Responses to comments of Reviewer #1

We wish to express our great appreciation for your review and constructive comments. In the revised manuscript, we have made substantial changes to strengthen its readability, and incorporated all your comments. In the response below, we address each of these comments individually. Your comments are *italicized* and our responses follow immediately. Changes to the manuscript text are included in blue.

The manuscript presents a new global tropical cyclone dataset that integrates the IBTrACS and ERA5 reanalysis data to reconstruct key TC characteristics like Vmax, Rmax, and Pmin. The authors use random forest algorithm to reduce biases in the ERA5-derived characteristics, enhancing the data availability and spatiotemporal coverage of the best track dataset. This manuscript demonstrates a certain level of innovation and scientific value, and it is generally well-organized. I recommend accepting the manuscript with minor revisions in the following.

1. The approach of combining IBTrACS and ERA5 data using machine learning like Random Forest models appears to be well-justified based on the reported improvements in bias reduction. However, it would be helpful to provide more details about the selection process for the RF model, particularly in comparison with other models that were tested but not selected.

Response: Thank you for this good comment. We have supplemented the details regarding the selection process for the RF model in the section 3.2, and have extensively rewritten most parts of this section. For the revised comparisons among different models, please see lines 162-170, Table 2, lines 181-183 and Table 3.

[lines 162-170]:

We optimize the machine learning models by Randomized Search Cross-Validation with mean square error as the loss function using Python. The models include 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) into the model training process. We randomly divide the dataset, made up of the input array and learning target, into two subsets, with 75% allocated for training and the remaining 25% for testing, following the methods of previous studies (e.g., Breiman, 2001; Guo et al., 2024). For a detailed account of the hyperparameter selections for each model, please refer to the Text S1 in supplementary materials. We find that RF provided the most robust predictions, as evidenced by higher correlations and smaller root mean square error (RMSE) values in most basins.

[Table 2]:

Table 2. Basic information on the comparison of the different model-derived with observed V_{max} in Western Pacific (WP), North Atlantic (NA), North Indian (NI), South Indian (SI) South Pacific (SP) and Eastern Pacific (EP). CE, 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

[lines 181-183]:

We also test several machine learning models (Table 3). Although the ANN-derived R_{max} exhibit stronger correlations with observations, the RMSE values of R_{max} derived by RF with observations are considerably smaller than that derived by other models.

[Table 3]:

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

2. One suggestion for improving writing could be to streamline the description of the wind profile models, as the detailed mathematical formulations might be overwhelming for some readers. Instead, focusing on the selected wind profile models and the comparative performance of all models in the main body of the manuscript (rather than in supplement and summarize the tables) would be more impactful.

Response: Per your comment, we have streamlined the description of the wind profile models, and moved the detailed mathematical formulations to the supplementary materials. Besides, we have added the comparative performance of all models. For the revised statements please see lines 208-210 and lines 276-285.

[lines 208-210]:

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, we select the optimal model to generate reconstructed R_{34}, R_{50}, and R_{64}, as described in detail in Section 4.

[lines 276-285]:

In the WP basin, the W06 model demonstrates the strongest correlation (R_{34}: 0.89, R_{50}: 0.82, R_{64}: 0.78), achieving the lowest RMSE and MAE. In NA basin, the CLE15 model outperforms others 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 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 surpasses other models in terms of correlation coefficient. Although other models produce slightly smaller RMSE and MAE values for R_{64} in the EP basin compared to W06, their correlation coefficients, which are < 0.2, justify our choice of W06. Consequently, we select W06 to forecast R_{34_RC}, R_{50_RC}, and R_{64_RC} for the WP, NI, SI, SP and EP basins, whereas for the NA basin, we use CLE15 to predict R_{34_RC} and W06 to predict R_{50_RC} and R_{64_RC}. The correlation coefficients are >0.75 for three outer size metrics in most basins (Table 6).

3. The reductions in bias for key metrics like Vmax and Rmax are impressive. However, while the manuscript acknowledges the limitations related to landfall TCs and the dependency on ERA5's spatial resolution, a more detailed discussion on how these limitations might affect specific use cases of the dataset could be beneficial.

Response: Thank you for this good comment. We have supplemented the detailed discussion. For the revised statements please see lines 295-297 and lines 35-59.

[lines 295-297]:

When employing this dataset for the purpose of examining the characteristics and impacts of TCs during their landfall, it is possible to overestimate their intensity while underestimating the scope of their influence.

[lines 301-302]:

Therefore, when assessing the impacts of TCs using this dataset, e.g., TC risk assessment, it is crucial to validate the results through observations from meteorological stations, buoys, and other relevant methods.

4. Ensure consistency in tense usage, particularly when discussing results and implications. For example, there is a mixture of the past simple tense and present simple tense in line 240.

Response: Per your comment, we have consistently applied the present simple tense throughout the revised manuscript. We have revised the sentences in line 240 as "Therefore, for clarity, the R_{max_ERA5} data are not shown with the reconstructed TC results in Fig. 5. The MAE exhibits a reduction of 39.57 km on a global scale, with a further reduction of over 59.37 km in the SI basin, as described in detail in Table 5."

5. Consider using active voice more frequently to make the writing more direct. For example, "Six wind profile models were used to compute the radii..." could be "We used six wind profile models to compute the radii..."

Response: Per your kind comments, we have revised the verb tenses in the revised manuscript as active voice, and have revised the sentence as "We use six wind profile models 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 good estimates for TC outer sizes, with correlation coefficients > 0.75 for three outer size metrics in most basins."