

Article

Predicting Time-Dependent Durability of FRP–Timber Bonds in Harsh Environments: A Comparative Study of Machine Learning Models

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Abstract

This study presents a comparative evaluation of three machine learning models, XGBoost, AdaBoost, and LightGBM, for predicting the time-dependent bond strength between fiber-reinforced polymer (FRP) and timber in both normal and harsh environments. A dataset was compiled (79 for normal conditions and 265 for harsh environments) incorporating material properties, geometric parameters, exposure time, and solution pH as input features. Hyperparameter optimization was performed for each model, and performance was evaluated using R^2 , RMSE, MAE, and MSE metrics. SHAP analysis and Partial Dependence Plots were employed to interpret feature importance and model behavior. Under normal conditions, XGBoost achieved the highest predictive accuracy (testing $R^2 = 0.944$, RMSE = 2.170, and MAE = 1.775), outperforming AdaBoost and LightGBM. However, in harsh environments, LightGBM demonstrated superior generalization, with the highest testing R^2 of 0.797 and the lowest RMSE of 0.549 and MAE of 0.431, outperforming XGBoost and AdaBoost. AdaBoost exhibited severe overfitting under harsh conditions, with a training-to-testing R^2 drop of 0.341. Feature importance analysis by SHAP analysis identified fiber tensile strength and exposure time as the most influential parameters governing bond performance. SHAP force plots demonstrated that fiber properties predominantly enhance bond strength, while pH consistently acts as a decreasing factor under harsh conditions. This research provides a robust predictive framework for FRP–timber bond durability, offering valuable insights for structural design and service life prediction in harsh environments.



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1. Introduction

The growing demand for sustainable construction materials has positioned timber as a preferred choice in modern structural engineering, owing to its renewable nature, high strength-to-weight ratio, and low carbon footprint [1]. However, inherent limitations of timber, including biological degradation, dimensional instability, and brittle failure under

flexural loading, necessitate the development of effective strengthening techniques [2]. The external bonding of fiber-reinforced polymer (FRP) composites to timber has emerged as a promising solution for rehabilitating existing structures and enhancing the load-bearing capacity of prefabricated timber members [3]. Carbon, glass, and aramid FRPs have demonstrated significant improvements in the stiffness, strength, and ductility of timber components, with CFRP increasing flexural strength by up to 40% [3,4]. More recently, hybrid FRP composites incorporating both synthetic and plant-based natural fibers have gained attention as sustainable alternatives, offering comparable mechanical performance while reducing environmental impact [1,3]. Despite the recognized benefits of FRP–timber composite systems, their long-term durability in harsh environments remains a critical concern that hinders widespread adoption [1,2]. In service, these composites are inevitably exposed to hygrothermal environments, acidic and alkaline solutions, seawater, and ultra-violet radiation, all of which can significantly degrade bond integrity at the FRP–timber interface [2,3]. Temperature and moisture are particularly detrimental, aggravating creep deformation by up to 87% and altering failure modes from timber cracking to interfacial debonding [2]. Water molecules readily intrude into the timber–epoxy interface, disrupting the hydrogen-bonding network and reducing interaction energy by 40.6%, ultimately leading to interfacial degradation [2]. The bond between FRP and timber is governed by complex, non-linear interactions among material properties, geometric parameters, and environmental exposure conditions, making its prediction challenging using traditional empirical models. Recent advances in machine learning (ML) have provided powerful tools for modeling such complex relationships in composite materials [5–8]. Ensemble-boosting algorithms including XGBoost, AdaBoost, and LightGBM have demonstrated exceptional capabilities in predicting the mechanical properties and durability of FRP composites under various environmental conditions [4]. However, existing studies have largely focused on single environmental factors or specific fiber types, and comparative evaluations of different ML algorithms for predicting time-dependent bond durability in multiple harsh environments remain limited [5].

Schober et al. [9] presented a comprehensive state-of-the-art review on FRP reinforcement of timber structures, covering material formulations, application areas, design approaches, and quality control issues. The authors highlighted that despite the significant advantages of bonding FRP to timber for repair and strengthening, the lack of established design rules has strongly restrained the practical application of this technique in structural rehabilitation. Vahedian et al. [10] conducted full-scale experimental investigations on CFRP-strengthened glulam-laminated timber beams, examining the effects of the bonded length, width, and thickness of FRP on flexural strength and ultimate load capacity. Their results demonstrated that increasing bond length and width significantly improved mechanical performance, while further increases in bond thickness predominantly enhanced stiffness and ductility. An analytical model was developed to predict ultimate flexural capacity, showing satisfactory correlation with the experimental results. Ghanbari-Ghazijahani et al. [11] experimentally and numerically investigated the bending and shear strengths of lightweight timber I-beams reinforced with composite materials. Their study developed different strengthening strategies based on failure modes observed in plain specimens, achieving up to a 70% increase in load-carrying capacity and substantial improvements in energy absorption and ductility for reinforced composite beams. Finite element models reliably predicted and verified the experimental results. Biscaia et al. [12] analyzed the debonding process between CFRP laminates and old timber bonded joints using different strengthening techniques. Through single-lap shear tests, the authors observed the non-linear local behavior of the CFRP-to-timber interface and presented an interfacial bond–slip model, with its calibration procedure. The study compared externally

bonded reinforcement (EBR) and near-surface mounted (NSM) techniques, concluding that NSM demonstrated superior performance regardless of mechanical anchorage installation. The effective bond length was determined for each bonding technique. Biscaia et al. [13] further proposed an analytical solution based on a tri-linear bond–slip model to describe the full-range debonding process of CFRP-to-timber interfaces. Validation of the analytical solutions was carried out against experimental data obtained from single-lap shear tests. Particular attention was given to the analysis of slip behavior, strain development in the CFRP, and the distribution of bond stresses across the adhesive interface. The full load–slip response was subsequently characterized, and the various phases of the debonding progression were clearly distinguished along the load–slip curve. The shear behavior of small-scale timber beams strengthened with FRP composites was examined by Ling et al. [14], with particular attention paid to the effects of FRP type, layer number, and attachment method. Greater strengthening efficiency was found to be associated with CFRP reinforcement than with GFRP, as evidenced by shear capacity gains of 32.9% for a single layer and 68.6% for two layers of longitudinally applied unidirectional CFRP. A predictive analytical solution for the shear capacity of FRP-strengthened timber members was further developed, and satisfactory correlation with the experimental results was reported. Andor et al. [15] conducted experimental and statistical analysis of spruce timber beams reinforced with CFRP fabric, examining varying amounts of reinforcement. The results showed a moderate increase in load-bearing capacity and ductility (30%) and a small increase in elastic stiffness (16%). Statistical analysis revealed that the performance of reinforced spruce beams was significantly affected by the presence of knots in the material. A combined experimental, theoretical, and numerical study of timber–CFRP beams adhesively bonded with polyurethane (PUR) was undertaken by Kawecki and Podgórski [16]. Detailed analysis of double-lap connections revealed that omission of the cohesive stiffness of the adhesive layer resulted in an overestimation of the overall beam stiffness. It was further established that the application of PUR adhesive rendered simple perfect-bond models unsuitable for describing the connection behavior. Accurate prediction of elastic stiffness was, however, achieved through finite element modeling in which the input properties were obtained from double-lap joint analysis. Among the various machine learning approaches available, boosting algorithms were selected for this study due to their widespread adoption, computational efficiency, and proven effectiveness for complex engineering regression problems. Specifically, XGBoost, AdaBoost, and LightGBM were chosen for the following reasons. Boosting algorithms are among the most widely used and well-established ensemble methods in machine learning. They have consistently demonstrated superior performance over other algorithms (including Random Forest and neural networks) for small-to-medium-sized tabular datasets. Unlike neural networks, which typically require large datasets to achieve good generalization, boosting algorithms are highly efficient with smaller datasets (79–265 samples) due to their sequential learning and regularization mechanisms. XGBoost and LightGBM incorporate multiple regularization mechanisms (subsample, colsample, learning rate, and L1/L2 regularization) that prevent overfitting, a critical advantage for relatively small datasets [17].

This study addresses this gap by presenting a comprehensive comparative analysis of three machine learning models, XGBoost, AdaBoost, and LightGBM, for predicting the time-dependent bond strength between FRP and timber in both normal and harsh environments. The primary objectives of this study are to develop and compare these machine learning models, identify the key factors controlling bond performance through SHAP analysis and Partial Dependence Plots, determine which algorithm performs best under each environmental condition, and interpret the model predictions to elucidate the underlying degradation mechanisms governing FRP–timber bond durability. Leveraging an extensive experimental dataset comprising 344 data points from prior investigations, this study incorporates material properties, geometric parameters, exposure time, and solution pH as input features. Hyperparameter optimization is systematically performed for each model, and performance is rigorously evaluated using multiple statistical metrics. Furthermore, SHAP analysis and Partial Dependence Plots are employed to interpret feature importance and elucidate the underlying degradation mechanisms. The findings provide a preliminary predictive framework for FRP–timber bond durability, offering insights that may assist in estimating bond performance within the investigated parameter ranges. However, given that the models are based on laboratory-scale tests, restricted parameter ranges, and no independent external validation, they should be viewed as preliminary tools rather than as validated design provisions. Further validation through independent experimental data is required before application to structural design or service life prediction.

2. Bond Strength Between FRP and Timber

The interfacial bond between fiber-reinforced polymer (FRP) and timber represents a critical aspect of structural performance, governing the load transfer efficiency and overall durability of hybrid composite systems [18–20]. As shown in Figure 1, this study employed advanced machine learning methodologies to predict the bond strength at the FRP–timber interface in both normal and harsh environments. Under normal conditions, the bond behavior is primarily governed by mechanical interlocking and adhesive interactions, where fiber properties, particularly tensile strength (S_f) and geometric characteristics such as width (b_f), bond length (L_b), and thickness (t_f), play dominant roles in determining the ultimate bond capacity. The experimental database demonstrates that carbon FRP (CFRP) with high tensile strength consistently exhibits superior bond performance compared with glass (GFRP) and aramid (AFRP) fibers. However, when subjected to harsh environmental exposures, including acidic (pH 2.5), alkaline (pH 12.5), and neutral aqueous solutions over extended durations of up to 12 months, the bond integrity undergoes significant time-dependent degradation. These environmental conditions induce complex deterioration mechanisms: acidic solutions promote hydrolysis of the epoxy adhesive and attack the adhesive–timber interface, while alkaline conditions chemically degrade glass fibers through silica dissolution. The machine learning models developed in this study capture these non-linear and fiber-dependent degradation patterns, with exposure time emerging as the predominant factor affecting bond durability in harsh conditions. Through the XGBoost, AdaBoost, and LightGBM algorithms, the predictive framework successfully models the intricate relationships between material parameters, environmental factors, and bond strength within the investigated ranges. This demonstrates the potential of machine learning for this application; however, the framework should be considered preliminary, and further validation is required before use in design or service-life estimation.

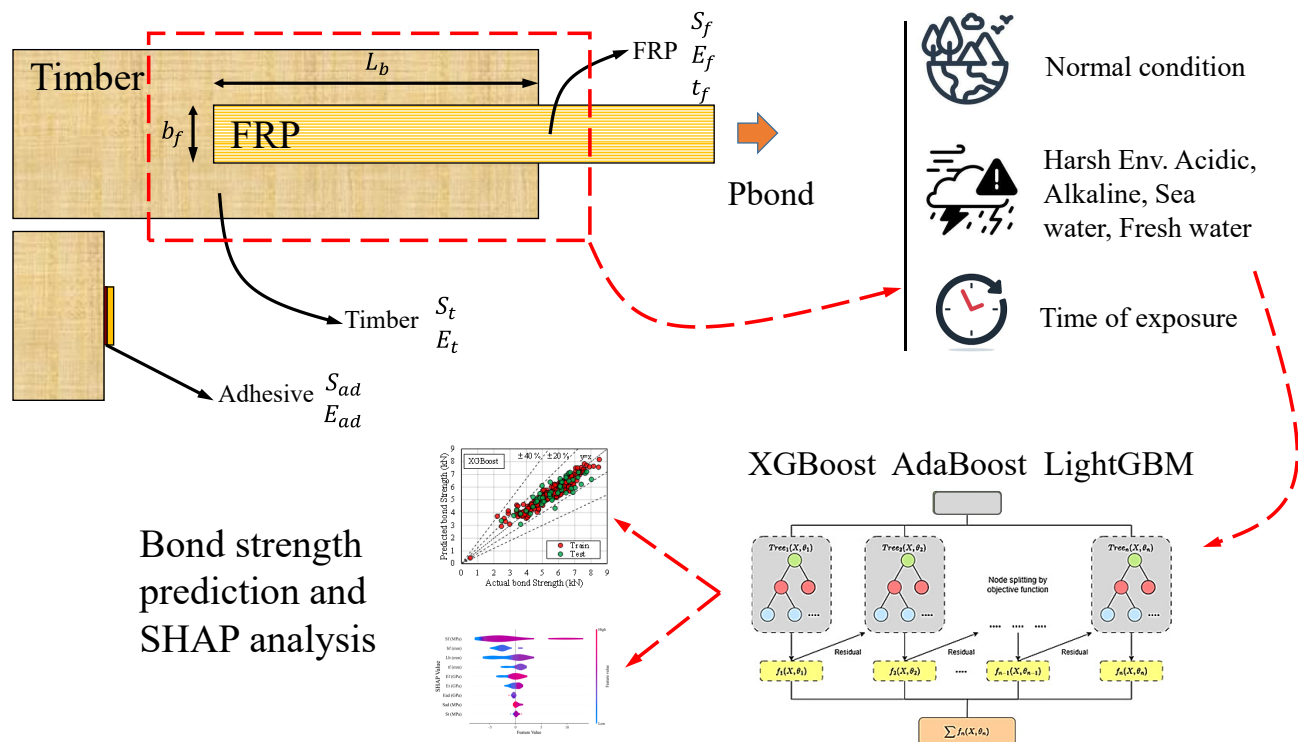


Figure 1. Bond strength prediction between FRP and timber in normal and harsh environments using machine learning methods.

3. Dataset

The dataset for this study was gathered from multiple research papers investigating FRP-to-timber bonds, both under normal conditions and in more harsh environments. These experimental results, originally from tests carried out by Yarigarravesh et al. [21] and Toufigh et al. [22] for harsh environments and Wan et al. [23], Vahedian et al. [24], Biscaia et al. [13,25], Lee et al. [26], Valluzzi et al. [27] and Toufigh et al. [22] for normal conditions, were then used to carry out a detailed analysis with the aid of machine learning techniques. The bond behavior was examined in two stages. In the first stage, performance under normal environmental conditions was evaluated, while in the second stage, the effects of harsher conditions on the bond were explored. A total of 79 data points were considered from the first stage, and 265 data points were taken from the second. To ensure robust model development and unbiased performance evaluation, the complete dataset was systematically partitioned into training and testing subsets. For the normal-conditions dataset (79 samples), 63 samples (79.7%) were allocated for training and 16 samples (20.3%) for testing. For the harsh-environment dataset (265 samples), 212 samples (80.0%) were used for training and 53 samples (20.0%) for testing. The main statistical features of the dataset are summarized in Tables 1 and 2, and the distribution of the standardized data for both phases is shown in Figure 2. In these tables, the subscripts t, ad, and f are used to denote timber, adhesive, and fiber, respectively. The subscripts S and E refer to the strength and modulus of elasticity. Lb represents the bond length on the timber surface, and Pbond indicates the bond strength between timber and FRP. It should be noted that, for the tests reported in Table 2, several parameters were kept constant throughout the experiments. These fixed values included $E_t = 8.9$ GPa, $S_t = 4.2$ MPa, $E_{ad} = 3.1$ MPa, $S_{ad} = 75$ MPa, $b_f = 50$ mm, $L_b = 170$ mm, and $t_f = 0.117$ mm. Only the environmental conditions and the properties of the FRP were varied during the testing process.

Table 1. Statistical properties for normal conditions.

Parameter	Mean	Standard Deviation	Minimum	1st Quartile (Q1)	3rd Quartile (Q3)	Maximum
Et (GPa)	12.58	4.49	6.34	9.3	16.18	19.75
St (MPa)	46.37	19.99	4.2	41.5	49.3	88.35
Ead (GPa)	3.73	1.89	0.79	2.5	4.5	8.89
Sad (MPa)	32.46	15.09	15.2	26.9	30	75
Ef (GPa)	187.92	66.76	21.4	192	228.89	244
Sf (MPa)	2333.78	876.58	222	2497	3133	3430
Bf (mm)	42.03	17.64	10	35	50	100
Lb (mm)	195.44	180.69	30	105	170	800
tf (mm)	0.84	0.87	0.117	0.117	1.4	2.8
Pbond (kN)	17.19	14.29	3.35	8.05	20.4	76.4

Table 2. Statistical properties for harsh environment.

Parameter	Mean	Standard Deviation	Minimum	1st Quartile (Q1)	3rd Quartile (Q3)	Maximum
Ef (GPa)	49.21	18.42	21.7	27.9	64.2	67.8
Sf (MPa)	480.87	171.97	222	295	601	708
t (day)	139.87	117.39	14	42	270	360
pH	7.85	3.35	2.5	7	10	12.5
Pbond (kN)	5.59	1.28	0.54	4.76	6.47	8.51

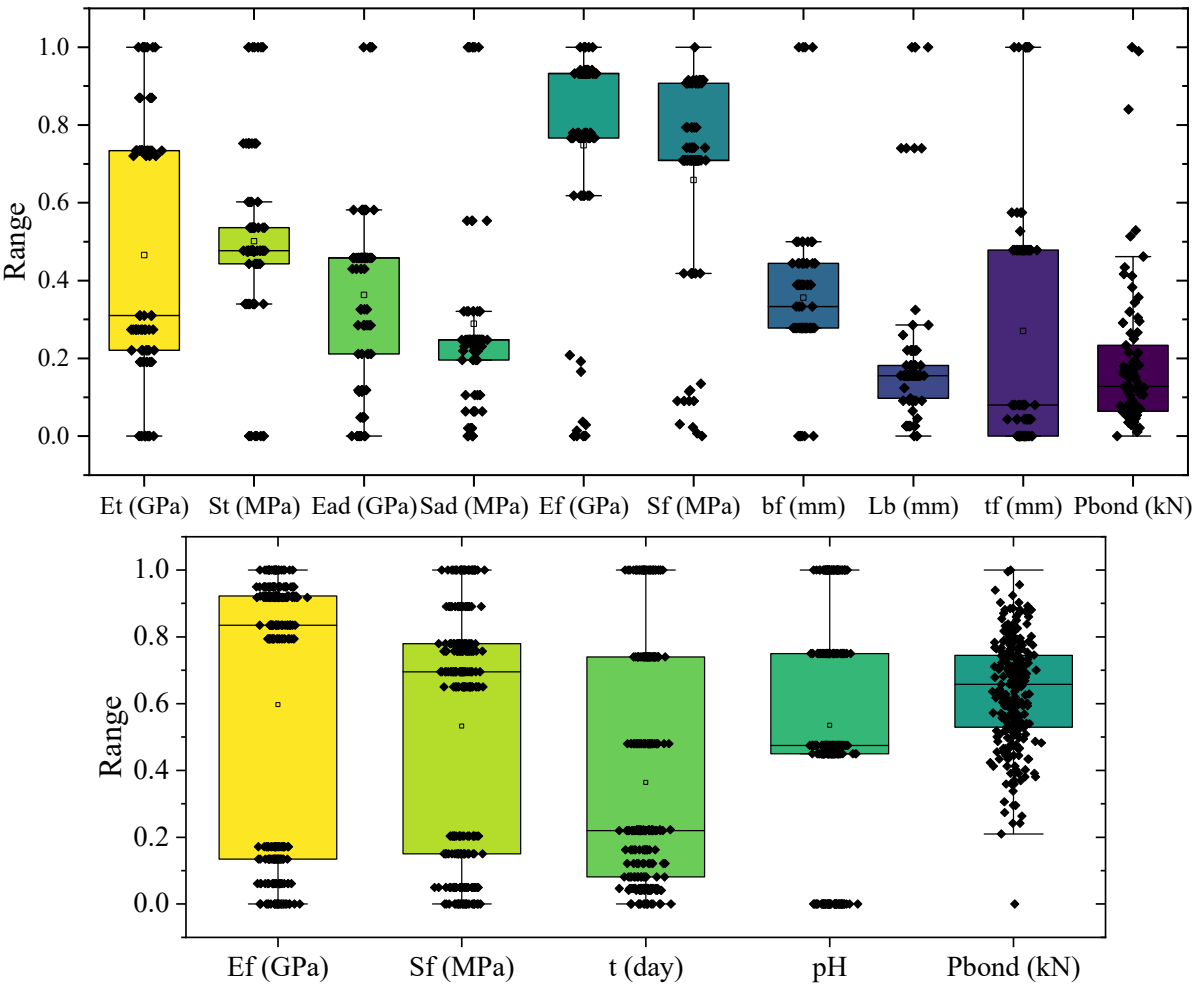


Figure 2. Data distribution for normal and harsh environments.

It should be noted that pH is used in this study as a simplified proxy for environmental severity. While pH captures the acidity or alkalinity of the exposure solution, it does not fully represent the complexity of different environmental conditions, such as the salinity of seawater or the specific ionic composition of various solutions. The effects of these factors are implicitly captured to some extent through the experimental data, but pH alone should be interpreted as a simplified indicator of environmental conditions rather than a complete characterization.

Among the input features, adhesive strength (S_{ad}) exhibits the narrowest distribution. The limited variability of this feature suggests that adhesive properties were well-controlled and may contribute less to the predictive power of the model compared with parameters with greater diversity. FRP width (b_f), bond length (L_b), and FRP thickness (t_f) show moderate distributions with some high outliers, reflecting the geometric diversity of the specimens tested. FRP modulus (E_f) and tensile strength (S_f) exhibit distributions concentrated at relatively high values, reflecting the inclusion of various fiber types, carbon, glass, and aramid, each possessing distinct mechanical properties. The higher concentration is consistent with the presence of carbon FRP, which exhibits superior stiffness and strength compared with glass and aramid fibers. Exposure time (t) shows a broad distribution spanning the full range from minimum to maximum, capturing the experimental design where specimens were immersed in chemical solutions for durations ranging from weeks to months. This wide spread is essential for modeling the time-dependent degradation of bond strength. Solution pH is distributed across the entire range from acidic (2.5) to highly alkaline (12.5), representing all five environmental conditions investigated in both studies. This range enables the model to capture the non-linear and fiber-dependent effects of different chemical environments on bond performance. Overall, the distribution analysis confirms that the dataset is sufficiently diverse and representative for training a robust machine learning model. The varying degrees of spread across different features, from the narrow distribution of adhesive strength to the wider spread of timber and FRP properties, reflect the underlying physical variability of the materials and experimental conditions. This diversity is essential for capturing the complex, non-linear interactions that govern the bond behavior at the FRP–timber interface under environmental exposure.

To establish a rational basis for feature selection in the proposed machine learning model, a correlation analysis was performed between the bond strength of FRP–timber and material and geometric parameters. The parameters included timber elastic modulus (E_t) and strength (S_t); adhesive modulus (E_{ad}) and strength (S_{ad}); FRP modulus (E_f) and strength (S_f); FRP width (b_f); bond length (L_b); and FRP thickness (t_f). The resulting correlation coefficients are shown in Figure 3.

Among all parameters, bond length (L_b) exhibited the strongest positive correlation with bond strength ($r = 0.71$), followed by FRP thickness (t_f , $r = 0.66$), FRP width (b_f , $r = 0.57$), and FRP tensile strength (S_f , $r = 0.56$). These findings indicate that the geometric characteristics of the FRP and the strength of the fiber are the primary mechanical drivers of bond performance. This observation is consistent with the experimental results reported by Yarigarravesh et al. [21] and Toufigh et al. [22], where specimens with higher-strength fibers, such as CFRP, consistently demonstrated higher bond strengths compared with glass or aramid FRPs under equivalent environmental exposures. Furthermore, the strong influence of FRP width and bond length aligns with the single-lap shear test configuration employed in both studies, where larger bonded areas inherently distribute shear stresses more effectively. Conversely, timber properties showed negligible correlations with bond strength (E_t : $r = 0.09$; S_t : $r = 0.03$). This suggests that, under the environmental aging conditions investigated (acidic, alkaline, seawater, and freshwater exposures over durations of up to 12 months), the degradation of the timber substrate does not directly govern the

interfacial bond failure [21]. Bond failure was predominantly dictated by adhesive–FRP or adhesive–timber interface deterioration, particularly under prolonged chemical exposure. The adhesive modulus (E_{ad}) showed a weak positive correlation ($r = 0.26$), while adhesive strength (S_{ad}) exhibited a weak negative correlation ($r = -0.15$). The latter, although modest, may reflect a physical trend observed in the failure mode analyses: stronger adhesives tend to be more brittle, promoting sudden debonding at the interface rather than gradual load transfer [28–30]. This is indirectly supported by the observation that, under no-exposure conditions, failure modes I and II (timber substrate failure and FRP–adhesive failure) occurred, whereas after prolonged exposure to aggressive solutions, mode III (adhesive–timber failure) became dominant [21,22]. The FRP modulus (E_f) showed only a weak correlation ($r = 0.20$), suggesting that stiffness matching between the FRP and the timber substrate is less critical than the tensile strength of the FRP itself. This is consistent with the conclusion of Toufigh et al. [22].

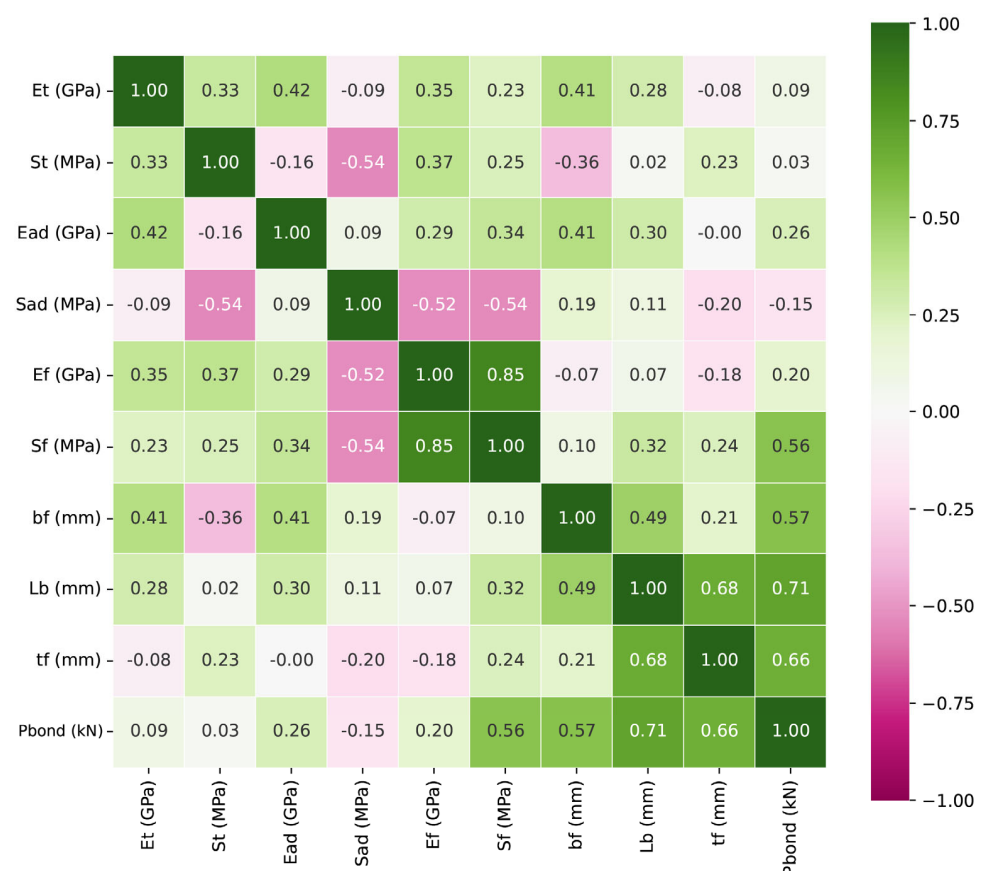


Figure 3. Correlation coefficients for inputs and output under normal conditions.

In addition to material and geometric parameters, the effects of exposure time (t) and solution pH on the interfacial bond strength are shown in Figure 4. Exposure time exhibited a negative correlation with bond strength ($r = -0.46$), indicating that as the duration of environmental exposure increased, the bond strength consistently decreased. This finding is strongly supported by the experimental results of both Yarigaravesh et al. and Toufigh et al. The normalized bond strength of most FRP–timber specimens declined progressively from 2 weeks to 13 weeks of immersion across all chemical solutions [21]. Similarly, in the long-term study, bond strength reductions continued to accumulate from 1 month up to 12 months of exposure [22]. The magnitude of this correlation ($r = -0.46$) reflects that degradation was not perfectly linear with time; in many cases, the most severe reductions occurred within the first several weeks of immersion, followed by a

more gradual decline. This is particularly evident in the acidic exposure of CFRP–timber specimens [21], where bond strength dropped sharply after 8 weeks, while other specimens showed more gradual deterioration.

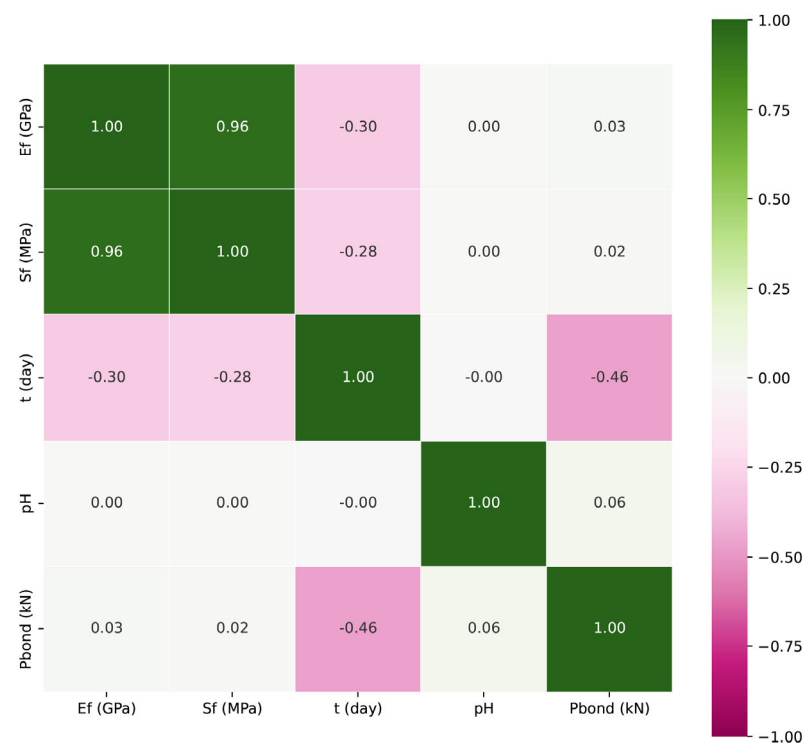


Figure 4. Correlation coefficient for inputs and output in harsh environment.

In contrast, solution pH exhibited a near-zero correlation with bond strength ($r = 0.06$). This indicates that, across the full range of pH values investigated (2.5 to 12.5), there is no simple linear trend relating pH to bond strength. This result is physically meaningful and consistent with the experimental observations reported in both articles [21,22]. As demonstrated in Yarigaravesh et al.'s study [21], the relationship between pH and bond degradation is non-monotonic and fiber-dependent. Specifically, at pH 2.5 (acidic), carbon FRP–timber specimens suffered the most severe reduction (57% after 13 weeks); at pH 12.5 (highly alkaline), glass FRP–timber specimens suffered the most severe reduction (47% after 13 weeks); at pH 7 and 7.25 (neutral, fresh and sea water), reductions were moderate (approximately 20–43% depending on fiber type); and at pH 10 (mild alkaline), reductions were generally lower than at pH 12.5 but still significant for glass FRP. Thus, plotting bond strength against pH would reveal a U-shaped or irregular pattern rather than a straight line. Acidic and highly alkaline conditions both cause substantial degradation, but through different chemical mechanisms. Neutral conditions cause the least degradation for most fiber types. This non-linear behavior results in a near-zero linear correlation coefficient ($r = 0.06$), because the positive and negative slopes across different pH regions cancel each other out when a straight line is fitted. It should be emphasized that pH is used here as a simplified proxy for environmental severity and does not fully characterize the complexity of different environmental conditions, such as the salinity of seawater or the specific ionic composition of various solutions.

The physical mechanisms underlying this non-linear response are discussed in both articles and in Saadatmanesh et al.'s study [31]. Acidic solutions (pH 2.5) promote hydrolysis of the epoxy adhesive and attack the adhesive–timber interface, particularly affecting carbon and aramid FRP bonds. Alkaline solutions, especially at pH 12.5 containing sodium hydroxide, chemically attack the glass fibers themselves, as glass is known to be susceptible

to alkali corrosion. Neutral pH environments primarily cause physical swelling and weakening of the timber substrate and adhesive, without the severe chemical attack characteristic of extreme pH values.

4. Machine Learning Methods and Hyperparameter Optimization

4.1. Model Development

A rigorous protocol was followed for developing and evaluating the machine learning models:

Step 1—Data Preparation: After stratified splitting, the training data were used exclusively for all model development activities. Feature scaling (standardization) was performed using only the training data statistics, with the same scaling parameters subsequently applied to the test data to prevent data leakage.

Step 2—Cross-Validation: For each model, 5-fold cross-validation was performed on the training data to evaluate performance stability and guide hyperparameter selection. The 5-fold CV involved partitioning the training data into five equal-sized folds, training on four folds, and validating on the remaining fold, repeating this process five times with each fold serving as the validation set once.

Step 3—Hyperparameter Optimization: Hyperparameters were optimized using Bayesian Optimization, with the objective of minimizing the average cross-validated MSE. The optimization process was performed exclusively on the training data. A total of 100 optimization iterations were conducted for each model–condition combination, and the hyperparameters yielding the lowest average CV-MSE were selected as optimal.

Step 4—Final Model Training: With the optimal hyperparameters identified, each model was retrained on the complete training set to produce the final model.

Step 5—Test Set Evaluation: The fully trained models were evaluated once on the held-out test set to obtain unbiased estimates of generalization performance.

All models were implemented in Python 3.9 (v2020) using the following libraries: scikit-learn 1.0.2 (for AdaBoost and data preprocessing), XGBoost 1.6.0, and LightGBM 3.3.2. The random seed was fixed at 42 for all operations to ensure reproducibility. The search ranges for hyperparameter optimization are provided in Tables 3–5.

Table 3. Optimal values of parameters for XGBoost.

Parameter	Normal Condition Model	Harsh Environment Model	Search Range
Colsample bytree	0.85992	0.66239	[0.3, 1.0]
Learning rate	0.14402	0.02684	[0.001, 0.3]
Max depth	9	9	[2, 20]
N estimators	192	192	[10, 300]
Subsample	0.88699	0.88322	[0.3, 1.0]
Random state	42	42	42

Table 4. Optimal values of parameters for AdaBoost.

Parameter	Normal Condition Model	Harsh Environment Model	Search Range
N estimators	73	164	[10, 300]
Learning rate	0.64456	0.83212	[0.001, 0.3]
Max depth	3	7	[2, 20]

Table 5. Optimal values of parameters for LightGBM.

Parameter	Normal Condition Model	Harsh Environment Model	Search Range
Colsample bytree	0.63300	0.67336	[0.3, 1.0]
Learning rate	0.27214	0.09823	[0.001, 0.3]
Max depth	7	6	[2, 20]
N estimators	237	157	[10, 300]
Subsample	0.89923	0.71649	[0.3, 1.0]
Random state	42	42	42

4.2. XGBoost

Among the various ensemble learning techniques, Extreme Gradient Boosting, commonly referred to as XGBoost, stands out for its computational speed and operational efficiency. Originally introduced by Chen et al. [32] and later refined through collaborative contributions from an open-source community, this algorithm builds upon the foundational principles of Gradient Boosting. It operates by sequentially integrating decision trees as weak learners, with each new tree being added to correct the residual errors left by its predecessors. This stepwise refinement allows the model to progressively reduce prediction inaccuracies. Beyond its boosting mechanism, XGBoost offers practical advantages such as parallelized computation, built-in handling of missing entries, and a wide range of tunable hyperparameters, which together make it highly adaptable to complex, data-intensive problems [33]. The specific parameter configuration adopted for the XGBoost model is provided in Table 3.

4.3. AdaBoost

Adaptive Boosting, commonly known as AdaBoost, belongs to the family of ensemble learning methods and can be adapted for both classification and regression tasks [34]. In the regression context, the algorithm operates by sequentially training weak regressors (typically decision trees) and adjusting sample weights based on the prediction errors of the previous model. For regression tasks, AdaBoost typically employs a linear loss function or square error loss to compute the error of each base estimator, and the sample weights are updated based on the relative error of each prediction. In this study, the base estimator used for AdaBoost regression is a decision tree regressor, and the number of estimators and learning rate were optimized as presented in Table 4.

4.4. LightGBM

Light Gradient Boosting Machine, or LightGBM [35], is a cutting-edge algorithm introduced by Microsoft with the primary goal of accelerating the training process for boosting-based models while maintaining efficient memory usage. In line with other boosting frameworks, it constructs a sequence of weak learners, typically decision trees, and aggregates their outputs to form a final model with superior predictive accuracy. What sets LightGBM apart, however, are the substantial gains it offers in both computational speed and resource economy. These improvements are largely attributed to innovations such as histogram-based tree construction and gradient-based one-side sampling (GOSS), which effectively curtail the data volume processed during training without sacrificing model precision. The algorithm further leverages a histogram approach, where continuous feature values are discretized into bins, and sample counts within those bins are used to expedite the search for optimal splitting points. Additionally, a leaf-wise tree growth strategy is employed, constrained by a specified maximum depth to prevent overfitting [36]. The final parameter configuration adopted for LightGBM in this study is presented in Table 5.

5. Performance Evaluation

Upon fitting the data with the various candidate models, an evaluation of their respective accuracies and error distributions was carried out using multiple standard criteria. The chosen performance indicators comprised R^2 , $RMSE$, MAE , and MSE , all computed according to the relationships presented in Equations (1)–(4). For the R^2 metric, higher values, specifically those closer to 1, are indicative of better model fit and predictive capability. The other three criteria, which capture different aspects of prediction deviation, should be reduced to the smallest possible values for optimal performance.

$$R^2 = 1 - \frac{\sum_{i=1}^n (Pexp_i - Pmod_i)^2}{\sum_{i=1}^n (Pexp_i - \bar{Pexp})^2} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Pexp_i - Pmod_i)^2} \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |Pexp_i - Pmod_i| \quad (3)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (Pexp_i - Pmod_i)^2 \quad (4)$$

where $Pexp$ refers to the experimentally measured bond strength, $Pmod$ indicates the output generated by the ML model, and n is the number of data samples. $RMSE$ serves as a valuable metric because it incorporates errors from every observation; the closer its value is to zero, the better the model's predictive ability [37–39]. A well-performing model is typically signified by high R^2 , together with low $RMSE$, MAE , and MSE metrics.

From the results presented in Table 6, XGBoost achieved the highest testing R^2 (0.9440) on the selected test set, followed closely by AdaBoost (0.9388), while LightGBM exhibited the lowest testing R^2 (0.7937) and the highest error metrics on this particular split. However, it is important to note that these rankings are based on a single train–test split. With only 16 test observations for the normal-condition dataset, the relative ranking of the models may be sensitive to the specific samples allocated to the test set. From Table 7, which presents the results for harsh environments, a critical distinction emerges between training and testing performance. AdaBoost achieved the highest training R^2 of 0.9587 with remarkably low training errors ($RMSE = 0.2619$; $MAE = 0.1764$); however, its testing R^2 dropped sharply to 0.6176, with the largest test errors ($RMSE = 0.7531$; $MAE = 0.5605$). This represents a generalization gap of $\Delta R^2 = 0.3411$, indicating severe overfitting to the training data. XGBoost showed more balanced performance with training $R^2 = 0.8711$ and testing $R^2 = 0.7572$ ($\Delta R^2 = 0.1139$), demonstrating moderate generalization capability. Remarkably, LightGBM, despite having the lowest training R^2 of 0.7670, achieved the highest testing R^2 of 0.7969, outperforming both XGBoost and AdaBoost on unseen data. Notably, LightGBM's testing R^2 actually exceeded its training R^2 ($\Delta R^2 = -0.0299$). This counterintuitive result, where the model with the poorest training performance yields the best testing performance, underscores the importance of evaluating models on validation data rather than relying solely on training metrics. The relatively better test performance of LightGBM in harsh environments on the selected test set may be attributed to its histogram-based tree construction, gradient-based one-side sampling (GOSS), and leaf-wise growth strategy with depth constraints, which collectively help prevent overfitting while capturing complex, non-linear degradation patterns. Based on the error and accuracy metrics reported in Tables 6 and 7, the scatter plots for both training and testing values across the three machine learning models are presented in Figures 5 and 6. In these plots, red dots are used to represent the training data, while green dots are used for the testing data. A

45-degree reference line corresponding to $y = x$ is also included, along with additional lines marking the $\pm 20\%$ error boundaries. As observed in Figure 5, the training data were effectively learned by the XGBoost model, and only a small margin of error is observed in the testing data, suggesting that overfitting was not a concern in this case. For the AdaBoost model, however, a noticeably higher error is observed within the training data, with some instances approaching the 40% error range. The LightGBM model demonstrates a considerably larger error overall, with deviations exceeding 40% recorded for certain portions of both training and testing datasets. It is also evident from Table 7 that, in harsh environments, both the error magnitude and data dispersion tend to be elevated. This trend is further supported by Figure 6, where even the LightGBM model, which performed relatively well previously, is shown to exhibit high dispersion. Such behavior is recognized as one of the inherent difficulties associated with time-dependent and environmentally influenced data. For the XGBoost model, an error exceeding 20% is still observed within the training data. Interestingly, this pattern appears reversed for the AdaBoost model, where the testing data exhibit larger errors than the training data. For the LightGBM model, errors are consistently produced across both datasets.

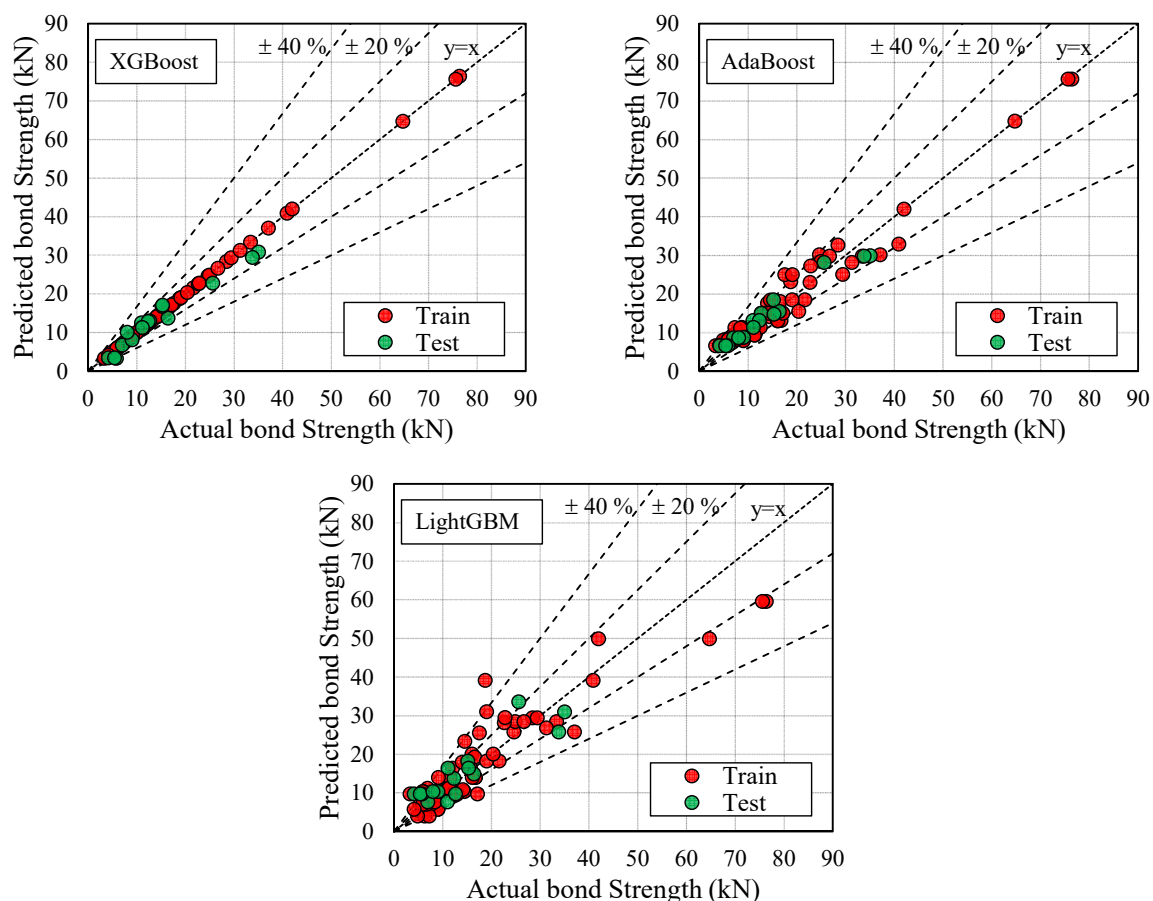


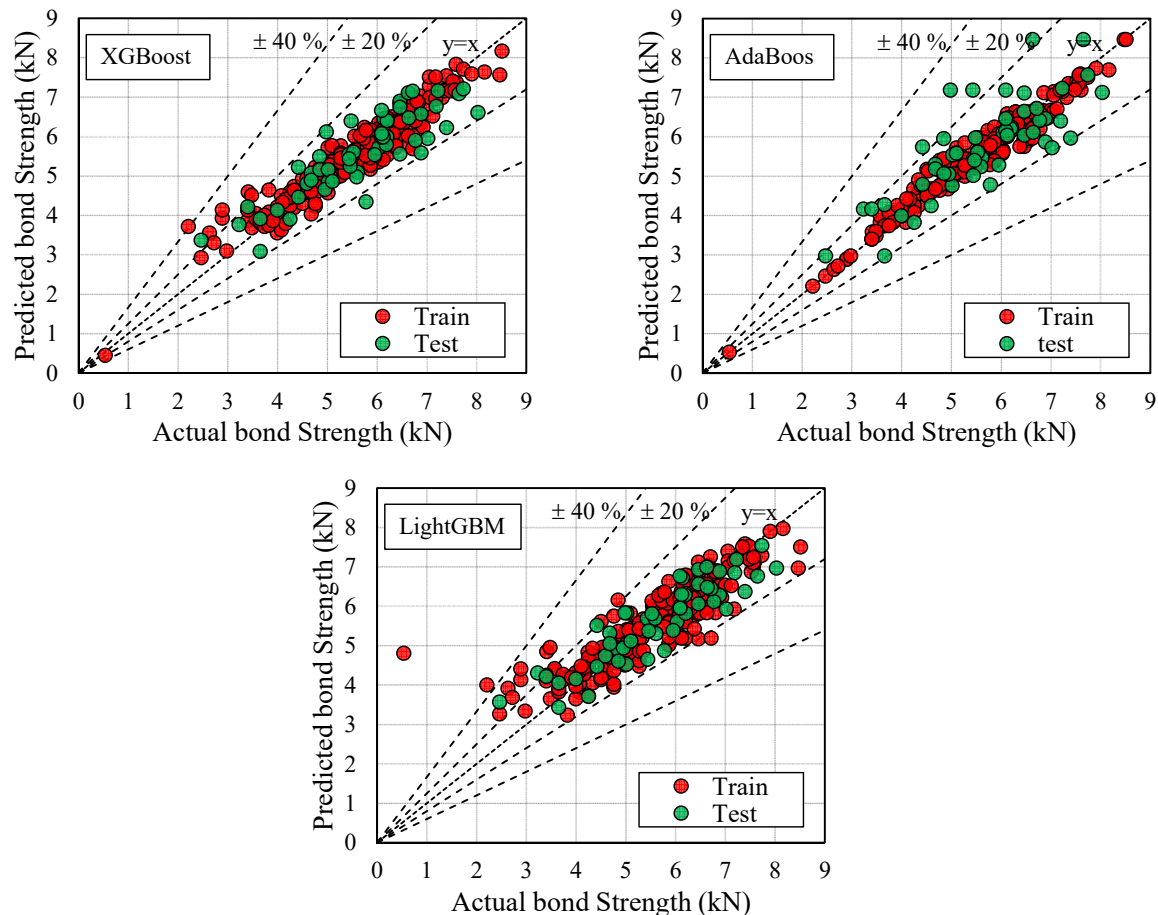
Figure 5. Comparison of experimental and ML-predicted bond strengths for normal conditions.

Table 6. Performance of different models for normal conditions.

Parameter	XGBoost		AdaBoost		LightGBM	
	Training	Testing	Training	Testing	Training	Testing
R^2	1.0000	0.9440	0.9597	0.9388	0.8492	0.7937
MSE	0.0000	4.7105	9.2048	5.1470	34.4824	17.3566
RMSE	0.0025	2.1704	3.0339	2.2687	5.8722	4.1661
MAE	0.0019	1.7752	2.4135	1.8003	4.0070	3.5288

Table 7. Performance of different models for harsh environment.

Parameter	XGBoost		AdaBoost		LightGBM	
	Training	Testing	Training	Testing	Training	Testing
R^2	0.8711	0.7572	0.9587	0.6176	0.7670	0.7969
MSE	0.2140	0.3602	0.0686	0.5672	0.3869	0.3013
RMSE	0.4627	0.6001	0.2619	0.7531	0.6220	0.5489
MAE	0.3188	0.4741	0.1764	0.5605	0.4467	0.4310

**Figure 6.** Comparison of experimental and ML predicted bond strengths for harsh environment.

In Figures 7 and 8, the ratio of the predicted bond strength to the actual bond strength is shown, along with the fitted lines that have been drawn over these values. Ideally, what is aimed for is a slope of zero and an intercept equal to one, so that the fitted lines end up approaching the horizontal line $y = 1$ as closely as possible. For the XGBoost, AdaBoost, and LightGBM models, the slopes of these lines were found to be -0.0003 , -0.0008 , and -0.0009 , respectively. This indicates that the slope obtained for the XGBoost model is considerably smaller than those of the other two models, amounting to roughly 38% and 30% of the slopes calculated for AdaBoost and LightGBM, respectively. The intercepts for XGBoost, AdaBoost, and LightGBM are 0.9988, 1.1310, and 1.1374, respectively. The intercept for XGBoost is very close to 1.0, which means that this model lands quite near the ideal line. Among the three, LightGBM appears to be the least accurate in this particular context. When the same analysis is carried out in harsh environments, and the results are shown in the corresponding figure, the slopes for XGBoost, AdaBoost, and LightGBM are observed to be 1.0×10^{-5} , 0.0002, and 0.0001, respectively. All three models exhibit slopes close to zero, indicating reasonable prediction accuracy across the range of bond

strengths. The intercepts under these conditions are 1.0045, 0.9859, and 1.0268 for XGBoost, AdaBoost, and LightGBM, respectively. While XGBoost shows the best slope (nearest to zero) and intercept (nearest to 1.0) in this specific ratio analysis, this must be weighed against LightGBM's superior overall performance metrics (higher R^2 , lower RMSE, and lower MAE) and absence of overfitting. The ratio analysis alone is insufficient to declare overall superiority, and the collective evidence supports LightGBM as the preferred model for harsh environments.

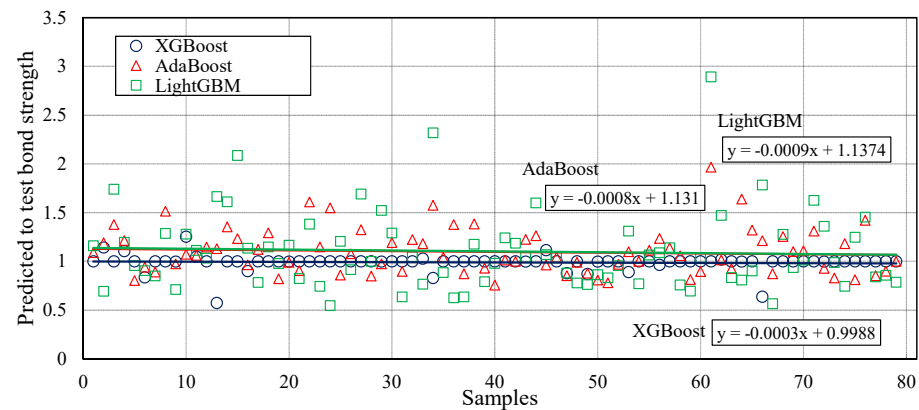


Figure 7. Ratio of ML-predicted bond strengths to experimental values and regression line for different models under normal conditions.

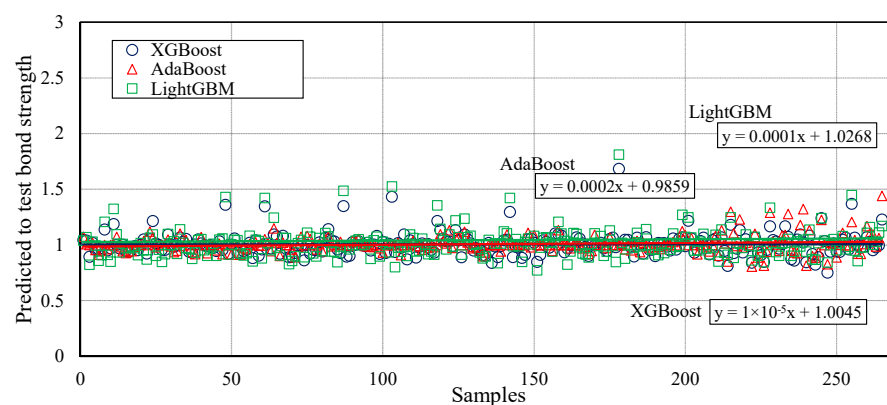


Figure 8. Ratio of ML-predicted bond strengths to experimental values and regression line for different models in harsh environment.

The predicted and experimental bonding strength ratios are visually presented in Figure 9. To evaluate the predictive capability of the proposed model, the calculated bonding strength ratios were plotted against their corresponding experimental values, and a linear regression was performed for each variable under investigation. An ideal predictive model would yield a slope of zero and an intercept of 1.0, indicating perfect agreement. For the FRP material strength, the fitted line exhibited a slope of 3×10^{-5} and an intercept of 0.9288, suggesting a near-horizontal trend with a slight systematic underestimation at higher ratios. Similarly, the modulus of elasticity of FRP produced a slope of 0.005 and an intercept of 0.8953, reflecting a modest deviation from ideality with a consistent negative bias. The time of exposure resulted in a slope of 0.004 and an intercept of 0.9911, which approaches the ideal conditions closely, implying excellent predictive alignment. Lastly, the pH variable yielded a slope of 0.0059 and an intercept of 0.9967, indicating a remarkably strong correspondence to the ideal line. Overall, while minor offsets were observed for material strength and modulus, the intercepts for time and pH were particularly close to unity, affirming the model's general reliability across the tested parameters.

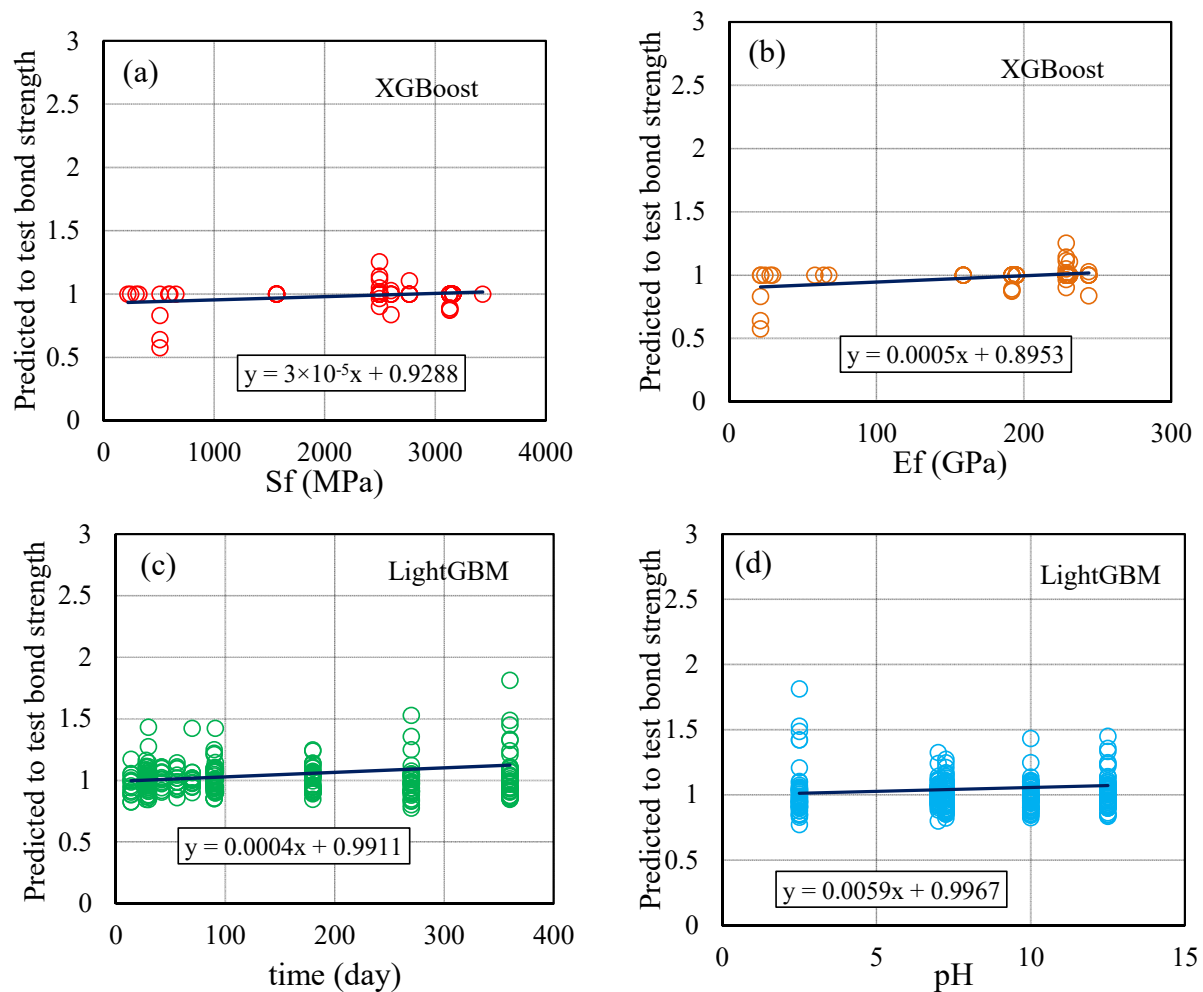


Figure 9. Bond strength prediction-to-test ratios: (a) strength of FRP; (b) modulus of elasticity; (c) time of exposure; and (d) pH of environment.

6. SHAP Analysis

6.1. Feature Importance

Once the machine learning model has been properly fitted to the data with an appropriate level of accuracy, SHAP analyses can be utilized for the purpose of determining feature importance, and the order of importance for the features in the normal and harsh environment models is shown in Figures 10 and 11. From this analysis, it is found that, under normal conditions, the features are ranked in terms of importance as follows: fiber strength is given the highest importance, followed by fiber width, bond length, fiber thickness, and fiber elastic modulus. It is observed that almost all of the fiber material properties are assigned greater importance. Adhesive properties are ranked next, while timber strength is considered the least important among them.

As the majority of tensile stresses are sustained by the fibers, the material and geometric parameters of these fibers exert a direct and substantial influence on the bond strength. It has also been reported in the literature [21,22] that higher bond strengths are respectively exhibited by fibers with greater tensile strength, such as carbon (1560 MPa), aramid (708 MPa), and glass (538 MPa). Greater significance is attributed to fiber width and bond length, as a larger surface area is exposed to shear stresses. Nevertheless, once the bond length exceeds a critical threshold, no further increase in bond strength is observed. The thickness of the fiber is also considered a parameter of considerable importance, as evidenced by the finding that pultruded sheets with thicknesses greater than 1 mm demon-

strated higher ultimate strength compared with thinner wet lay-up sheets with thicknesses below 0.5 mm [23]. Moreover, the bond strength is directly correlated with the square root of the thickness. In the subsequent category, the elastic modulus of the fibers is regarded as a factor of major significance, given that the strain distribution along the bonded joint is governed by the elastic modulus, and its association with fracture energy characteristics renders it a critical parameter.

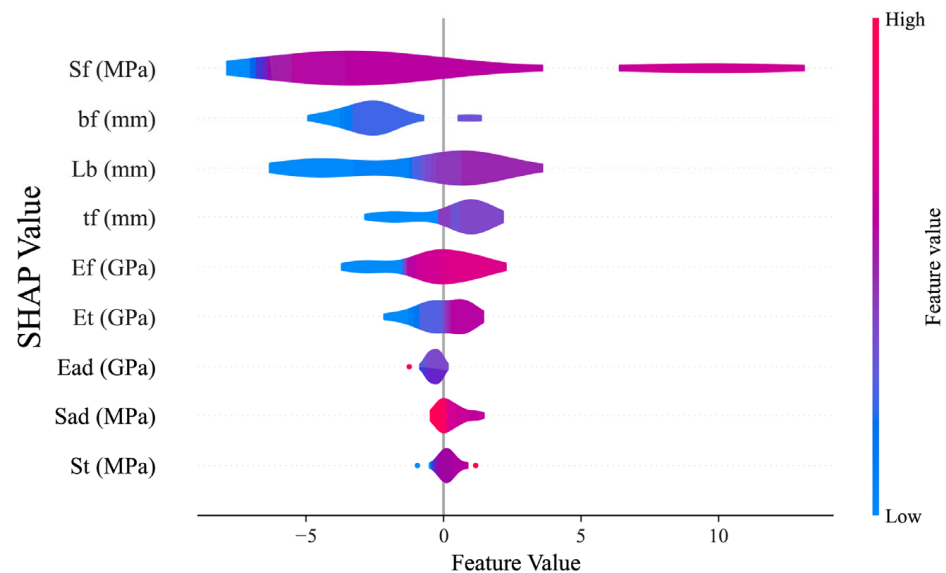


Figure 10. SHAP summary plot of features for normal conditions.

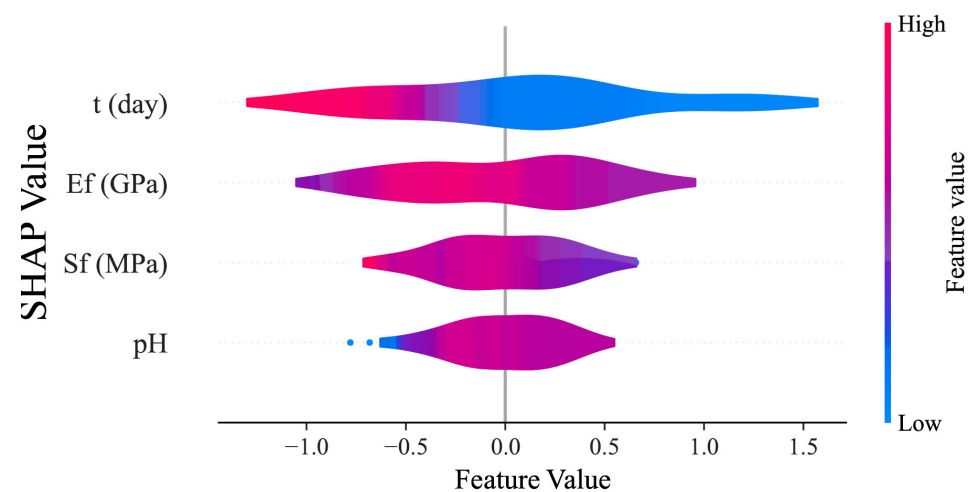


Figure 11. SHAP summary plot of features for harsh environment.

With respect to environmental effects, exposure time is identified as the predominant factor affecting bond durability. Given that continuous chemical penetration into the timber substrate induces hydrolysis, swelling, and interfacial degradation of the FRP-to-timber bond, such phenomena are inherently time-dependent. Extended exposure durations are associated with progressively greater reductions in bond strength. For instance, a reduction in CFRP bond of approximately 13% was recorded after 2 weeks of immersion in an acidic solution, which increased to approximately 57% after 13 weeks, thereby emphasizing the temporal dependence of bond performance [21]. Similarly, GFRP fibers subjected to an alkaline solution at pH 12.5 exhibited a strength reduction of about 29% at 2 weeks and approximately 47% at 13 weeks. The fiber type also exerts a considerable influence on bond strength, depending on its elastic modulus and tensile strength; accordingly, CFRP materials

were observed to be more severely affected by acidic environments (57% reduction), GFRP materials by alkaline environments (47% reduction), and AFRP specimens demonstrated intermediate behavior [21]. Comparable trends are noted with respect to pH, wherein acidic solutions are more detrimental to CFRP systems, while alkaline solutions are more deleterious to GFRP systems. The degradation mechanism is governed by pH, such that acidic solutions target the epoxy matrix of the adhesive and the timber substrate, promoting hydrolysis at the bond interface, whereas alkaline solutions facilitate degradation of glass fibers through silica dissolution.

6.2. Partial Dependence Plots (PDPs)

Partial Dependence Plot (PDP) diagrams, as employed in SHAP analyses, are recognized as important tools for examining the average output response with respect to variations in each of the input parameters. The PDPs for normal and harsh environments are shown in Figures 12 and 13. An approximately parabolic relationship is observed between the SHAP value and fiber strength, with a sharp increase noted at strength levels exceeding 3000 MPa. Furthermore, the highest response value is obtained at fiber widths of approximately 100 mm, whereas lower sensitivity is exhibited at widths below 60 mm. It appears that bond lengths exceeding 300 mm do not substantially influence the response and merely result in increased material consumption; accordingly, the critical bond length for the fibers is established at approximately 300 mm. A pronounced increase in response is observed for thicknesses ranging between 0.117 mm and 0.5 mm, with reduced sensitivity being exhibited at greater thickness values. With respect to the elastic modulus of the fibers, a general upward trend is observed, although linearity is not exhibited. A similar trend is noted for the elastic modulus of timber. In the examination of elastic modulus and adhesive strength, an approximately inverse relationship is observed: as adhesive strength increases, adhesive brittleness is enhanced, and consequently, the adhesive strength is diminished.

In the time-dependent study, a sharp decrease in the response value is observed with increasing exposure duration of the connection in harsh environments, which is attributed to processes associated with chemical interactions occurring within the adhesive or the connecting fibers. With regard to the elastic modulus, two distinct regions of differing slopes are identified; nevertheless, a positive and increasing trend is exhibited by both branches on the response. A positive increasing trend is observed for fiber strengths up to 321 MPa, whereas no such trend is seen in the strength range between 560 and 708 MPa. Within this interval, an approximately inverse trend is observed, which is indicative of brittle fracture of the connection due to the very high strength of the fibers, whereby damage is concentrated within the adhesive zone. In the pH study, an inverted U-shaped trend is exhibited by the response. This behavior is attributable to the differential effects of acidic and alkaline environments on carbon and glass fibers, which respectively influence hydrolysis processes or the interaction of fiber materials. The importance of exposure time is influenced by pH. As shown in Figure 13, the degradation rate with respect to time is more pronounced under extreme pH conditions (pH 2.5 and 12.5) compared with neutral conditions (pH 7). This indicates that the combined effect of time and pH is greater than the sum of their individual effects, reflecting the accelerated chemical degradation in harsh environments.

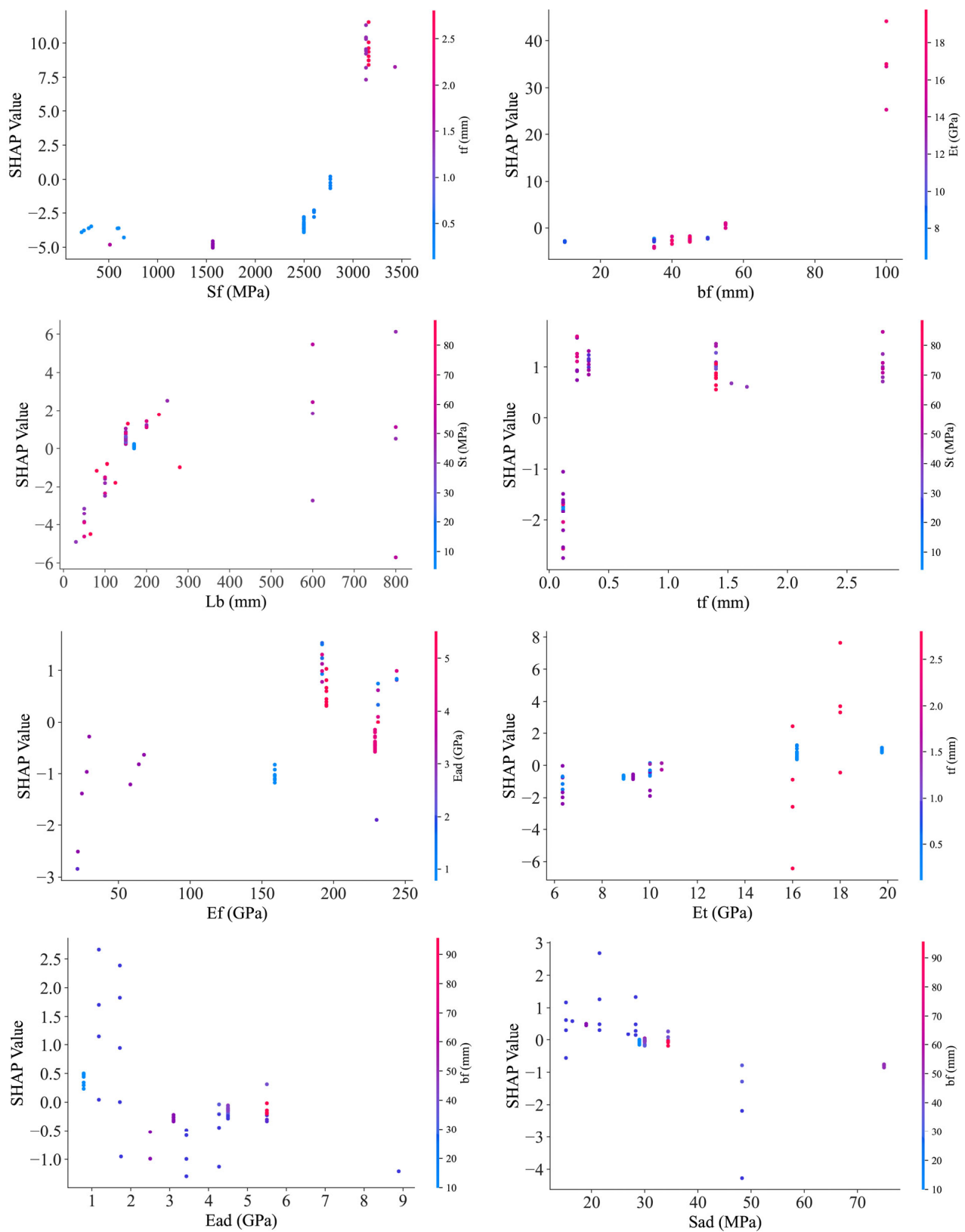


Figure 12. PDP plots for normal conditions (train and test data).

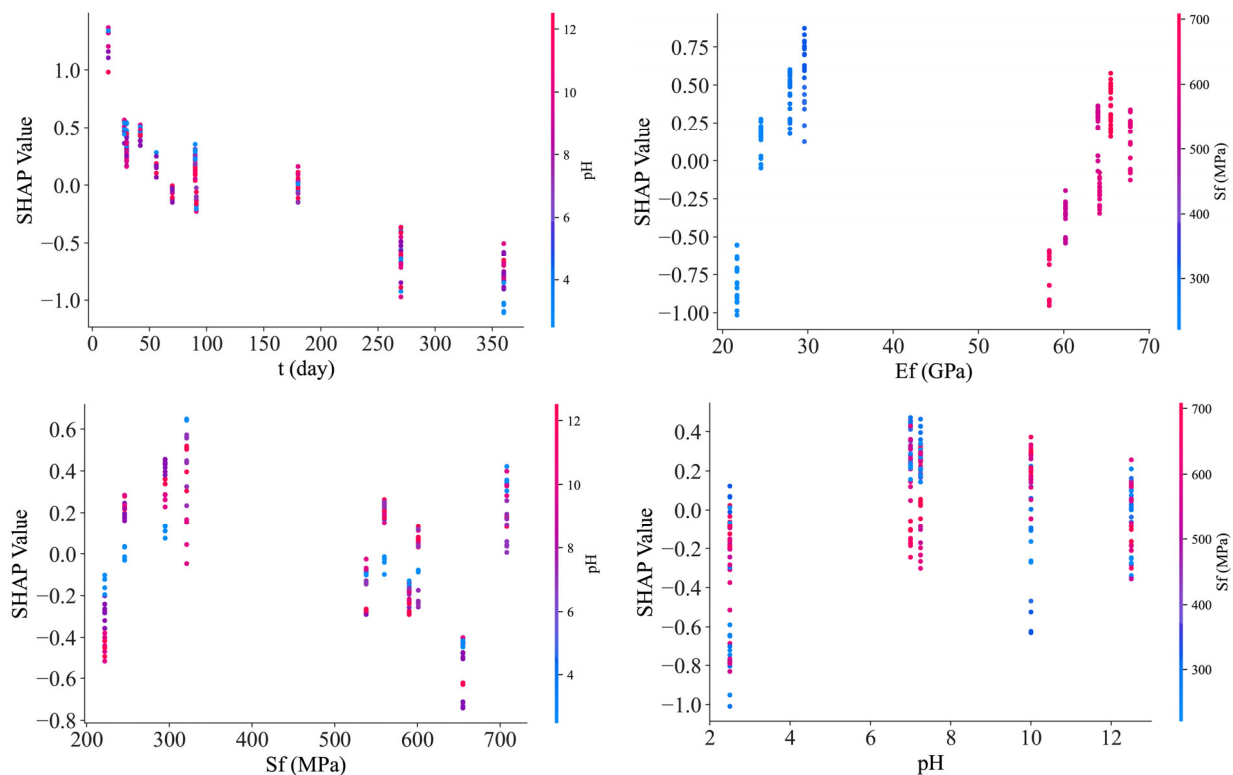


Figure 13. PDP plots for harsh environment (train and test data).

6.3. Force Plots

Force plots are employed as a way of examining the local behavior of the models with respect to specific samples. The samples utilized in the analysis are presented in Table 8 and shown in Figures 14 and 15. Samples S1N and S2N correspond to normal conditions, while samples S1H and S2H correspond to harsh environments. The measured bond strength values for samples S1N and S2N were recorded as 35.06 kN and 17.55 kN, respectively, whereas the values predicted by the machine learning algorithms were obtained as 30.86 kN and 17.55 kN, corresponding to errors of 12% and 6%, respectively. These error magnitudes are considered acceptable within the context of machine learning models and are indicative of satisfactory predictive performance by the model.

Table 8. Samples for force plots.

Sample	Et (GPa)	St (MPa)	Ead (GPa)	Sad (MPa)	Ef (GPa)	Sf (MPa)	bf (mm)	Lb (mm)	tf (mm)	t (Day)	pH	Pbond (kN)	
												Actual	Predicted
S1N	10.01	49.3	8.89	26.9	192	3133	35	150	1.4	-	-	35.06	30.86
S2N	10.01	49.3	3.43	48.3	192	3133	35	150	1.4	-	-	18.65	17.55
S1H	8.9	4.2	3.1	75	65.5	708	50	170	0.117	14	2.5	7.59	7.84
S2H	8.9	4.2	3.1	75	65.5	708	50	170	0.117	28	12.5	6.65	6.54

In order to reach the bond strength value from the base value to 30.86 kN, the most significant factor contributing to the increase in strength is identified as fiber strength, followed by its elastic modulus. It is observed that the fiber characteristics play a substantial role in enhancing the strength. Conversely, for the purpose of achieving balance and attaining the final strengths, the width parameter of 35 mm is recognized as a decreasing factor. Furthermore, a low base strength value is noted for the second sample. Nevertheless, the fiber strength parameter and its thickness are identified as the primary factors responsible for increasing it, while the adhesive strength factors and fiber width are considered

decreasing factors. In both samples, the adhesive characteristics and the timber elastic modulus are found to play a diminishing role. However, the mechanical and geometric properties of the fibers are observed to exert an increasing influence, elevating the base strength value toward the predicted value.

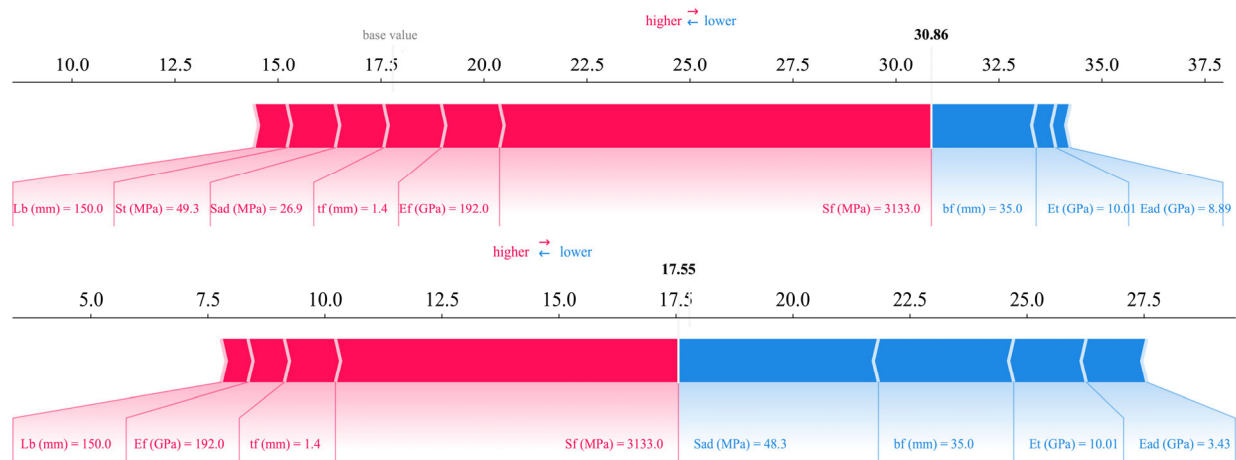


Figure 14. Force plots for samples 1 and 2 for normal conditions.

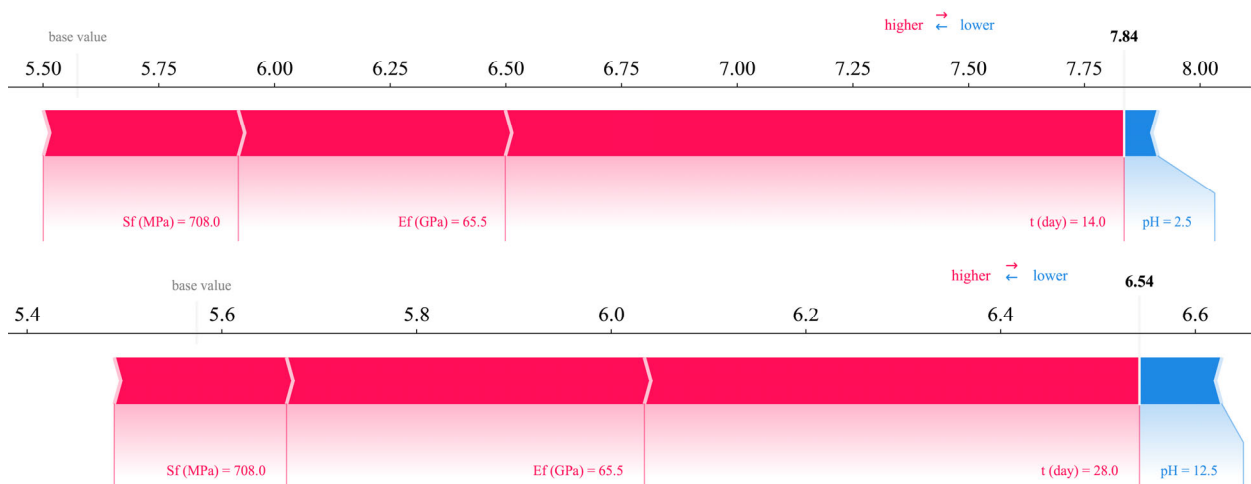


Figure 15. Force plots for samples 1 and 2 for harsh environment.

In both samples subjected to harsh environments, a decreasing role is attributed to pH in order to reach the base strength toward the predicted value. Conversely, exposure times of 14 and 28 days are identified as having an important role in increasing the strength, wherein an increasing role is observed in combination with the elastic modulus and strength values of 65 GPa and 708 MPa. Almost all factors are found to exhibit an increasing role; however, the pH values of 2.5 and 12.5 in these samples are associated with a decreasing role. This observation indicates that, in achieving a given strength, even the time factor may manifest in a negative direction and contribute to an increasing role in strength.

7. Limitations and Future Work

The authors acknowledge that the harsh environment dataset is derived from only a few experimental studies. Experimental studies were conducted. While the cross-validation results demonstrate the model's ability to generalize across different exposure regimes within the same experimental framework, true external validation requires data from independent laboratories. Furthermore, because observations from the same experimental program may share common materials, preparation procedures, and laboratory conditions,

the random splitting employed in this study may produce somewhat optimistic estimates of generalization. When a larger and more diverse database becomes available, future work should employ study-grouped or leave-one-study-out validation to provide more realistic performance estimates. Future work should focus on expanding the experimental database, including different timber species and adhesive systems, incorporating additional environmental exposures (seawater, UV radiation, and freeze–thaw cycles). Long-term extrapolation beyond the observed exposure range (14–360 days) is not supported by the data. Given the limited number of test samples, particularly for the normal-condition dataset ($n = 16$), the observed ranking may be sensitive to the specific split. Future work should employ repeated random subsampling to provide more statistically robust model comparisons.

8. Conclusions

This study employed three machine learning models, XGBoost, AdaBoost, and LightGBM, to predict the time-dependent bond strength between FRP and timber in both normal and harsh environments. Based on the selected test set, XGBoost demonstrated the highest predictive accuracy under normal conditions (testing $R^2 = 0.9440$), while LightGBM exhibited superior generalization in harsh environments (testing $R^2 = 0.7969$). However, these findings are based on a single train–test split, and the ranking of models should be interpreted with caution, particularly for the normal-condition dataset with only 16 test observations. The SHAP analysis identified fiber tensile strength and exposure time as the most influential parameters. Based on the analysis, the following conclusions can be drawn:

- This research revealed that bond degradation follows non-linear patterns with environmental exposure, where acidic conditions most severely affect CFRP bonds (57% reduction), and alkaline conditions most impact GFRP bonds (47% reduction).
- Under normal environmental conditions, XGBoost achieved the highest testing R^2 of 0.9440 with the lowest RMSE and MAE, significantly outperforming AdaBoost and LightGBM.
- In harsh environments, LightGBM achieved the highest testing R^2 (0.7969) on the selected test set, with RMSE = 0.5489 and MAE = 0.4310, compared with XGBoost and AdaBoost. However, these differences should be interpreted with caution, as statistical significance testing was not performed.
- Under normal conditions, fiber tensile strength (S_f) was the most influential feature, followed by fiber width (b_f), bond length (L_b), and fiber thickness (t_f), while timber properties showed a negligible correlation with bond strength.
- Exposure time exhibited a strong negative correlation ($r = -0.46$) with bond strength, whereas pH showed no linear correlation ($r = 0.06$) due to its non-monotonic, fiber-dependent effects on bond degradation.
- Acidic environments (pH 2.5) caused the most severe reduction in CFRP bonds (57% after 13 weeks), while alkaline conditions (pH 12.5) most degraded GFRP bonds (47% after 13 weeks), highlighting the fiber-specific susceptibility to different chemical exposures.
- SHAP analysis revealed that fiber properties dominate bond performance under normal conditions, while exposure time becomes the predominant factor affecting bond durability in harsh environments, with pH showing complex U-shaped influence patterns.
- Future work should explore neural networks and deep learning approaches for capturing more complex degradation patterns as experimental databases expand, as well as ensemble methods that combine multiple algorithms to achieve optimal performance across both normal and harsh conditions.

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