MJFAS
Malaysian Journal of Fundamental and Applied Sciences

Parveen *et al.* | Malaysian Journal of Fundamental and Applied Sciences, Vol. 21 (2025) 2844–2856

RESEARCH ARTICLE

MLR-based Study of the Wind-pressure Profile in Arabian Sea Cyclones

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Abstract

Tropical cyclones (TCs) in the Arabian Sea have become more frequent and intense, due to climatic variability. These changes represent an increasing hazard to coastal communities and infrastructure throughout the area. Accurate calculation of cyclone wind and pressure fields is critical for cyclone forecasting, early warning systems and disaster response. Usually cyclones are studied with the help of wind-pressure models. One such model is Holland Model which utilizes a wind-pressure profile parameter B. This parameter which is a power exponent plays an essential role in shaping wind and pressure profiles. It defines that how sharply the pressure drops from the outer environment to the cyclone's center. Although various models for estimating the wind-pressure profile parameter B exist for basins such as the Atlantic, Northwest Pacific and Bay of Bengal, no such model has been specifically developed for the Arabian Sea. This study addresses this gap by constructing and evaluating multi- linear regression (MLR) models to create such power exponents for Arabian Sea cyclones using best-track cyclone data from the IBTrACS dataset (1980–2023) which is the satellite data. Four models B_α, B_β and B_γ for wind-pressure profile parameter B are developed for Arabian Sea cyclones incorporating different combinations of meteorological variables, including maximum sustained wind, central pressure, pressure drop, radius of maximum wind (RMW) and latitude. Model's performance is assessed using adjusted R^2, predicted R^2, RMSE and MAE. Model B_γ is the best-performing model with the predicted R^2 of 78%, with the lowest standard error (0.1395). We have also calculated B, the Holland's wind-pressure profile parameter, on Arabian Sea data. The data used here is satellite data instead of aircraft data. Further, all these models including B are applied to the 20% test dataset to validate the predicted wind-pressure profile parameters. Finally, we will compare B_α, B_β and B_γ with B. For the test data B_γ shows good accuracy. Its correlation with B values is 0.7796. These models are used to generate both the wind and pressure profiles of Cyclone Tauktae. Finally, results obtained by MLR are compared with the results obtained by B. Among all MLR models B_γ gives results closest to B model. So, the model B_γ is recommended as the most reliable MLR model for estimating the wind-pressure parameter for the Arabian Sea.

Keywords: Holland parameter B, Wind-Pressure Profile, Multi-linear regression (MLR), Arabian Sea Cyclone.

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Received: 6 July 2025
Accepted: 2 Sept. 2025

Introduction

The Arabian Sea is growing increasingly vulnerable to major tropical cyclones (TCs), since their number and severity have increased since last decade. This Change is mostly caused by rising sea surface temperatures and climate changes [1]. Tropical storms in this region provide severe meteorological conditions such as high winds, torrential rainfall and coastal flooding [2]. These events can cause serious damage to human life, homes, infrastructure and agriculture especially in countries like Oman, Pakistan, India and Iran. Coastal areas, which are often highly populated, face the greatest risk [3]. Because of these threats, it is very important to improve the way we forecast cyclones. In particular, we need accurate models that can estimate the wind and pressure profile inside a cyclone, so that we can reduce the damage through better early warning systems and disaster planning [4]. One of the most commonly used model to study the internal structure of tropical cyclones is the Holland model, which provides a parametric formulation of the radial pressure and wind profile [5]. At the center of this model is the wind-pressure profile parameter B**,** a power exponent that controls the steepness of the cyclone's pressure gradient [6]. The pressure distribution in the Holland model is defined as:

$$P(r) = P_c + \Delta P\, e^{-\left(\frac{Rmax}{r}\right)^B} \quad \rightarrow (1)$$

Where P(r) is the pressure at a radial distance r, P_n is the ambient pressure, P_c is the central pressure, $\Delta P = P_n - P_c$ is the pressure drop between environmental and central pressure, R_{max} is the radius of maximum wind and B is the shape parameter as defined above. As B increases, the pressure gradient nearby R_{max} becomes sharper, resulting in higher wind speeds near the storm center [7].

The wind-pressure profile parameter B is also embedded in the gradient wind speed formulation (ignoring Coriolis force), given by [8]:

$$V(r) = \left[\frac{B}{\rho air} \cdot \left(\frac{Rmax}{r}\right)^B \cdot e^{-\left(-\frac{Rmax}{r}\right)^B}\right]^{\frac{1}{2}} \quad \rightarrow (2)$$

From this, the maximum wind speed can be derived:

$$V_{max} = \sqrt{\frac{B\Delta P}{e\rho}} \quad \rightarrow (3)$$

$$B = \frac{V^2{}_{max} e\rho}{P_n - P_c} \quad \rightarrow (4)$$

Here, ρ represents air density, e is the natural logarithm base and V_{max} is maximum sustain wind ,These equations show that B serves as a mathematical link between storm intensity and pressure structure, making its accurate estimation crucial for both scientific understanding and effective forecasting.
Historically, the concept of cyclone pressure fields modeling originated with Schloemer's exponential model [6]:

$$P(r) = P_c + \Delta P\, e^{-\frac{R_{max}}{r}} \quad \rightarrow (5)$$

Later, Holland improved this model by introducing the profile parameter B to better capture variability in pressure decay. The inclusion of B allows the model to pretend a wider range of cyclone structures from compact, intense systems to broader, weaker ones.

To understand the effect of the wind-pressure profile parameter B visually, Figure 1(a) illustrates pressure profiles generated by using Equation (1) and Figure 1(b) illustrates wind profile generated by using Equation (2). As shown in Figure 1(a), increasing B sharpens the pressure gradient near R_{max} and Figure1(b) shows the gradient wind speed increases near the core while decreasing further outward [7].

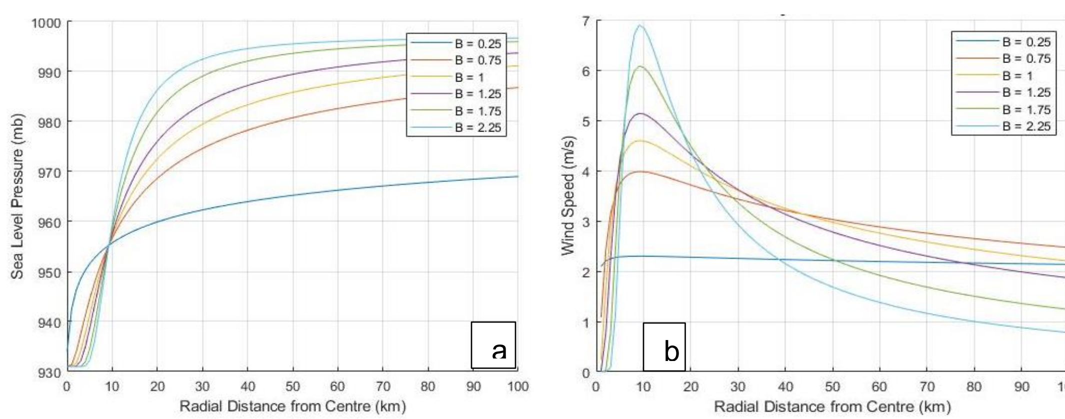


Figure 1. Effect of parameter B on wind-pressure profile (a) pressure versus radial distance from Cyclone center and (b) Wind speed versus radial distance from Cyclone center.

Since the development of the analytical wind-pressure Holland model (1980), numerous statistical, mathematical and numerical models have been developed to estimate the wind-pressure parameter B using cyclone observational data across various ocean basins [5]. In the Australian region, Love *et al*. proposed one of the initial statistical model, suggesting a logarithmic relationship between wind-pressure profile parameter B and pressure drop (ΔP), highlighting how wind-pressure profile parameter B increases with increasing storm intensity [9]. Hubert *et al*. [10] refined this with a simple linear model directly relating wind-pressure profile parameter B to the deviation of central pressure from a reference value (980 hpa), while Harper and Holland proposed another linear form that adjusted wind-pressure profile parameter B relative to a baseline pressure of 900 hpa, suitable for operational use in Australia [11]. In the Atlantic basin, Vickery *et al*. presented a more comprehensive linear regression model combining both ΔP and radius of maximum wind (RMW) to recognize their combined influence on cyclone structure [12]. Willoughby and Rahn built on this method by adding wind speed and latitude to RMW, allowing for better depiction of cyclones throughout latitudinal zones [13]. In the Bay of Bengal, Jakobsen *et al***.** applied a physical model derived from the gradient wind balance equation, expressing wind-pressure profile parameter B in terms of wind speed and ΔP, which proved effective in modeling storm surge conditions in shallow coastal waters [14]. A significant development was made by Holland, who introduced a reviewed form of the wind-pressure profile parameter B, termed B_s, which combined not only ΔP but also cyclone translation speed, the rate of central pressure change ($\partial P_c/\partial t$) and latitude. This made the model more approachable to dynamic storm conditions [15]. Harper *et al*. and Knaff *et al*. created region-specific calibration formulas in the Northwest Pacific (NWP) using ΔP, RMW and latitude for pre and post-landfall circumstances [7]. More recently, Fang *et al*. developed advanced statistical and machine learning models, comparing them to classical methods and representing that including RMW, pressure trends and latitude significantly improves the accuracy of wind-pressure profile parameter B and B_s estimates in the NWP region [16].

Despite this extensive study in other ocean basins, there is presently no statistical model for estimating the wind-pressure profile parameter B for the Arabian Sea**.** In this study, we aim to address this gap by developing an MLR model for estimating the wind-pressure profile parameter B.

Materials and Methods

Data Source

This study used tropical cyclone data for the Arabian Sea from the International Best Track Archive for Climate Stewardship (https://www.ncei.noaa.gov/products/international-best-track-archive), Version 4, which covered the period 1980 to 2023. The dataset contains essential cyclone variables include such as date, time, latitude, longitude, maximum sustained wind speed (WIND), minimum central pressure (P_c) and radius of maximum wind (RMW). These records were obtained directly from the NOAA Climate Data Repository. To assure data quality and consistency, the following Quality control criteria [8] were applied: (1) Geographical boundaries were limited to 50–75°E longitude and 5–25°N latitude to capture the Arabian Sea region; (2) only cyclones with WIND ≥ 35 m/s were retained to focus on storms of at least tropical storm intensity; (3) central pressure values were constrained to the range of 870–1000 hpa; and (4) RMW values exceeding 150 km were excluded to remove weak or abnormally large systems. A total of 310 profile were retained from these criteria. The dataset was randomly split into a training set (80%) and test set (20%) to validate model performance.

Methods

Step 1: Exploratory and Descriptive data Analysis

Descriptive Analysis is used to understand the distribution and central tendencies of key parameters [18] .The analysis involved to calculating the central tendency (mean, median and mode), dispersion (standard deviation, minimum and maximum), and distribution shape (skewness). Mean (μ) and Standard Deviation (σ) evaluate the average behavior and variability of each parameter. Its mathematical expression is as given in equation (6) & (7).

$$\boldsymbol{\mu} = \frac{1}{n}\sum_{i=1}^{n} \boldsymbol{xi} \quad \rightarrow (6)$$

$$\boldsymbol{\sigma} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\boldsymbol{xi} - \boldsymbol{\mu})^2} \quad \rightarrow (7)$$

Histograms with fitted normal distribution curves were employed to visually assess distribution patterns and detect asymmetry. This analysis describes the intensity and structural aspects of tropical cyclones in the Arabian Sea.

Step 2: Pearson Correlation Test

To explore the linear relation between two variables with values ranging from -1 (strong negative correlation) to +1 (strong positive correlation) Pearson correlation coefficients were calculated [19]. The correlation coefficient r is computed as:

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^{\ 2}}} \qquad \rightarrow (8)$$

Step 3: Multicollinearity Test

To estimate multicollinearity between the independent variables, the Variance Inflation Factor (VIF) was calculated for each predictor using the formula below [20].

$$VIF_i = \frac{1}{1-R_i^2} \qquad \rightarrow (9)$$

Where R_i^2 is the coefficient of determination for the i^{th} independent variable regressed against the remaining values. VIF values below 5 are generally considered acceptable, while values exceeding 10 are often cited as indicative of serious Multicollinearity. However, following the argument presented by O'Brien (2007), such rules of thumb should not be rigidly applied. O'Brien highlights that even VIF values of 10, 20 or higher may be acceptable if the regression coefficients remain statistically significant, confidence intervals are narrow and the model has high descriptive power. In this study, although maximum sustained wind and P_c suggested VIF values surpassing 10, both variables were retained due to their strong theoretical importance, high statistical significance ($p < 0.001$), and the excellent performance of the regression models [20]. Thus, while Multicollinearity is recognized, it does not compromise the validity or interpretability of the regression results.

Step 4: Multiple Linear Regression (MLR)

Multiple linear regression is known as statistical method was used to model the relation between one independent variable (response) and two or more independent variables (predictors) [21]. The general MLR equation is:

$$B_i = B_0 + B_1\ x_{i1} + B_2\, x_{i2} + B_3\, x_{i3} + \cdots \dots \dots \dots + B_j\, x_{ij} + \epsilon_i \qquad \rightarrow (10)$$

Where: B_i is dependent variable, x_i represents independent variables, B_j is regression coefficients and ϵ_i is the random error term.

MLR assumes a linear relationship between the dependent variable and each predictor and estimates regression coefficients that quantify the contribution of each independent variable. This method is widely used for prediction, trend analysis and understanding the influence of multiple factors on a target outcome

Step 5: Model Evaluation Criteria

Model performance was estimated using the statistical metric such as Coefficient of Determination (R^2) which measures goodness of fit of a model. If R^2 value is near to 1, it indicates a better fit of the model to the data, Adjusted (R^2) accounts for extra predictors, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) [17].

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}(\mathrm{O_i}-\mathrm{F_l})^2}{= \sum_{i=1}^{n}(\mathrm{O_i}-\bar{\mathrm{O}}_l)^2} \qquad \rightarrow (11)$$

$$\mathrm{R}^2_{\mathrm{adj}} = 1 - \frac{(1-\mathrm{R}^2)(1-\mathrm{n})}{\mathrm{n}-\mathrm{p}-1} \qquad \rightarrow (12)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{i=1}^{n}(\mathrm{F_i}-\mathrm{O_l})^2} \qquad \rightarrow (13)$$

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}|\mathrm{F_i}-\mathrm{O_l}| \qquad \rightarrow (14)$$

Where, F_l is the predicted value, O_l is the observed value, $\bar{O}_l$ is mean of observed values, p is number of predictors and n is the number of observations. Lower RMSE and MAE values indicate higher prediction accuracy.

Results and Discussion

Data Analysis

To study the structural characteristics of intense tropical cyclones over the Arabian Sea, the descriptive, exploratory and correlation analysis was executed on six key variables: latitude (LAT), maximum sustained wind speed (WIND), central pressure (P_c), pressure drop (ΔP), radius of maximum wind (RMW) and Holland B parameter. The summary of descriptive statistics are presented in Table 1.

Table 1. Descriptive Analysis of Key Cyclone Parameters

S.no	Variable	Mean	St.Dev	Minimum	Median	Maximum	Mode	N for Mode	Skewness
1	LAT (°N)	16.734	3.013	10.370	16.900	23.000	14.4	6	-0.08
2	WIND (m/s)	48.262	10.095	33.439	46.300	69.449	38.583	17	0.28
3	P_c (hpa)	955.45	16.11	924.00	957.00	992.00	937	12	-0.14
4	ΔP (hpa)	49.23	16.79	19.00	46.00	82.00	36, 67	9	0.24
5	RMW (km)	27.530	13.818	9.260	27.780	92.600	27.78	53	1.48
6	B Parameter	1.5223	0.2205	0.9447	1.5512	1.9239	1.49407	6	-0.58

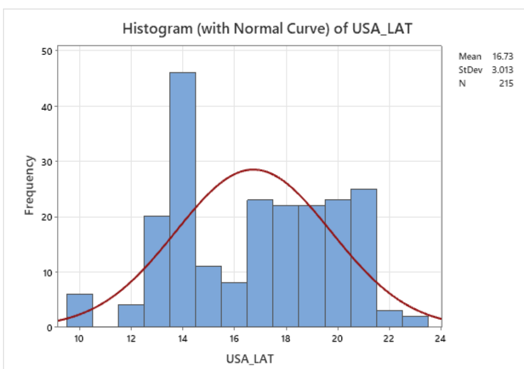


Figure 2. Histogram with Normal Curve of LAT

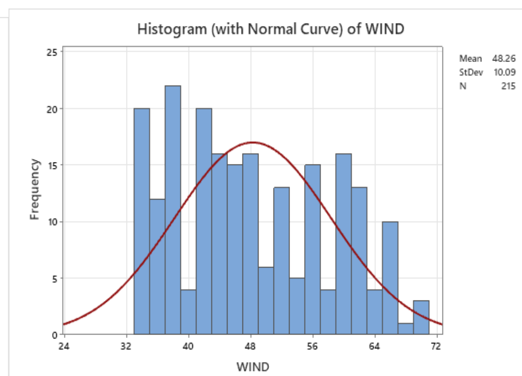


Figure 3. Histogram with Normal Curve of WIND

As shown in Figure 2, the frequency distribution of cyclone formation latitude (LAT) with a fitted normal curve in the Arabian Sea reveals that the majority of cyclones are develop between 14°N and 20°N. The average latitude is 16.73°N, with a standard deviation of 3.013, indicating a wide spread around the average. The distribution is approximately symmetric, with a skewness of -0.08, indicating a minor preference for lower latitudes. The histogram resembles the normal curve. Figure 3 depict that the frequency distribution of maximum wind speed (WIND) with a fitted normal curve reveal that most cyclone wind speeds range from 33 m/s to 69 m/s, with a mean of 48.26 m/s and a standard deviation of 10.10**.**

The distribution is moderately right-skewed **(**skewness = 0.28**)**, indicating a higher frequency of moderate wind speeds and a few cyclones with extreme intensities. The mode, 38.58 m/s**,** was seen 17 times, reflecting the most common intensity range. The curve fits reasonably well, confirming a somewhat normal pattern with moderate variability.

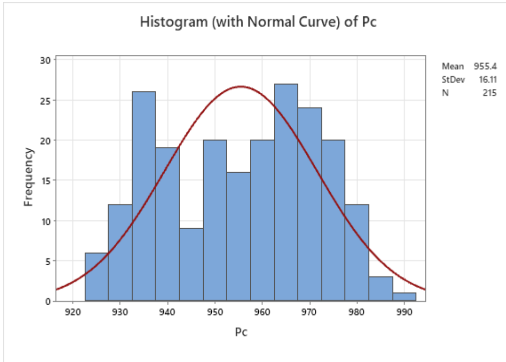


Figure 4. Histogram with Normal Curve of P_c

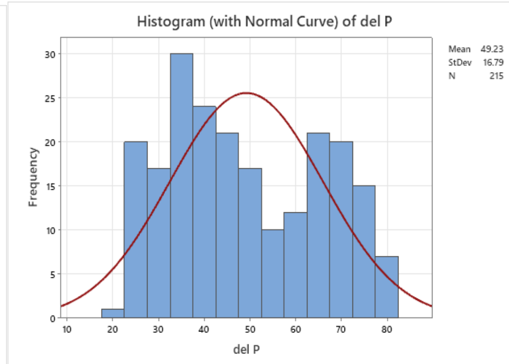


Figure 5. Histogram with Normal Curve of ΔP

Figure 4 displays the frequency distribution of central pressure (P_c) based on a fitted normal distribution. The chart indicates that cyclone core pressures varied from 924 hpa to 992 hpa, with a mean of 955.45 hpa and a standard deviation of 16.11. The distribution is nearly symmetrical, supported by a skewness of – 0.14, implying a balanced occurrence of low and high central pressures. The most frequently observed pressure was 937 hpa, appearing 12 times. The symmetry confirms Pc's normally distributed nature in this dataset. Referring to Figure 5, the frequency distribution of pressure drop (ΔP) indicates that most cyclones experienced a pressure drop between 19 hpa and 82 hpa, with a mean of 49.23 hpa and a standard deviation of 16.79. The distribution is slightly right-skewed (skewness = 0.24), suggesting that while moderate pressure drops are common, some cyclones had very high drops. Two modes (36 hpa and 67 hpa) appeared most frequently. This indicates that while moderate pressure drops dominate, a few cyclones exhibit much larger pressure differences, reflecting higher intensity systems.

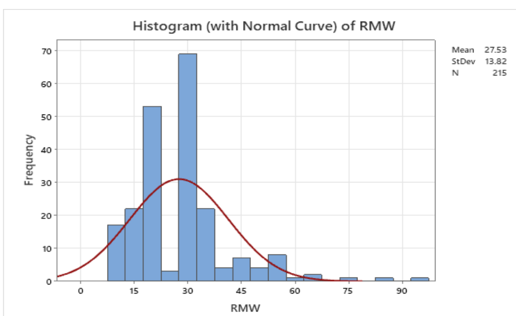


Figure 6. Histogram with Normal Curve of RMW

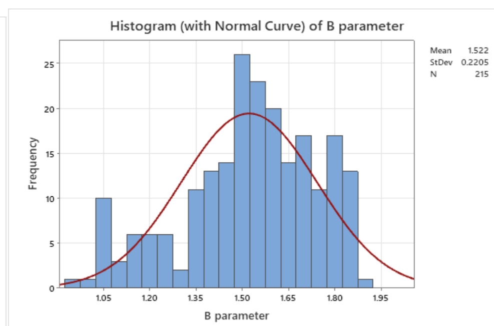


Figure 7. Histogram with Normal Curve of B

Figure 6 depicts that frequency distribution of RMW, which has a right-skewed profile, with the majority of values between 10 km and 40 km and a few extreme cases reaching up to 92.6 km. The average RMW is 27.53 km with a standard deviation of 13.82 and the high skewness (1.48) indicates significant variability in cyclone structure. The normal curve does not fit perfectly, highlighting the presence of outliers and asymmetry in cyclone wind radius distribution. Figure 7 shows the profile parameter B, which controls the sharpness of the pressure gradient, has a mean of 1.5223 and a standard deviation of 0.2205 with values ranging from 0.9447 to 1.9239. The negative skewness of - 0.58 indicates a left-skewed distribution, with more frequent higher B values and fewer low-B outliers. The mode 1.4941 occurred 6 times. The fitted normal distribution has a minor asymmetry indicating natural variations in the sharpness of the pressure gradient in Arabian Sea cyclones.

According to the descriptive study, the majority of Arabian Sea cyclones originate between 14 and 20 degrees N, with modest wind speeds and near-normal core pressure distributions. Pressure drop and wind speed are marginally right-skewed, however RMW is significantly skewed and showing structural variability. The Holland B parameter is left-skewed indicating frequent strong pressure gradients. Overall, the data show both common tendencies and significant variation in cyclone structure throughout the area.

The Pearson correlation test evaluates linear relationships among the cyclone parameters of latitude, wind speed, pressure drop (ΔP), radius of maximum wind (RMW), central pressure (P_c) and the Holland B parameter. The outcomes are presented in Table 2 below.

Table 2. Pearson Correlation Test for Tropical Cyclone Parameter

S.no	Variables	Correlation Coefficient (r)
1	ΔP and WIND	0.952
2	P_c and WIND	- 0.959
3	P_c and ΔP	- 0.977
4	B parameter and WIND	0.557
5	B parameter and ΔP	0.283
6	B parameter and LAT	0.312
7	B parameter and RMW	- 0.220
8	P_c and RMW	0.335
9	RMW and WIND	- 0.376
10	RMW and ΔP	- 0.370

As shown in Table 2, the most significant positive correlation is between wind speed and pressure drop ($r = 0.952$), confirming that greater pressure gradients are connected with higher wind intensities. Similarly, central pressure shows strong negative correlations with both wind speed and pressure drop, reinforcing its inverse role in cyclone intensity. The Holland B parameter shows a moderate positive relationship with wind speed and latitude, suggesting that more intense and equator ward cyclones tend to exhibit steeper pressure gradients. However, its correlation with RMW and P_c is weak, indicating that wind-pressure profile parameter B is more strongly influenced by dynamic factors such as intensity than by storm size or absolute pressure alone. These findings support the regression model outcome, where wind speed, pressure drop and latitude were significant predictors of the B parameter, while RMW was not, due to its weak correlation with intensity related variables.

VIF Test and MLR Model:

To model the wind-pressure profile parameter B based on observed cyclone characteristics, four ordinary least squares (OLS) regression models were developed and assessed. These models employed various combinations of predictors, including maximum wind speed (WIND), central pressure (P_c) pressure drop (ΔP), radius of maximum wind (RMW) and latitude (LAT). Here we use 80% of data to build the MLR. Table 4 Represent the performance of each model.

MLR Model B_α:

A multi-linear regression analysis was conducted to model the wind-pressure profile parameter B using wind speed (WIND), latitude (LAT) and radius of maximum sustained winds (RMW) as predictors. The regression equation comes out to be the following.

$$B_\alpha = 0.3568 + 0.019716\ \text{WIND} - 0.00170\ \text{LAT} + 0.001351\ \text{RWM} \quad \rightarrow (15)$$

This explains that 78.00% of the variance in the Holland profile parameter B (adjusted R^2 = 77.91%, predicted R^2 from 10-fold cross-validation = 77.73%). All predictors were statistically significant ($p < 0.001$), but LAT variable was statistically insignificant ($p = 0.238$).Despite moderate Multicollinearity between WIND and ΔP (VIF<2), the model's overall fit was moderate (standard error = 0.1395). Its performance was statistically comparable to Model B_β and Model B_γ But more complex and less interpretable due to the non-significant predictor.

MLR Model B_β:

A multi-linear regression model was developed to estimate the wind-pressure profile parameter B by using maximum wind speed (WIND) and latitude (LAT). The regression equation is:

$$B_\beta = 0.4817 + 0.018349\ \text{WIND} - 0.00274\ \text{LAT} \quad \rightarrow (16)$$

The model demonstrates excellent performance, explaining adjusted R^2 = 77.31%, cross-validated R^2 = 77.26 in the wind-pressure profile parameter B. The WIND predictors are highly significant ($p < 0.001$), including latitude borderline statistical significance for LAT ($p = 0.058$). This makes B_β less reliable due to one marginal predictor. No Multicollinearity is present for WIND and LAT (VIF = 1.08). The standard error of the regression (S = 0.1414) and cross-validation error (10-fold S = 0.1414) are both low confirming strong predictive accuracy. The residual diagnostics indicate some large residuals. No serious violations of regression assumptions are observed. Model B_γ is better than Model B_β, suggesting that including RMW significantly improves the estimation of the wind-pressure profile parameter B for cyclones in the region.

MLR Model B_γ:

Multi-linear regression is used to model the wind-pressure profile parameter B based on WIND and radius of maximum wind (RMW). The model equation is:

$$B_\gamma = 0.3292 + 0.019650\ \text{WIND} + 0.001410\ \text{RWM} \quad \rightarrow (17)$$

The model explains approximately 77.89% adjusted R^2 in wind-pressure profile parameter B, with a cross-validated R^2 of 77.75%, indicating strong and stable predictive performance. Both WIND and RMW are statistically significant ($p < 0.05$), and the close match between training and cross-validation metrics (10-fold R^2 = 77.73%) indicates high model stability and minimal over fitting. Multicollinearity present between WIND and RMW (VIF < 2) does not affect model validity. Residual analysis confirms that no influential outliers are detected. Model B_γ is a consistent predictor of the B parameter and support its use in modeling cyclone structure in the Arabian Sea.

Note:

Models which included central pressure (P_c), pressure drop (ΔP) and latitude (LAT) in various combinations, consistently underperformed with adjusted R^2 values around 62.88%–62.94% and significantly higher standard errors (~0.1807–0.1808). Moreover, most included predictors such as RWM and LAT were statistically insignificant ($p > 0.75$) in these models. These models suffer from both weak fit and poor generalization performance (10-fold R^2 around 62.50–62.85%). Therefore, in subsequent analysis we will restrict our focus to the models B_α, B_β, and B_γ only.

Comparative Analysis of Models

To assess the best predictive approach for estimating the wind-pressure profile parameter B for Arabian Sea cyclones, three multi-linear regression models were developed and evaluated based on statistical performance and theoretical relevance. Table 3 represents the performance of each models .Model B_α incorporating maximum sustained wind speed (WIND) and radius of maximum wind (RMW), explained that the adjusted R^2 = 77.89% of the variance in B with a predicted R^2 of 77.75%. Although WIND and RMW were statistically significant. Model B_β improved upon this by replacing RMW with latitude (LAT), achieving an adjusted R^2 of 77.37% and a predicted R^2 of 77.18%. All predictors were significant and latitude added substantial value although multicollinearity exists between WIND and LAT. Model B_γ which included WIND, RMW and LAT. It explained that 78.00% of the variance (adjusted R^2) with a predicted R^2 of 77.73 %, with the standard error (0.1395) is achieved. WIND and RMW predictors were highly significant and although moderate multicollinearity existed between WIND and RMW, it did not affect the model's predictive reliability. Based on these results, Model B_α is recommended as the most robust and accurate method for estimating the wind-pressure profile parameter B, balancing theoretical consistency with excellent predictive power. In contrast, Model B_γ appears to be the weakest, largely due to its reliance on the LAT variable, which has limited explanatory power and is not statistically significant in the context of wind-pressure profile parameter B estimation.

Table 3 Performance metrics of multi-linear Regression models

Model	Predictors	R^2 (%)	Adj. R^2 (%)	Pred. R^2 (%)	S	10-fold S	10-fold R^2 (%)	Significant Predictors	Insignificant Predictors
B_α	WIND,LAT and RWM	78.00	77.91	77.73	0.1395	0.1399	77.75	WIND(p=0.000), RWM (p=0.000)	LAT(p=0.238)
B_β	WIND,LAT	77.00	77.31	77.18	0.1414	0.1414	77.26	WIND (p=0.000)	LAT(p=0.058)
B_γ	WIND, RWM	78.00	77.89	77.75	0.1395	0.1400	77.73	WIND p=0.000), RWM (p=0.000)	–

Model Validation on Test Data

We applied MLR models B_α, B_β and B_γ to the remaining 20% (96 data points) of the dataset to validate their predictive accuracy and performance. Each model utilized a distinct combination of predictor variables to estimate the wind-pressure profile parameter B. The wind-pressure parameter B values predicted by MLR models are compared with the values calculated by the Holland model. Show in Figure 8.

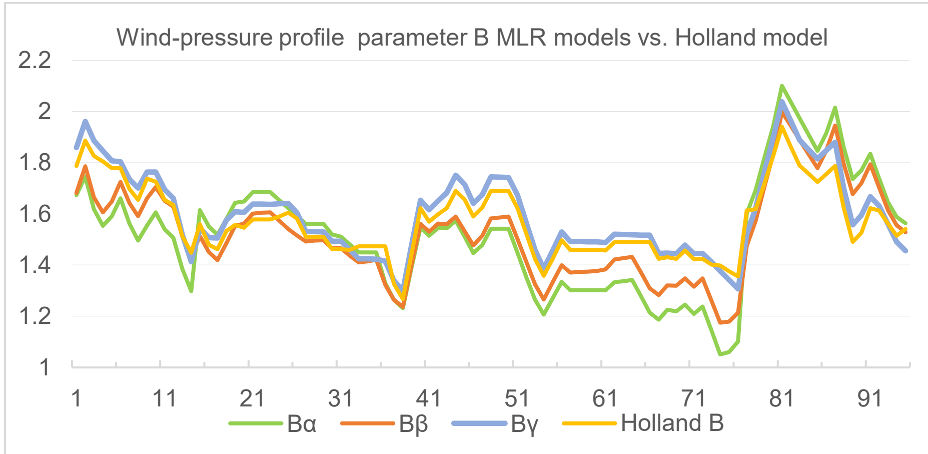


Figure 8 Comparison of wind-pressure profile parameter estimated from MRL Models B_α, B_β and B_γ with Holland parameter B

The comparative result of MLR models and Holland model are discuss in Table 4. Results show that, Model B_γ shows overall best performance as compared to other models, achieving an R^2 of 0.7564. It also demonstrated the lowest error metrics MSE (0.0759) and RMSE (0.2756), signifying excellent predictive accuracy and minimal deviation from wind-pressure profile parameter B values by Holland model. Model B_β exhibited moderate predictive power with an R^2 of 0.6747. It had relatively higher residual error and RMSE (0.2925) indicating greater deviations from Holland modal values. Model B_α Show improved performance with an R^2 of 0.6038 and a reduced RMSE of 0.2778 indicating a better fit and lower prediction error compared to Model B_β while comparing to Holland model values.

Among the tested models, the WIND + RMW predictor combination provided the most reliable and parsimonious fit. Both predictors were statistically significant ($p < 0.001$), with the model achieving high explanatory power ($R^2 \approx 78\%$) and the lowest RMSE in validation (0.2756). Although including LAT marginally increased validation R^2, its insignificance and higher error values make it less robust compared to the WIND–RMW model.

Table 4. Comparison of wind-pressure profile parameter estimated from MRL Model B_α, B_β and B_γ. With Holland B

S.no	Model	Predictors	R^2	Residual	Residual^2	MSE	RMSE
1	B_α	WIND, RMW and LAT	0.6038	0.2778	0.0772	0.0772	0.2778
2	B_β	WIND and LAT	0.6747	0.2925	0.0856	0.0856	0.2925
3	B_γ	WIND and RMW	0.7564	0.2756	0.0759	0.0759	0.2756

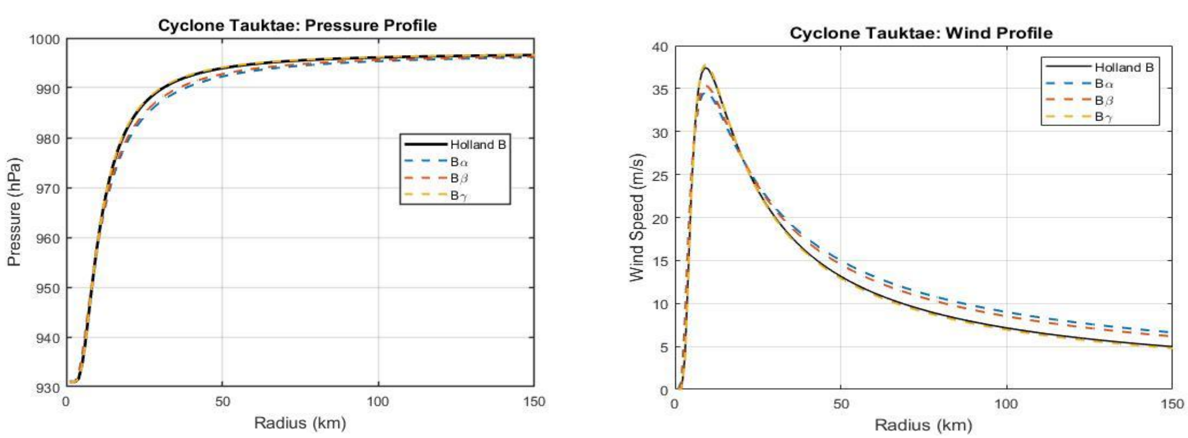
Cyclone Tauktae Wind-pressure profile: Analysis of MLR Models and comparison with Holland Model

A real case validation of MLR models presented here is conducted using the data of Cyclone Tauktae. It will ensure that the MLR models developed in this study are not only mathematically accurate but also physically meaningful. Cyclone Tauktae is the most intense recent category 4 cyclones in the Arabian Sea. The central pressure, maximum sustained wind, Radius of Maximum wind, latitude and longitude data for cyclone Tauktae are taken from the IBTrACS .The wind-pressure profile parameter B, which controls the shape of the cyclone's radial pressure and wind distribution are estimated by using multi-linear regression models B_α, B_β and B_γ and compared with Holland model. These estimated wind-pressure profile parameter B values are then applied to the empirical Holland wind-pressure model (Equation 1 and Equation 2) to generate wind and pressure profiles for Cyclone Tauktae. The wind-pressure profile are tested by Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Correlation Coefficient (R^2), and Nash–Sutcliffe Efficiency (NSE), to compare the accuracy of each MLR models wind-pressure profile with Holland model wind-pressure profile show in Table 5.

Table 5. Wind-pressure Profile Error Metrics of MLR Models Compared to Holland B Model

Tauktae Cyclone Pressure Profile					
S.no	**Model**	**RMSE**	**R²**	**MAE**	**NSE**
1	B_α	0.3631	0.9999	0.3234	0.9996
2	B_β	0.4295	0.9999	0.3821	0.9994
3	B_γ	0.3630	0.9999	0.3233	0.9996
Tauktae Cyclone Wind Profile					
1	B_α	0.3687	0.9999	0.3503	0.9980
2	B_β	0.4378	0.9998	0.4161	0.9972
3	B_γ	0.3685	0.9999	0.3501	0.9980

Model B_γ demonstrated the highest accuracy in both wind-pressure profile estimations. For the pressure profile it achieved the lowest RMSE (0.3630), lowest MAE (0.3233) and perfect correlation and efficiency scores R² (1.9999) and NSE (0.9996), indicating an almost exact match with the Holland profile. Model B_α, a simplified version using WIND, LAT and RMW, also performed very well, though slightly less accurate than B_γ. In contrast**,** Models B_β**,** showed higher error values and less reliable performance. Shown in Figurer 9(a). Similarly, Model B_γ also produced the most accurate wind profile.it achieved the lowest RMSE (0.3685) and MAE (0.3501), along with a perfect R² (0.9999), indicating near perfect alignment with the Holland model. Model B_α followed closely with an RMSE of 0.3687 and MAE of 0.3503, still offering a good approximation of the observed wind pattern. However, Models B_α and B_β**,** showing higher deviations and lower reliability in their wind profile predictions. Shown in Figure (b)



(a) **(b)**

Figure 9. Comparison of wind-pressure profile of cyclone Tauktae between MLR models and the Holland model (a) Pressure Profile (b) Wind Profile

This case study provides strong evidence that the MLR-Base models designed specifically for Arabian Sea cyclones are practically effective. In particular, Model B_γ is validated as the most reliable and physically consistent model for estimating the wind-pressure profile parameter B parameter and its results are equally accurate and reliable as Holland Model. The Holland wind-pressure profile of Cyclone Tauktae confirms its usefulness for future applications in cyclone modeling, forecasting and hazard assessment in the Arabian Sea region. The B_α model also showed strong performance, supporting its utility as a simplified but reliable model. But models B_β wind-pressure profile showed relatively larger deviations with the comparison of Holland Model.

Further, MLR B_γ model is used to analyze the wind-pressure profile of cyclone Tauktae. According to the B_γ model of wind profile, the strongest wind is observed between 6 km and 10 km from the center of the cyclone to the outer radius with wind speed range between 30.5 m/s to 37.78 m/s. This range is classified as the Severe Hazard Zone according to Siffir-Simpson Hurricane Scale [22], where the wind is strong enough to cause major structural damage, uproot trees, destroy power lines and trigger dangerous storm surges near the coast. For this zone, our forecasts are very close to the real-Tauktae observations(44 -47) m/s regarding major structural damages , uprooted trees, power outages and storm surge particularly in the areas like Vera Val, Diu and Mumbai as reported by the India Meteorological Department (IMD, 2021) . This confirms the validation of our findings using statistical techniques.

From 10 km to 30 km, wind speed is gradually decreasing from about 37.2 m/s to 30.2 m/s. This region falls under the Moderate Hazard Zone, where damage can include broken rooftops, damaged infrastructure, collapsed weak buildings and heavy rainfall. The forecasted impact in this zone closely aligns with observed damages in Junagadh and surrounding districts. These areas are still highly dangerous, especially for poorly constructed structures. This shows a close coincidence between the results obtained by our models and the real data.

Between 30 km and 60 km, the wind speed dropped further, ranging from 30.2 m/s down to 24.5 m/s. This is the Low Hazard Zone, where the cyclone may cause moderate damage such as fallen signboards, partial roof damage, urban flooding, and disruption of basic services like electricity and transportation conditions that were consistent with field reports from Rajkot and Bhavnagar. Beyond 60 km from the cyclone center, wind speeds fell below 24.5 m/s, marking the Very Low Hazard Zone. Here, the cyclone's impact becomes weaker, with risks limited to light flooding, waterlogging and minor infrastructure issues such as broken tree branches or brief power outages consistent with observations in cities like Ahmedabad [23]. These actual wind field data of the cyclone Tauktae validates the accuracy of the MLR.

Conclusions

In this study four multiple linear regression (MLR) models $B_{\alpha,}$ B_β and B_γ and one are developed to estimate the wind-pressure profile parameter B for tropical cyclones in the Arabian Sea. These models use cyclone key parameters (independent variables) such as wind speed (WIND), central pressure (P_c), pressure drop (ΔP), radius of maximum wind (RMW) and latitude (LAT). Model B_γ with independent variables, maximum sustained wind, ΔP and LAT (latitude) is the most statistically accurate model. It achieved the highest adjusted R^2 (78%) with the lowest standard error (0.1395), and all predictors were statistically significant. While Model $B_£$ with independent variable maximum sustained wind and ΔP also give strong accuracy. Models B_α and B_β, have moderate R^2 (77% and 78%) compare to the above models and showed higher residuals and error values. The models are validated by testing on 20% dataset and comparing the results with wind-pressure profile parameter B. Model B_γ showed excellent predictive accuracy, with an R^2 of 0.7564, RMSE of 0.2756, and MAE of 0.0759 demonstrating a strong fit. While Models B_α and B_β displayed weaker predictive accuracy ($R^2 = 0.6747$ and 0.6038, respectively) than the above two models. For further validation, these models were tested on the most intense category 4 Arabian Sea Cyclone Tauktae dataset. The wind-pressure profile of cyclone Tauktae estimated by MLR models were compared with B wind-pressure profile. Among all models B_γ have most closely accurate pressure and wind profile structures. Model B_γ is recommended as the most reliable statistical MLR model for estimating the wind-pressure parameter B for the Arabian Sea.

The model B_γ can be used to observe the wind and pressure profile of any cyclone. It provides a clear and accurate understanding of the cyclone's structure and dynamics. This model can be used to estimate the cyclone's intensity and assess its potential impact on surrounding regions.

Our future work will focus on refining these models by integrating advanced machine learning techniques, such as neural networks, which can capture nonlinear interactions among predictors more effectively. Additionally, incorporating more granular observational datasets, such as high-resolution

ERA5 reanalysis and satellite based wind field measurements. This will enhance both model robustness and generalizability. Ultimately, this work lays the foundation for a reliable, region-specific modeling framework to support operational cyclone forecasting in the Arabian Sea.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgment

This study is part of the first author's Master's Thesis entitled as "A Study of Arabian Sea Cyclones as a Physical Process: Tracking, Comparative Dynamics and Climatological Features". Sincere thanks to the Department of Mathematics, Sir Syed University Engineering and Technology for academic assistance.

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