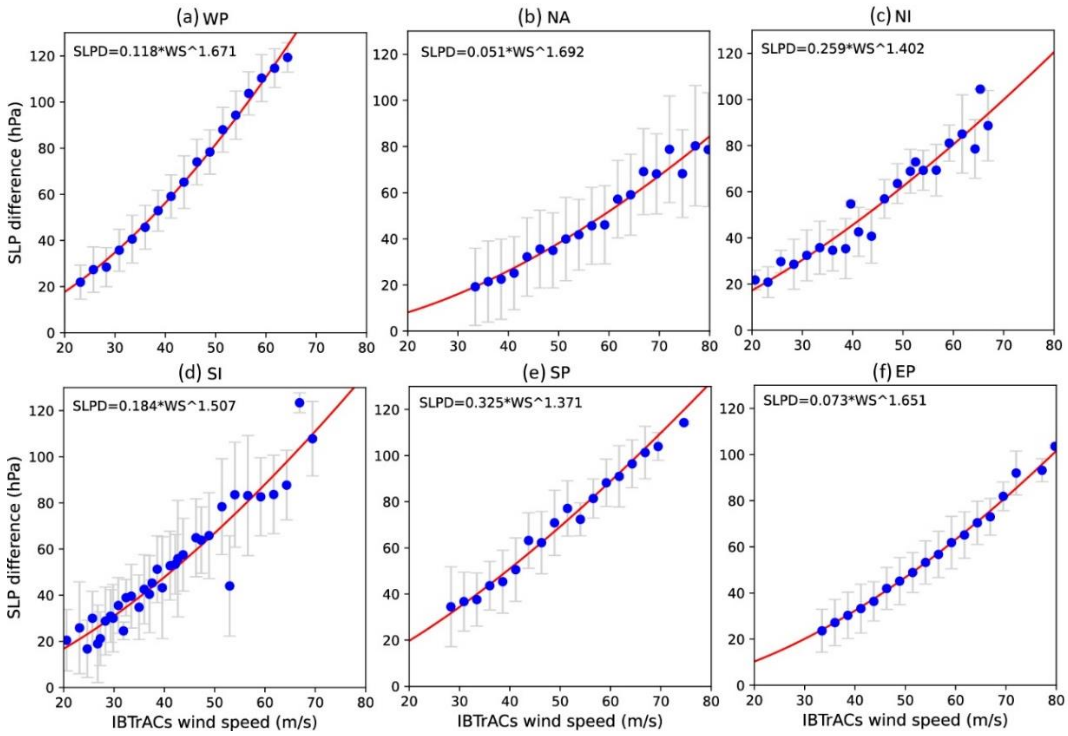

Figure 6: Similar to Figure 4, but for non-linear regression analyses between value-averaged IBTrACS maximum wind speeds and ~~sea level pressure~~the difference between environmental pressure and typical cyclone minimum central pressure (SLPD).

The mean and standard deviation values of various TC characteristics based on the testing datasets are plotted in Fig. 7 to compare the overall performance of the model in reconstructing TCs. Mean biases in R_{max} and P_{min} between the reconstructed TC and IBTrACS datasets ~~were~~ are both <3% in most basins, providing compelling evidence that the predictions ~~were~~ are in good agreement with observations. In contrast to those over the sea, the reconstructed dataset overestimate and underestimate landfall TC V_{max} and R_{max} ~~data were are overestimated and underestimated~~ in most basins, respectively, likely due to the decay of TC wind speeds after landfall, which is not considered in the RF-based models. Despite these differences, biases remain~~ed~~ within 5% in most basins, indicating that the reconstructed landfall TC characteristics ~~were~~ are closely aligned with those in the IBTrACS dataset.

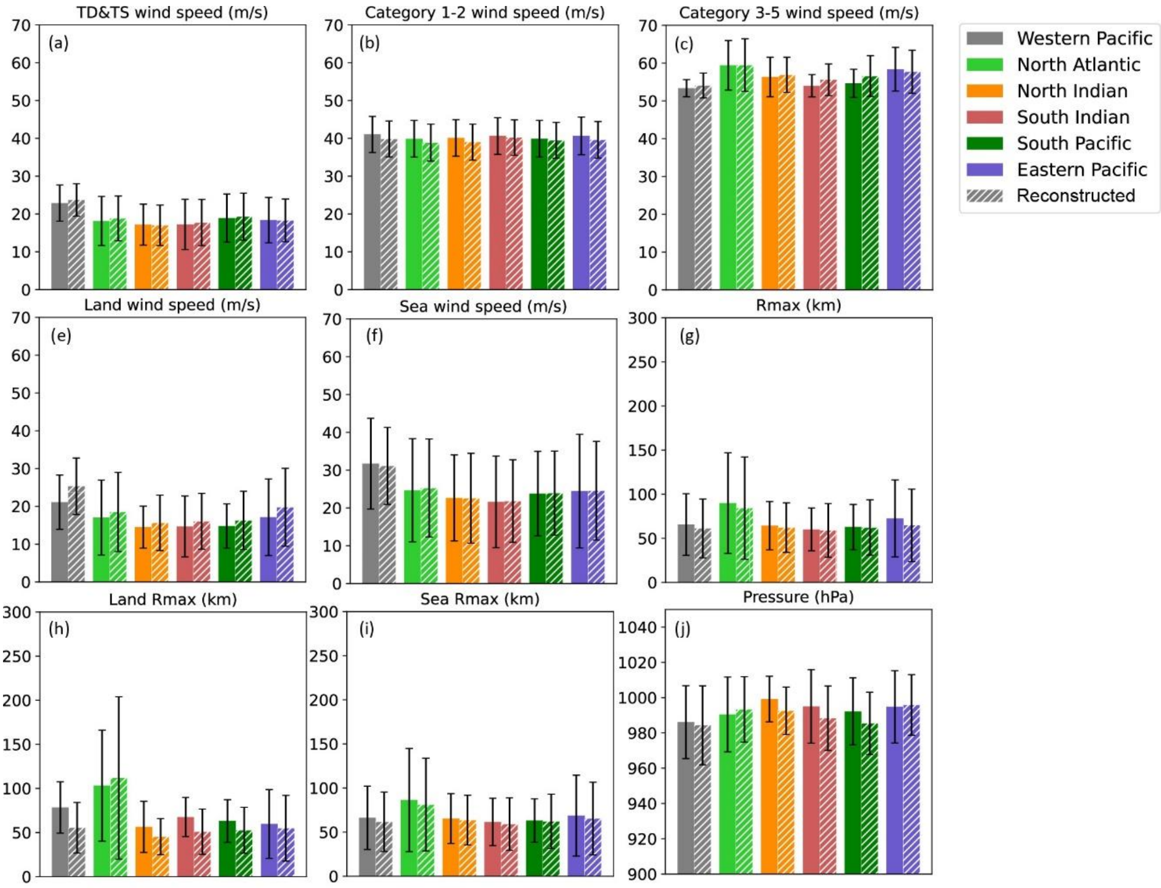

Figure 7: Bar charts for comparing the mean value of the different tropical cyclone characteristics. Each of the colors indicates a different basin. Solid and dashed bars represent IBTrACS and reconstructed tropical cyclone data, respectively.

After obtaining the reconstructed TC intensity dataset, we use six widely used models ~~were are used~~ to estimate R_{34_RC}, R_{50_RC}, and R_{64_RC}. We conduct~~ed~~ a comparative analysis of the model-derived results and observations to determine which radial wind profile estimate more closely approximated the TC outer radius, based on various statistical metrics (Table ~~S16~~S1–~~S611~~S6). In the WP basin, the W06 model demonstrates the strongest correlation~~In WP basin, The the W06 model results exhibited strongest correlation ,~~ (R_{34}: 0.89, R_{50}: 0.82, R_{64}: 0.78), achieving the lowest RMSE and ~~mean absolute error (MAE)lowest RMSE (R_{34}: 0.89, R_{50}: 0.82, R_{64}: 0.78), and lowest absolute mean absolute error (MAE).~~ In NA basin, the CLE15 model outperforms others for~~the CLE15 model performs better for~~ R_{34}, with a correlation coefficient of 0.87, RMSE of 78.77 km, and MAE of 53 km, whereas the W06 model performs better for~~with the correlation coefficient of 0.87, RMSE of 78.77 km and MAE of 53 km, whereas the W06 model results show a better performance for~~ R_{50} and R_{64}. For the NI and

SI basins, all models except W06 show poor correlation with observations, some even exhibiting negative correlations. In the SP and EP basins, W06 substantially ~~significantly~~ surpasses other models in terms of correlation coefficient. Although other models produce slightly smaller RMSE and MAE values for~~In NI and SI basins, with the exception of W06, the results of the remaining models exhibit a poor correlation with observations, with some even demonstrating a negative correlation.the W06 model results exhibit strongest correlation, In SP and EP basins, W06 remains the substainllysubstantially higher correlation coefficient than other models.for all basins except the North Atlantic~~NA basin~~, whereas the CLE15 model performed better for~~ ~~R_{34_RC}~~ ~~in the~~ NA basin~~North Atlantic basin. While the RMSE and MAE of~~ R_{64} in the EP basin compared to W06, their correlation coefficients, which are ~~below~~< 0.2, justify our choice of W06. Consequently, we select W06 to forecast~~derived by other models are marginally smaller those simulated by W06 in EP basin, their correlation coefficients of less than 0.2 lead use to select W06. Therefore, we used W06 to forecast~~ R_{34_RC}, R_{50_RC}, and R_{64_RC} for the ~~West Pacific~~WP, ~~North and South Indian Ocean~~NI, SI, SP~~, and South~~ and E~~ast~~P~~Pacific~~ basins, whereas for the ~~North Atlantic~~NA basin, we use~~d~~ CLE15 to predict R_{34_RC} and W06 to predict R_{50_RC} and R_{64_RC}. The correlation coefficients ~~were~~ are >0.75 for three outer size metrics in most basins (Table ~~4~~S16).

Table S~~16~~. Basic information on the comparison of the reconstructed data with the observational data for R_{34}, R_{50} and R_{64}. ME, mean errors; MAE, mean ~~of the~~ absolute ~~bias~~error; RMSE, root mean square error; CE, correlation coefficients. H80, D87, W06, E11, F13 and CLE15 refer to the wind field models proposed by Holland (1980), DeMaria (1987), Willoughby et al. (2006), Emanuel and Rotunno (2011), Frisius and Scgönemann (2013) and Chavas et al. (2015)

	Optimal profile	ME (km)	MAE (km)	RMSE (km)	CE
WP R34	W06	-24.79	46.75	64.54	0.89
WP R50	W06	-14.60	26.00	33.27	0.82
WP R64	W06	-14.14	18.28	22.71	0.78
NA R34	CLE15	-25.19	53.00	78.77	0.87
NA R50	W06	-11.58	32.71	57.39	0.84
NA R64	W06	2.67	18.52	30.37	0.87
NI R34	W06	-23.19	31.19	41.59	0.74
NI R50	W06	-14.66	20.49	25.69	0.63
NI R64	W06	-11.63	16.62	21.17	0.62
SI R34	W06	3.57	45.71	56.68	0.74
SI R50	W06	14.35	29.69	36.18	0.46
SI R64	W06	9.68	18.54	21.57	0.43
SP R34	W06	-5.00	33.51	46.25	0.83

SP_{R50}	W06	11.75	21.53	27.25	0.77
SP_{R64}	W06	12.75	15.60	18.56	0.77
EP_{R34}	W06	32.25	44.43	51.31	0.81
EP_{R50}	W06	27.19	31.77	36.61	0.68
EP_{R64}	W06	18.74	21.66	25.24	0.51

~~**Table 6. Basic information on the comparison of the ERA-5 and reconstructed data with the observation data fored Basic information on evaluation indices for R_{34}, R_{50} and R_{64} in Western Pacific. ME, mean errors; MAE, mean of the absolute bias; RMSE, root mean square error; CE, correlation coefficients. H80, D87, W06, E11, F13 and CLE15 refer to the wind field models proposed by Holland (1980), DeMaria (1987), Willoughby et al. (2006), Emanuel and Rotunno (2011), Frisius and Scgönemann (2013) and Chavas et al. (2015)**~~

	~~ME (km)~~	~~MAE (km)~~	~~RMSE (km)~~	~~CE~~
~~$\mathrm{H80}_{\mathrm{R34}}$~~	~~-80.39~~	~~89.34~~	~~110.54~~	~~0.68~~
~~$\mathrm{D87}_{\mathrm{R34}}$~~	~~-66.36~~	~~82.35~~	~~103.63~~	~~0.60~~
~~$\mathrm{W06}_{\mathrm{R34}}$~~	~~-24.79~~	~~46.75~~	~~64.54~~	~~0.89~~
~~$\mathrm{E11}_{\mathrm{R34}}$~~	~~-60.24~~	~~73.72~~	~~93.24~~	~~0.71~~
~~$\mathrm{F13}_{\mathrm{R34}}$~~	~~-106.04~~	~~110.49~~	~~132.57~~	~~0.68~~
~~$\mathrm{CLE15}_{\mathrm{R34}}$~~	~~-60.60~~	~~74.80~~	~~93.53~~	~~0.72~~
~~$\mathrm{H80}_{\mathrm{R50}}$~~	~~-50.42~~	~~54.66~~	~~64.76~~	~~0.54~~
~~$\mathrm{D87}_{\mathrm{R50}}$~~	~~-39.40~~	~~47.11~~	~~56.91~~	~~0.52~~
~~$\mathrm{W06}_{\mathrm{R50}}$~~	~~-14.60~~	~~26.00~~	~~33.27~~	~~0.82~~
~~$\mathrm{E11}_{\mathrm{R50}}$~~	~~-28.29~~	~~46.90~~	~~56.26~~	~~0.25~~
~~$\mathrm{F13}_{\mathrm{R50}}$~~	~~-65.31~~	~~67.30~~	~~77.81~~	~~0.50~~
~~$\mathrm{CLE15}_{\mathrm{R50}}$~~	~~-39.87~~	~~46.93~~	~~56.52~~	~~0.56~~
~~$\mathrm{H80}_{\mathrm{R64}}$~~	~~-32.13~~	~~33.66~~	~~39.06~~	~~0.60~~
~~$\mathrm{D87}_{\mathrm{R64}}$~~	~~-23.97~~	~~26.75~~	~~32.27~~	~~0.62~~
~~$\mathrm{W06}_{\mathrm{R64}}$~~	~~-14.14~~	~~18.28~~	~~22.71~~	~~0.78~~
~~$\mathrm{E11}_{\mathrm{R64}}$~~	~~-26.36~~	~~28.71~~	~~34.01~~	~~0.62~~
~~$\mathrm{F13}_{\mathrm{R64}}$~~	~~-41.06~~	~~41.86~~	~~47.22~~	~~0.56~~
~~$\mathrm{CLE15}_{\mathrm{R64}}$~~	~~-24.32~~	~~27.25~~	~~32.73~~	~~0.61~~

~~Table 7. Similar to Table S16, but in North Atlantic.~~

	ME (km)	MAE (km)	RMSE (km)	CE
H80$_{R34}$	-50.20	63.41	89.89	0.87
D87$_{R34}$	-22.85	58.87	82.83	0.85
W06$_{R34}$	-41.75	67.06	112.55	0.81
E11$_{R34}$	-19.90	54.17	80.59	0.85
F13$_{R34}$	-91.60	94.33	122.41	0.87
CLE15$_{R34}$	-25.19	53.00	78.77	0.87
H80$_{R50}$	-25.33	43.75	62.34	0.82
D87$_{R50}$	-6.81	45.40	66.86	0.79
W06$_{R50}$	-11.58	32.71	57.39	0.84
E11$_{R50}$	25.41	61.73	89.89	0.82
F13$_{R50}$	-50.70	54.88	72.66	0.83
CLE15$_{R50}$	-10.75	41.50	60.52	0.82
H80$_{R64}$	-15.35	27.55	39.46	0.82
D87$_{R64}$	-6.39	26.98	39.04	0.81
W06$_{R64}$	2.67	18.52	30.37	0.87
E11$_{R64}$	-8.73	26.15	37.58	0.83
F13$_{R64}$	-27.81	31.47	42.17	0.85
CLE15$_{R64}$	-5.52	26.38	37.92	0.83

~~Table 8. Similar to Table S16, but in North Indian.~~

	ME (km)	MAE (km)	RMSE (km)	CE
H80$_{R34}$	-71.01	72.12	87.65	0.17
D87$_{R34}$	-62.28	64.64	81.20	0.18
W06$_{R34}$	-23.19	31.19	41.59	0.74
E11$_{R34}$	-59.22	61.89	77.41	0.27
F13$_{R34}$	-88.25	88.42	102.12	0.12
CLE15$_{R34}$	-59.04	61.77	78.04	0.22
H80$_{R50}$	-40.23	41.11	49.98	-0.17
D87$_{R50}$	-32.57	35.01	45.31	-0.24
W06$_{R50}$	-14.66	20.49	25.69	0.63
E11$_{R50}$	-20.03	37.42	43.99	-0.57
F13$_{R50}$	-49.46	50.07	57.74	-0.29
CLE15$_{R50}$	-32.77	34.95	44.63	-0.18
H80$_{R64}$	-24.54	27.28	33.41	-0.18
D87$_{R64}$	-19.30	24.63	30.47	-0.23
W06$_{R64}$	-11.63	16.62	21.17	0.62
E11$_{R64}$	-22.20	25.82	31.92	-0.19
F13$_{R64}$	-29.87	31.81	38.26	-0.47
CLE15$_{R64}$	-18.94	24.54	30.71	-0.33

Table 9. Similar to Table S16, but in South Indian.

	ME (km)	MAE (km)	RMSE (km)	CE
H80$_{R34}$	-52.37	66.93	86.54	0.40
D87$_{R34}$	-39.35	65.36	83.62	0.24
W06$_{R34}$	3.57	45.71	56.68	0.74
E11$_{R34}$	-32.10	58.83	75.18	0.42
F13$_{R34}$	-77.33	82.86	103.96	0.40
CLE15$_{R34}$	-34.01	58.82	75.05	0.46
H80$_{R50}$	-16.33	33.34	42.84	0.06
D87$_{R50}$	-4.94	33.45	41.81	-0.01
W06$_{R50}$	14.35	29.69	36.18	0.46
E11$_{R50}$	10.50	40.17	49.96	-0.13
F13$_{R50}$	-31.74	39.51	50.65	-0.01
CLE15$_{R50}$	-6.01	33.58	41.64	0.02
H80$_{R64}$	-6.23	18.45	23.88	-0.01
D87$_{R64}$	2.01	18.92	23.27	0.05
W06$_{R64}$	9.68	18.54	21.57	0.43
E11$_{R64}$	-0.55	18.31	22.70	0.12
F13$_{R64}$	-17.11	21.82	28.37	-0.06
CLE15$_{R64}$	0.36	18.21	22.42	0.13

Table 10. Similar to Table S16, but in South Pacific.

	ME (km)	MAE (km)	RMSE (km)	CE
H80$_{R34}$	-59.42	67.85	82.65	0.66
D87$_{R34}$	-46.49	61.37	77.34	0.57
W06$_{R34}$	-5.00	33.51	46.25	0.83
E11$_{R34}$	-39.66	53.81	67.68	0.69
F13$_{R34}$	-85.65	88.49	104.22	0.68
CLE15$_{R34}$	-40.36	53.51	67.32	0.71
H80$_{R50}$	-21.77	30.51	36.71	0.64
D87$_{R50}$	-11.07	26.03	32.12	0.63
W06$_{R50}$	11.75	21.53	27.25	0.77
E11$_{R50}$	2.86	29.22	38.00	0.42
F13$_{R50}$	-38.11	41.99	49.05	0.62
CLE15$_{R50}$	-10.19	24.78	31.18	0.65
H80$_{R64}$	-2.51	13.33	16.38	0.64
D87$_{R64}$	5.80	14.17	17.05	0.66
W06$_{R64}$	12.75	15.60	18.56	0.77
E11$_{R64}$	4.97	14.14	17.02	0.68
F13$_{R64}$	-13.60	16.42	20.91	0.66

~~CLE15$_{R64}$~~	~~7.00~~	~~14.58~~	~~17.05~~	~~0.69~~

~~**Table 11. Similar to Table S16, but in Eastern Pacific.**~~

	~~ME (km)~~	~~MAE (km)~~	~~RMSE (km)~~	~~CE~~
~~H80$_{R34}$~~	~~-18.13~~	~~48.97~~	~~62.66~~	~~0.52~~
~~D87$_{R34}$~~	~~-7.32~~	~~55.07~~	~~69.07~~	~~0.41~~
~~W06$_{R34}$~~	~~32.25~~	~~44.43~~	~~51.31~~	~~0.81~~
~~E11$_{R34}$~~	~~4.02~~	~~50.50~~	~~64.00~~	~~0.53~~
~~F13$_{R34}$~~	~~-43.59~~	~~55.90~~	~~70.91~~	~~0.54~~
~~CLE15$_{R34}$~~	~~5.97~~	~~48.36~~	~~61.56~~	~~0.57~~
~~H80$_{R50}$~~	~~-9.60~~	~~27.55~~	~~36.73~~	~~0.32~~
~~D87$_{R50}$~~	~~-2.51~~	~~28.81~~	~~38.34~~	~~0.27~~
~~W06$_{R50}$~~	~~27.19~~	~~31.77~~	~~36.61~~	~~0.68~~
~~E11$_{R50}$~~	~~10.68~~	~~35.00~~	~~47.12~~	~~0.12~~
~~F13$_{R50}$~~	~~-23.54~~	~~31.68~~	~~40.92~~	~~0.31~~
~~CLE15$_{R50}$~~	~~1.73~~	~~27.70~~	~~37.00~~	~~0.34~~
~~H80$_{R64}$~~	~~-5.67~~	~~17.90~~	~~23.18~~	~~0.14~~
~~D87$_{R64}$~~	~~-0.32~~	~~18.69~~	~~23.92~~	~~0.11~~
~~W06$_{R64}$~~	~~18.74~~	~~21.66~~	~~25.24~~	~~0.51~~
~~E11$_{R64}$~~	~~0.59~~	~~17.86~~	~~22.98~~	~~0.19~~
~~F13$_{R64}$~~	~~-14.41~~	~~19.89~~	~~25.70~~	~~0.12~~
~~CLE15$_{R64}$~~	~~1.31~~	~~18.27~~	~~23.54~~	~~0.15~~

~~**Table 4: Similar to Table 2, but for R_{34}, R_{50} and R_{64}.**~~

	~~Optimal profile~~	~~ME (km)~~	~~MAE (km)~~	~~RMSE (km)~~	~~CE~~
~~WP $_{R34}$~~	~~W06~~	~~-24.79~~	~~46.75~~	~~64.54~~	~~0.89~~
~~WP $_{R50}$~~	~~W06~~	~~-14.60~~	~~26.00~~	~~33.27~~	~~0.82~~
~~WP $_{R64}$~~	~~W06~~	~~-14.14~~	~~18.28~~	~~22.71~~	~~0.78~~
~~NA $_{R34}$~~	~~CLE15~~	~~-25.19~~	~~53.00~~	~~78.77~~	~~0.87~~
~~NA $_{R50}$~~	~~W06~~	~~-11.58~~	~~32.71~~	~~57.39~~	~~0.84~~
~~NA $_{R64}$~~	~~W06~~	~~2.67~~	~~18.52~~	~~30.37~~	~~0.87~~
~~NI $_{R34}$~~	~~W06~~	~~-23.19~~	~~31.19~~	~~41.59~~	~~0.74~~
~~NI $_{R50}$~~	~~W06~~	~~-14.66~~	~~20.49~~	~~25.69~~	~~0.63~~
~~NI $_{R64}$~~	~~W06~~	~~-11.63~~	~~16.62~~	~~21.17~~	~~0.62~~
~~SI $_{R34}$~~	~~W06~~	~~3.57~~	~~45.71~~	~~56.68~~	~~0.74~~
~~SI $_{R50}$~~	~~W06~~	~~14.35~~	~~29.69~~	~~36.18~~	~~0.46~~
~~SI $_{R64}$~~	~~W06~~	~~9.68~~	~~18.54~~	~~21.57~~	~~0.43~~
~~SP $_{R34}$~~	~~W06~~	~~-5.00~~	~~33.51~~	~~46.25~~	~~0.83~~
~~SP $_{R50}$~~	~~W06~~	~~11.75~~	~~21.53~~	~~27.25~~	~~0.77~~

~~SP $_{R64}$~~	~~W06~~	~~12.75~~	~~15.60~~	~~18.56~~	~~0.77~~
~~EP $_{R34}$~~	~~W06~~	~~32.25~~	~~44.43~~	~~51.31~~	~~0.81~~
~~EP $_{R50}$~~	~~W06~~	~~27.19~~	~~31.77~~	~~36.61~~	~~0.68~~
~~EP $_{R64}$~~	~~W06~~	~~18.74~~	~~21.66~~	~~25.24~~	~~0.51~~

We use t~~T~~he ERA5 dataset ~~was~~ is ~~used~~ to derive parameters characterizing TC intensity and size in creating the TC reconstruction dataset. Then, we subject these parameters to a machine learning algorithm to produce more accurate data ~~these parameters were~~ are ~~subjected to a machine learning algorithm to produce more accurate data~~. Notably, we acknowledge that the TC intensity and size reconstructions developed in this study may be influenced by the limitations and uncertainties inherent in the IBTrACS and ERA5 datasets.~~Notably, the TC intensity and size reconstructions developed in this study may be influenced by limitations and uncertainties inherent to the IBTrACS and ERA5 datasets~~. The RF models ~~were~~ are unable to differentiate between landfall and offshore TCs due to the limited data available concerning landfall TCs in the IBTrACS dataset, which results~~ed~~ in higher V_{max} and lower R_{max} values for landfall TCs. ~~Therefore, w~~When employing this dataset for the purpose of examining the characteristics and impacts of TCs during their landfall, it is possible to~~, there exists a propensity to~~ overestimate their intensity while underestimating the scope of their influence~~the extent of their influence.~~ Additionally, we estimate R_{34}, R_{50} and R_{64} ~~were~~ are ~~estimated~~ using wind profile models rather than RF models due to the paucity of relevant data, which results~~ed~~ in a lower level of accuracy than for these TC characteristics. Moreover, there ~~was~~ is some dependency between the reconstructed and IBTrACS-derived R_{max} values, likely due to the insufficient spatial resolution of the ERA5 dataset. ~~Finally~~Finally,~~Besides,~~ TC positions in the IBTrACS data exhibit~~ed~~ some degree of inaccuracy during the pre-satellite time period. Therefore, when assessing the impacts of TCs ~~with~~using this dataset, e.g., TC risk assessment, it is crucial to validate the ~~finding~~results through ~~a combination of~~ observations from meteorological stations, buoys, and other relevant ~~observational mean~~methods. Notwithstanding these limitations, the TC reconstruction dataset exhibits~~ed~~ a markedly high degree of accuracy and extensive spatiotemporal coverage. Basic information on the reconstructed TC data is presented in Table ~~5~~7.

Table ~~5~~7: Basic information on the number of recorded tropical cyclone characteristics from 1959 to 2022 recorded in reconstructed data.

Basin	V_{max}	P_{min}	R_{max}	R_{34}	R_{50}	R_{64}
Western Pacific	152208	152208	152208	127668	39659	24302
North Atlantic	55608	55608	55608	31829	19106	11719
North Indian	24047	24047	24047	4614	1840	1039
South Indian	86606	86606	86606	35768	18500	10395
South Pacific	45112	45112	45112	23312	10547	5454
Eastern Pacific	59112	59112	59112	33772	19214	13026
Global	422693	422693	422693	256963	108866	65935

5. Data and Code availability

All data have been published in the form of CSV files, and are made publicly available through Zenodo repository with the address: https://doi.org/10.5281/zenodo.13919874~~https://doi.org/10.5281/zenodo.12740372~~ (Xu et al., 2024). ERA5 data can be publicly accessible at https://doi.org/10.24381/cds.bd0915c6 (Hersbach et al., 2023a) and https://doi.org/10.24381/cds.adbb2d47 (Hersbach et al., 2023b). IBTrACS data is accessible at https://doi.org/10.25921/82ty-9e16 (Gahtan et al., 2024). The processing codes can be made available upon request to the corresponding author. This study provides a detailed description of the TC size and intensity reconstruction dataset, which includes the maximum sustained wind speed, the radius of~~to~~ maximum wind~~ speed~~, the minimum central pressure and the radii to locations with sustained wind speeds of 34, 50, and 64 knots during 1959–2022.

6. Conclusion

The considerable number of unrecorded TC characteristics in the IBTrACS dataset and large biases inherent in the ERA5 dataset ~~prompte~~prompt~~d~~ us to generate a long-term TC reconstruction dataset. We construct~~ed~~ the dataset by integrating TC characteristics from the IBTrACS and ERA5 datasets using RF-based models, an empirical wind–pressure relationship, and six wind profiles for the period 1959–2022. The TC reconstruction dataset is approximately 3–4 times larger than the IBTrACS dataset in terms of data points per characteristic, with much higher data accuracy than shown for ERA5-derived results.

We examine s~~S~~ix TC characteristics ~~were are examined~~ to evaluate the reconstructed dataset. A comparison of maximum sustained wind speeds between the IBTrACS and reconstructed TC datasets reveals~~ed~~ that the latter underestimated observational data by approximately 2.82 m/s, which is a considerably smaller bias than that shown by the ERA5 dataset (16.73 m/s) on a global scale. For the radius of~~to~~ maximum wind~~ speed~~ (R_{max}), the mean error and RMSE decrease~~d~~ markedly, from −41.64 and 67.66 km (IBTrACS R_{max} – ERA5 R_{max}) to 1.37 and 22.19 km (IBTrACS R_{max} – reconstructed R_{max}), respectively. In addition, the correlation coefficient for R_{max} between the IBTrACS and ERA5 datasets ~~was~~ is 0.44, which increased to 0.94 between the IBTrACS and TC reconstruction datasets. The mean bias in minimum central pressure between the IBTrACS and reconstructed TC datasets ~~was~~ is <3% in most basins. We use s~~S~~ix wind profile models ~~were are used~~ to compute the radii to locations with sustained wind speeds of 34, 50, and 64 knots (R_{34}, R_{50}, and R_{64}), and the selected wind profile models (CLE15 for R_{34} in the North Atlantic, W06 for others) show~~ed~~ good estimates for TC outer sizes, with correlation coefficients > 0.75 for three outer size metrics in most basins. Overall, the TC reconstruction dataset ~~agreed~~ agrees closely with the IBTrACS data in terms of TC intensity and size.

In conclusion, the TC reconstruction dataset may prove invaluable for advancing our understanding of TC climatology, thereby facilitating risk assessments and defenses against TC-related disasters. The future availability of reanalysis data with finer spatial resolution and longer temporal coverage, such as the in-progress ERA6, will facilitate the creation of more accurate TC reconstructions with longer time spans using the methods presented in this study.

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