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STATISTICAL MODELING OF MILD-STEEL CORROSION UNDER MARINE ENVIRONMENTAL CONDITIONS AT A MAJOR SEAPORT

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KEYWORDS

Marine atmospheric corrosion; mild steel; chloride deposition; sulfate deposition; time of wetness; statistical modeling.

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ABSTRACT

Background: Marine environments expose metals to chloride and sulfate deposition, moisture, and changing atmospheric conditions that may accelerate corrosion. Understanding these relationships is essential for developing effective corrosion monitoring and maintenance strategies for marine infrastructure. **Objective:** This study aimed to assess marine atmospheric corrosivity at West Wharf, investigate associations between environmental exposure variables and mild-steel corrosion, and develop statistical models to characterize accumulated corrosion. **Methods:** Mild-steel coupons were exposed at West Wharf, and corrosion was quantified using the weight-loss method. Chloride and sulfate deposition rates and time of wetness (TOW) were measured during the observation period. Descriptive statistics, Pearson correlation analysis, polynomial regression, and multivariable regression modeling were used to examine environmental associations and characterize corrosion patterns. Model adequacy was evaluated using goodness-of-fit measures, the Durbin–Watson test, and heteroscedasticity diagnostics. **Results:** The mean chloride deposition rate, sulfate deposition rate, and TOW were 76.44 ± 19.62 mg/m^2·d, 151.33 ± 30.78 mg/m^2·d, and 1754.27 ± 1423.19 h, respectively. Mild-steel corrosion exhibited positive correlations with chloride deposition (r = 0.39) and TOW (r = 0.24), whereas the correlation with sulfate deposition was weak (r = 0.06). The polynomial regression model explained 93.9% of the observed variation in corrosion (R^2 = 0.939, p = 0.001), with statistically significant linear (p = 0.017), quadratic (p = 0.032), and cubic (p = 0.040) terms. The multivariable model explained 91.0% of the variation. Chloride deposition was positively associated with corrosion (β = 0.45, p = 0.043), whereas sulfate deposition showed a negative adjusted association (β = −1.42, p = 0.001). The lagged term was also statistically significant (β = 0.01, p = 0.007). **Conclusion:** Mild-steel corrosion at West Wharf was associated with variations in marine environmental exposure, with chloride deposition showing a positive relationship with corrosion. The fitted models may help characterize site-specific corrosion patterns and inform monitoring and maintenance planning. Further validation using independent observations and additional exposure periods is needed to establish their predictive reliability and generalizability.

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Introduction

Corrosion is a complex electrochemical process that causes the degradation of metals, particularly mild steel, through their interaction with electrolytes and environmental conditions (Balangao, J. K. (2024)). Corrosion begins when a continuous electrolyte layer forms on the metal surface, enabling anodic and cathodic reactions. In mild steel, this process can result in relatively uniform corrosion (Fernandes, and Montemor, 2015)

Chloride ions are particularly important in accelerating corrosion because increasing chloride concentrations promote degradation of the zinc coating and eventually expose the underlying steel, with corrosion rates generally increasing with both chloride concentration and exposure duration (Liu and Li, 2025).Sulfates can also contribute to the deterioration of protective corrosion products, while sulfate-reducing bacteria (SRB) may further intensify corrosion in marine environments through biofilm formation and the production of corrosive metabolites, resulting in higher corrosion rates than under sterile conditions (Ayodele et al., 2025).

Modelling is an essential and core phenomenon in time series, Qureshi et al. (2024) and Yousfani et al. (2024) compared hybrid, machine learning, and conventional time-series models for Bitcoin price forecasting and Pakistan's export modeling, respectively. Noor et al. (2026) and Abbasi et al. (2026) explored decomposition-based hybrid forecasting, while Nasir et al. (2026) combined optimized VMD, fuzzy entropy, and PatchTST for financial forecasting. Time of wetness is another critical factor because prolonged exposure to moisture maintains the electrolyte necessary for electrochemical reactions and consequently increases corrosion progression. For example, steel exposed to seawater for 180 days exhibited substantial degradation and increasing corrosion rates over time (Ayodele et al., 2025). Although corrosion-product or rust layers may initially provide some degree of protection by acting as a barrier between the metal and the environment, high chloride and sulfate concentrations can destabilize or damage these layers, resulting in continued or accelerated corrosion (Rendón & Valencia, 2024). (Ali (2026); Ali, M. S., & Bano, S. (2026)). investigated molecular featurization, while Ali and Mohlenkamp (2026) and Ali and Bano (2026) proposed attention-based molecular representation methods for property prediction. Ali et al. (2026) examined fiscal deficits and macroeconomic dynamics in Pakistan, whereas Sofia et al. (2026) analyzed climate variability and its effects on wheat and maize productivity.

Corrosion is a major global challenge that causes material degradation, infrastructure deterioration, economic losses, and safety risks across industrial sectors. Globally, corrosion is estimated to cost more than $2.5 trillion annually and is associated with a substantial proportion of infrastructure failures, while approximately 150 million tons of steel are reportedly lost each year because of corrosion-related deterioration (Luaibi & Al-Tweel, 2025; Guma & Dele, 2025; Adannou et al., 2025). The severity of corrosion is governed by environmental conditions, material characteristics, and operational parameters. Factors such as humidity, temperature, and corrosive species including CO_2 and H_2S can accelerate corrosion, while metal composition, protective coatings, pH, and current density influence the susceptibility and rate of degradation (Adannou et al., 2025; Prošek et al., 2025; Aulia et al., 2025).

In Pakistan, corrosion presents an important economic and infrastructural concern, particularly for aging and marine-exposed structures. Karachi's East and West harbors are especially vulnerable because the marine environment promotes deterioration of steel components used in docks, ships, and other transportation-related infrastructure. Continuous corrosion can reduce structural integrity, increase maintenance and replacement costs, and contribute to operational disruptions and safety hazards (Kassinis et al., 2025). The broader economic burden of corrosion has been estimated at approximately 5% of GDP in developed economies, illustrating the considerable financial implications associated with corrosion management and infrastructure deterioration (Silva et al., 2025). These challenges highlight the importance of systematic corrosion monitoring and protection, particularly in harsh marine environments where prolonged exposure can accelerate material degradation.

Effective corrosion management can reduce these economic and safety impacts by extending infrastructure service life and minimizing unnecessary repair and replacement. Karachi Harbour provides a harsh marine environment in which prolonged exposure to seawater, chloride and sulfate ions, pollutants, moisture, and changing weather conditions can accelerate metal corrosion, potentially affecting the durability and service life of sea-going vessels and harbour infrastructure. **Therefore, this study is undertaken to assess the actual corrosiveness of Karachi Harbour water and to understand how environmental and pollutant conditions influence metal degradation.** The study aims to evaluate corrosion using suspended metal coupons and the weight-loss method in accordance with ISO 9223, analyze the relationship between corrosion rate, marine pollutant concentrations, and weather conditions, and develop mathematical models for predicting the corrosiveness of the West Wharf water channel. The results will provide a basis for corrosion monitoring, maintenance planning, and effective protection of metallic structures and components exposed to Karachi Harbour waters.

Methodology

Modus of Operandi: The current assessment was relied upon to choose the damaging tendency of Karachi harbor (West Wharf) which is considered as the focal point of various transportation works out, transport building and fix practices through mass disaster and toxic substance centre assessment as demonstrated by ISO9223 standard. During the examination, following modus of operandi was changed

Selection of Material: Mild steel is a kind of steel that contains under 0.25% carbon being used all through the world as a result of its obvious properties, straight forwardness of assembling, weld limit, availability and simplicity. Mild steel is comprehensively used for the production of developments and equipment in marine, current and outside applications.

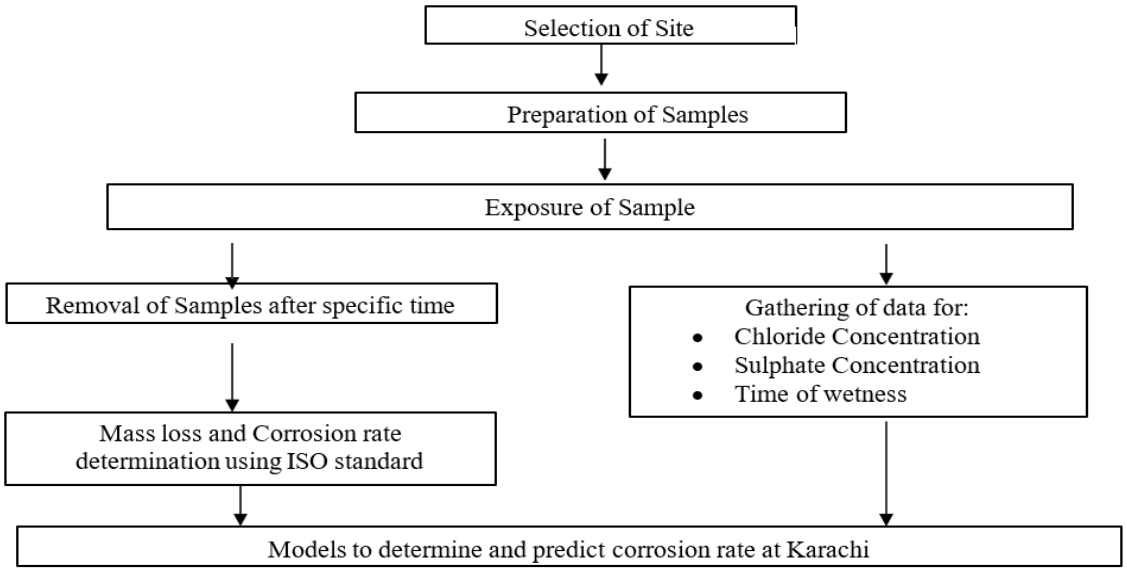

Figure 3.1 Modus of operandi for research work

Commercial grade mild steel S275JR (with zinc covering of 2 µm) test coupons of size 103 x 152 x 3 mm were picked for direct study. ASTM G50 was followed for arranging test coupons. Cleaning and degreasing of test coupons were driven through acetone (C3H6O) in the lab and like manner vanished using hot air. Datum mass of test coupons was recorded i.a.w ASTM G1 using AFD 1000 electronic decreased balance. Master minded test coupons were then fixed pack in impermeable sacks and dispatched to the test station for experimentation. Compound synthesis of the models are recorded under:

Table 1: Chemical composition of mild test coupons

Specimens	Chemical Composition Weight Percentage						
	Fe	C	Zn	Mn	Al	O	S
Mild-Steel (Bare)	98.95	0.24	-	1.6	0.049	7.85	0.055

Selection of Exposure Site: Karachi is having a shore line belt of 70Km covering the district between DHA Phase-VIII and Ras Muari. The site of Karachi harbored West Wharf (24° 82′ N 66° 97′ E) was picked for transparency of test coupons and confirmation of natural danger. The picked receptiveness site is enclosed by crucial foundations and developments including Pakistan International Container Terminal (PICT), Karachi International Container Terminal (KICT), Karachi Shipyard and Engineering Works (KS&EW) and Naval assets which economically influences public exchequer due to marine corrosion.

Being a marine site, it was envisioned that the subject site would be stacked down with high chloride substance as well. Furthermore, choosing the danger of picked station is of key importance

due to the nature of SO_4^{-2}, merchant and sea vessels effluents and wastes, coal dumping activity at the east wharf and mechanical waste entering in Karachi harbour through Lyari and Malir streams which makes the site incredibly dirtied and more engaging for research.

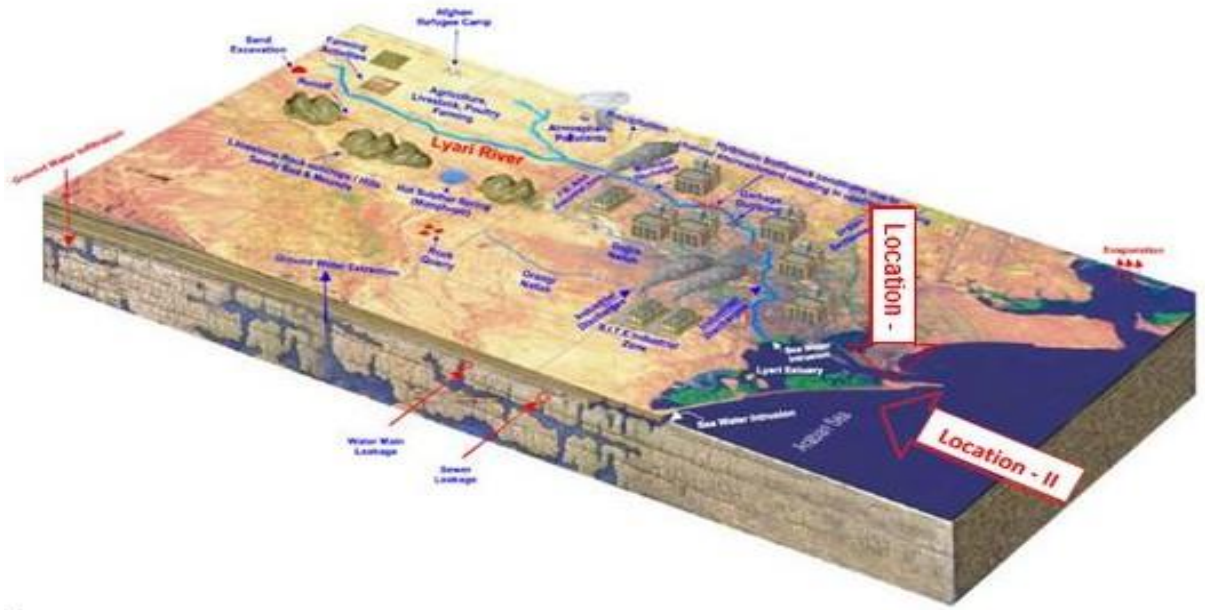

Figure 3.2 Geographical location of test site

Gauging of Meteorological Parameters: Step by step meteorological data of test site contain following were gotten from Karachi Meteorological office to deliver the month to month bits of knowledge of generally extraordinary, least and typical characteristics:

- Humidity and Temperature of water
- Rainfall
- Salinity i.e. chloride and SO_4^{-2}content.
- Dissolved Oxygen

Determination of Marine Corrosivity of Karachi Harbor: As shown by the ISO 9223 standard, the damaging tendency of picked test station was set up by assessing the following central limits:

- Physical factors such as sea water temperature, water velocity, surface moistening, suspended solids and water pressure.
- Chemical factors are dissolved oxygen (DO), CO2, SO_4^{-2}, pH, pollutants and carbonate solubility.

Biological factors that affect marine corrosion are bacteria, biomass, pollutants and marine corrosion.

Measurement of Chloride Concentration: In marine environment, chloride ions are one of the most common inorganic anions. It creates corrosion in metal alloys. Due to inclusion of domestic & industrial waste in marine water, level of chloride increased to threatening level. The level of chloride concentration is measured by utilizing AQUASOL test kit of code AE-203 which is based technique of titrimetric.

Measurement of SO_4^{-2} Concentration: Total Dissolved Salts in marine water contains sulphates, which can form salts with sodium, potassium, magnesium, and other cations. Sulphates SO^{-2} are abundant in nature and can be found in amounts ranging from a few to several hundred milligrammes per litre in natural waterways. The concentration of sulphates is measured by utilizing instant test kit AQUASOL of the code AE-209.

Figure 3.3: AQUASOLE test kit [27]

Measurement of TOW: Period of wetness (TOW) is the period during which relative moistness remained more than 80% at a temperature more than 0°C [22]. In this examination, TOW was dictated by using a month to month ordinary of temperature and relative sogginess (RH).

Corrosion Model for Mild Steel: Real strategies are routinely used to assess unusualness and tangled issue of climatic utilization and its contributory factors for deciding the rot of marine-related system. Mathematical models are made to have an unchallenged appreciation of any trademark and real ponders happening. Subsequently, these mathematical models sought to be affirmed with help of explicit assessments. At the present moment, botches may hazard the undertakings. To think about these missteps and weakness, genuine models are made in kind of a condition or set of conditions.

These models can moreover be depicted as a traditional verbalization of theory or a test course of action which achieved making the saw data. Thusly, showing can be suggested as developing a mathematical enunciation that explains the response of a concerned self-assertive variable. The

subjective elements are generally called subordinate factors and trick factors are known as self-sufficient components. These free factors are to elucidate the direction of the dependent variables being used in the mathematical models.

In this analysis, bivariate and multivariate tests were used for the head way of delicate and stimulated steel disintegration models. Models were worked for the conjecture of utilization speed of test coupons as a component of time and ward factors like SO^{-2}, Cl^{-} and TOW. Finally, the strength of the models was checked through heteroscedasticity tests.

Results

Descriptive characteristics of marine exposure variables

The mean concentration of sulfate (151.33 ± 30.78) was higher than that of chloride (76.44 ± 19.62), whereas TOW showed the greatest variability (1754.27 ± 1423.19). TOW also demonstrated positive skewness (1.077) and higher kurtosis (3.268), indicating greater dispersion and deviation from symmetry compared with the other pollutants. The Jarque–Bera test showed no significant departure from normality for Cl^{-}, SO_4^{2-}, or TOW ($p > 0.05$).

Table 1: Descriptive statistics and normality distribution of marine pollutants at Karachi Harbour

Marine pollutant	Mean ± SD	Range	Skewness	Kurtosis	Jarque–Bera	p-value
Cl^{-}	76.44±19.62	48.97–108.10	0.005	1.660	0.8918	0.640
SO_4^{2-}	151.33±30.78	101.00–190.00	−0.117	1.637	0.9564	0.619
TOW	1754.27±1423.19	360.07–5026.60	1.077	3.268	2.3569	0.3077

Note: Cl^{-} = chloride; SO_4^{2-} = sulfate; TOW = time of wetness. Chloride and sulfate values are expressed as deposition flux (mg/m^2·d), rather than aqueous concentration.

Seasonal variation in marine exposure

Marked seasonal variation was observed in chloride and sulfate deposition and TOW at the West Wharf test site. Chloride deposition ranged from 48.97 mg/m^2·d in January to 108.10 mg/m^2·d in August, with an annual mean of 76.44 mg/m^2·d (figure 1). Sulfate deposition ranged from 101.00 mg/m^2·d in January to 190.00 mg/m^2·d in May, with an annual mean of 151.33 mg/m^2·d (figure 2).

TOW also demonstrated substantial seasonal variation. The maximum TOW was recorded in August (5026.26 h), whereas the minimum value was observed during November and December (360.07 h). The annual mean TOW was 1754.27 h. These findings demonstrate that the marine exposure conditions at West Wharf were not constant throughout the observation period (figure 3).

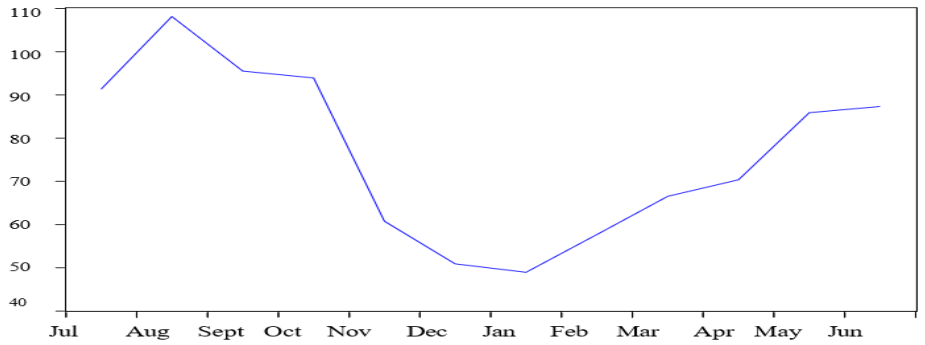

Figure 1: Chloride concentration at west wharf test site

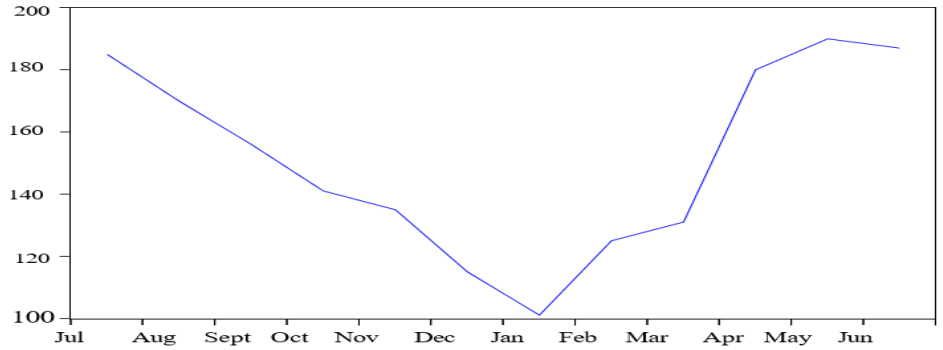

Figure 2: SO_4^{-2} concentration at west wharf test site

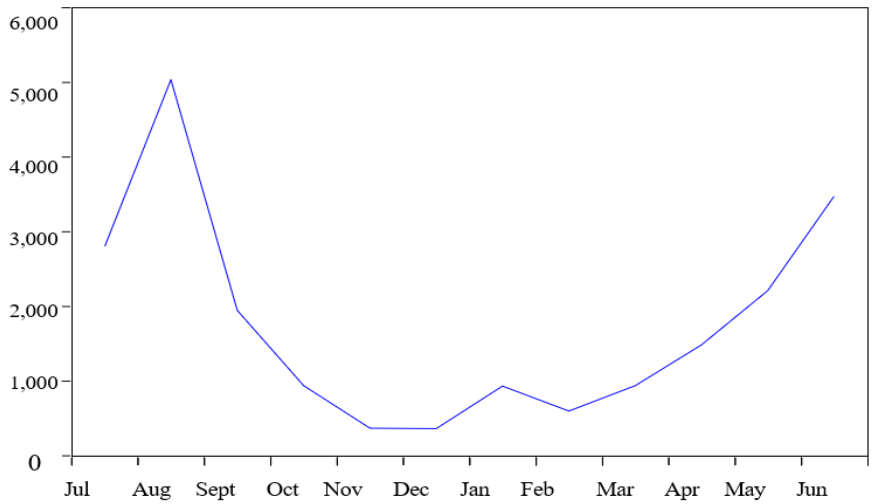

Figure 3: Time of wetness at west wharf test site

Correlation between mild-steel corrosion and marine exposure variables

Pearson correlation analysis was performed to assess the associations between mild-steel corrosion and the measured marine exposure variables. Mild-steel corrosion showed a moderate positive correlation with chloride deposition (r = 0.39) and weaker positive correlations with sulfate deposition (r = 0.06) and TOW (r = 0.24).

The environmental exposure variables themselves were strongly positively correlated. Chloride deposition was strongly correlated with sulfate deposition (r = 0.79) and TOW (r = 0.80), while sulfate deposition was also strongly correlated with TOW (r = 0.76).

Table 2: Correlation coefficients between the variables for mild steel.

	MS	Cl-	SO_4^{-2}
$Cl-1$	0.39	---	---
SO_4^{-2}	0.06	0.79	---
TOW	0.24	0.80	0.76

The scattered graph shows that the value of TOW is greater than the other pollutants values, which mean that TOW has more strong correlation than the other pollutants.

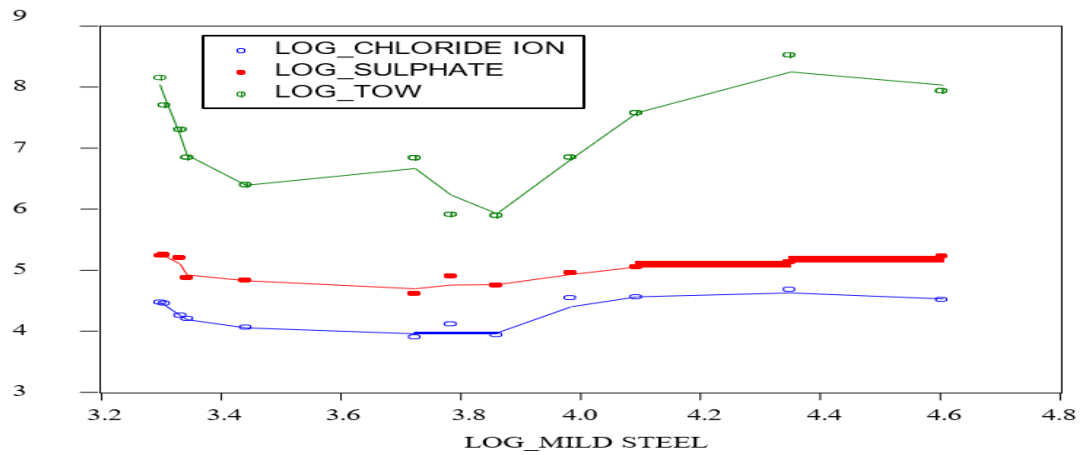

Figure 4: Scattered plot of mild steel versus marine pollutants and time of wetness along

The correlation analysis indicates that chloride had the strongest direct bivariate association with mild-steel corrosion among the three environmental variables. In contrast, TOW showed strong associations with both chloride and sulfate deposition, suggesting that moisture availability was closely related to the temporal variation in marine salt deposition.

The bivariate polynomial model demonstrated a strong and statistically significant nonlinear relationship between the corrosion rate (λ_t) and accumulated corrosion in mild steel at Dockyard

West. The model explained 93.9% of the observed variation in accumulated corrosion (R^2 = 0.939; adjusted R^2 = 0.940) and was statistically significant overall (F = 52.94, p = 0.001). In this model, λ_t represents the corrosion rate, while $\lambda_t^{\ 2}$, $\lambda_t^{\ 3}$, $\lambda_t^{\ 4}$, and $\lambda_t^{\ 5}$ represent the squared, cubed, fourth-power, and fifth-power transformations of the same corrosion-rate variable, respectively; they are not separate corrosion variables. The linear (λ_t : β = −118.90, p = 0.017), quadratic ($\lambda_t^{\ 2}$: β = 43.72, p = 0.032), and cubic ($\lambda_t^{\ 3}$: β = −7.303, p = 0.040) terms were statistically significant, whereas the fourth- and fifth-order terms were not (p = 0.060 and p = 0.100, respectively). The significance of the lower-order polynomial terms indicates that the association between corrosion rate and accumulated corrosion was nonlinear. The Durbin–Watson statistic of 2.80 indicated no substantial serial correlation in the residuals.

The multivariate model explained 91.0% of the observed variation in accumulated corrosion (R^2 = 0.910; adjusted R^2 = 0.890). Chloride deposits were positively associated with corrosion (β = 0.45, p = 0.043), whereas sulphate deposits showed a significant negative association (β = −1.42, p = 0.001). The lagged term was also statistically significant (β = 0.01, p = 0.007), indicating that the preceding-period component contributed to the model's prediction of accumulated corrosion. No significant heteroscedasticity was detected (F = 1.58, p = 0.29; Obs*R^2 = 4.27, p = 0.11), and the Durbin–Watson statistic was 1.28.

Table 3: Bivariate and multivariate corrosion models for mild steel at Dockyard West

Model	Variable/Parameter	Coefficient (β)	Standard Error	t-value	p-value	R^2	Adjusted R^2
Bivariate polynomial model	Constant	228.33	27.54	8.28	0.001	0.939	0.940
	λ_t	−118.90	36.51	−3.25	0.017		
	$\lambda_t^{\ 2}$	43.72	15.75	2.77	0.032		
	$\lambda_t^{\ 3}$	−7.303	2.93	−2.49	0.040		
	$\lambda_t^{\ 4}$	0.54	0.244	2.20	0.060		
	$\lambda_t^{\ 5}$	−0.014	0.0074	−1.94	0.100		
Multivariate model	Constant	287.52	31.24	9.20	0.001	0.910	0.890
	Chloride deposits (ρ_t)	0.45	0.18	2.46	0.043		
	Sulphate deposits (ξ_t)	−1.42	0.19	−7.58	0.001		
	Lagged term (τ_{t-1})	0.01	0.003	3.70	0.007		

Note: Bivariate model: F = 52.94, p = 0.001; explained variance = 95.56%; Durbin–Watson = 2.80. Multivariate model: explained variance = 90.86%; Durbin–Watson = 1.28; heteroscedasticity test F = 1.58, p = 0.29; Obs*R^2 = 4.27, p = 0.11.

Figure 5 shows a close agreement between the actual and estimated corrosion values across the observed range. The estimated curve follows the overall declining pattern of the observed corrosion values, with the greatest corrosion values occurring at the beginning of the observation period and progressively lower values thereafter. Although some deviations are visible at individual

observations, the overall correspondence between the actual and estimated values indicates that the bivariate polynomial model adequately represents the observed corrosion pattern.

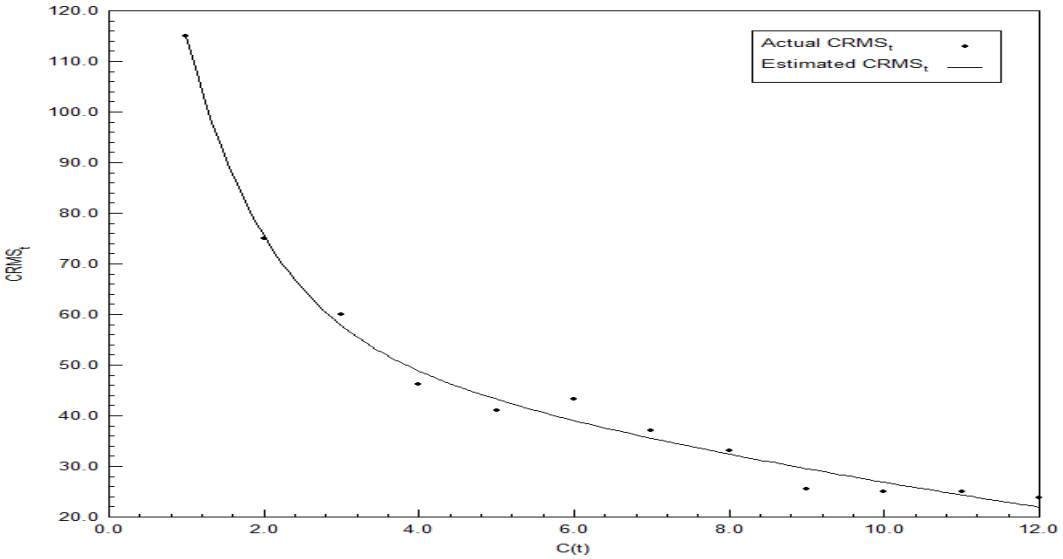

Figure 5: Actual and estimated plot for bivariate model for mild steel.

Figure 6 demonstrates a generally close correspondence between the actual and fitted corrosion values across the observations. Both series show a similar overall downward trend, with some fluctuations and differences between the observed and fitted values at individual points. The fitted values nevertheless follow the major changes in the observed corrosion pattern, indicating that the multivariate model provides a reasonable representation of the observed corrosion behavior.

Figure 6: Actual and estimated plot for multivariate model for mild steel

Discussion

The present study demonstrated substantial temporal variation in chloride deposition, sulfate deposition, and time of wetness (TOW) at Karachi Harbour (West Wharf), indicating variable marine exposure conditions. These findings are consistent with previous reports identifying salinity, humidity, industrial activities, and urban pollution as important characteristics of Karachi Harbour that may contribute to metallic deterioration (Kassinis et al., 2025; Irfan et al., 2025; Nergis et al., 2025).

Chloride deposition increased from 48.97 mg/m^2·d in January to 108.10 mg/m^2·d in August, while sulfate deposition ranged from 101.00 mg/m^2·d in January to 190.00 mg/m^2·d in May. Such seasonal variation is consistent with the influence of rainfall, evaporation, dilution, runoff, hydrological conditions, and anthropogenic inputs reported in other aquatic environments (DADA et al., 2025; Ezurike et al., 2026; Tirumalesh, 2007). However, the seasonal behavior of a coastal harbour may differ from freshwater systems because of marine aerosol, tidal processes, and local industrial influences.

TOW also showed considerable seasonal variation, ranging from 360.07 to 5026.26 h. TOW was strongly correlated with chloride (r = 0.80) and sulfate deposition (r = 0.76), indicating that periods of greater surface wetness tended to coincide with higher salt deposition. Since moisture provides the electrolyte necessary for electrochemical corrosion, this combination may contribute to sustained corrosion activity (Kassinis et al., 2025; Joseph, 2025).

Mild-steel corrosion showed a moderate positive correlation with chloride deposition (r = 0.39), while correlations with sulfate deposition (r = 0.06) and TOW (r = 0.24) were weak. The stronger

chloride association is consistent with the recognized role of chloride in marine corrosion through increased electrolyte conductivity and disruption of protective surface layers. Strong correlations among chloride, sulfate, and TOW ($r = 0.76–0.80$) indicate that these exposure variables were not independent, supporting the use of multivariable analysis (Xu et al., 2026).

In the multivariate model, chloride remained positively associated with accumulated corrosion ($\beta = 0.45$, $p = 0.043$). Sulfate showed a significant negative adjusted association ($\beta = -1.42$, $p = 0.001$); however, this should not be interpreted as a protective effect because sulfate was strongly correlated with chloride and TOW. The coefficient therefore represents a conditional association after adjustment for the other variables, and further assessment of multicollinearity would be appropriate (Wei et al., 2026).

The significant lagged term ($\beta = 0.01$, $p = 0.007$) suggests that preceding exposure conditions may contribute to subsequent corrosion observations, consistent with the cumulative nature of corrosion processes. The polynomial model also indicated a nonlinear temporal relationship, with significant linear, quadratic, and cubic terms, suggesting that corrosion did not follow a constant linear pattern throughout the observation period (Dalou et al., 2026).

Both models showed substantial within-sample fit, with R^2 values of 0.939 for the polynomial model and 0.910 for the multivariate model. The close agreement between observed and fitted values indicates that the models captured the main pattern in the study data. However, these R^2 values represent within-sample model fit and should not be interpreted as evidence of externally validated predictive performance. Independent validation would be required to assess the generalizability of the models.

The findings indicate that corrosion at West Wharf was associated with variable salt deposition, surface wetness, and temporal exposure patterns, with chloride showing the clearest positive statistical association. These findings may support site-specific corrosion monitoring and maintenance planning, particularly during periods of increased chloride deposition and prolonged wetness.

Conclusion

The study demonstrated considerable variation in chloride deposition, sulfate deposition, and time of wetness at Karachi Harbour (West Wharf). Mild-steel corrosion showed a positive association with chloride deposition, while the multivariate model identified chloride as a significant positive factor. The significant lagged effect and nonlinear relationship indicate that corrosion behavior varied with exposure over time. The negative adjusted association of sulfate should be interpreted cautiously because of its strong correlation with chloride and TOW. Overall, the models explained a substantial proportion of corrosion variability and may support site-specific corrosion monitoring and maintenance planning.

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