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Modeling the Water Quality Index (CCME WQI) of Six Pasig River Main Line Monitoring Stations and Forecasting Using Machine Learning Models

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Abstract This study evaluated the water quality of the Pasig River Main Line by applying the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) and implemented machine learning models to forecast future trends. Water quality data from six monitoring stations spanning 2010 to 2024 were consolidated and translated into annual WQI scores. Three predictive models: Artificial Neural Networks (ANN), Gradient Boosted Regression (GBR), and Long Short Term Memory (LSTM), were used and assessed using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2). Among the models evaluated, the LSTM model exhibited the most consistent performance, achieving the lowest RMSE in four out of six stations and the lowest MAE in three. It demonstrated stable training behavior without signs of overfitting and effectively captured directional trends in water quality. However, generalizability remained limited, as only one station achieved a high R^2 value, likely due to the small dataset. Forecasts from 2025 to 2030 using the LSTM model indicated minimal, decimal-level changes in WQI scores, suggesting that the Pasig River is unlikely to exhibit significant improvement or deterioration within the forecast period. These results show the utility of machine learning in environmental forecasting and the necessity of implementing targeted, data-informed interventions in river rehabilitation programs.

Keywords Pasig River, CCME WQI, Water Quality, Machine Learning

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1. Introduction

The Pasig River, a crucial 27-kilometer waterway connecting Laguna de Bay to Manila Bay, has a long history of supporting transportation and livelihoods in Metro Manila. However, in recent decades, it has experienced severe degradation due to rapid urbanization and industrialization. By the 1990s, the river was declared biologically dead because of extreme pollution from untreated domestic and industrial discharges [1]. Despite various rehabilitation efforts, it remains heavily polluted. Past efforts by government agencies like the Pasig River Rehabilitation Commission (PRRC) have involved waste removal and water quality monitoring [2]. However, critical water quality parameters such as Dissolved Oxygen (DO) and Biochemical Oxygen Demand (BOD) have continued to exceed acceptable limits.

To address the complexity of raw environmental data and make it more accessible, Water Quality Indices (WQIs) are widely used to simplify multiple variables into a single, interpretable score [3]. Among these, the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) is one of the most recognized and has been validated in various river systems for its communicative value [4]. While WQIs are effective for interpreting current conditions, they have limitations in forecasting future trends. Machine learning (ML) models, such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Gradient Boosting Regression (GBR), provide a solution by analyzing datasets and predicting environmental behavior with high accuracy.

The Pasig River itself has been the subject of numerous studies and policies due to its historical and ecological significance [5]. The decline of the Pasig River has been a documented issue since the 1930s, when migratory fish ceased to circulate in its waters, and by the 1950s, it was deemed unsuitable for bathing [6], [7]. The river's degradation continued, with industrial and chemical waste becoming prominent in the 1980s. This long history of pollution underscores the need for effective monitoring and forecasting [8]-[11]. The DENR Administrative Order No. 2016-08 classifies the river as a Class C water body, which is designated for aquatic life propagation and non-contact recreational use [6]. This order also sets the acceptable threshold values for key parameters used in this study, including pH, DO, BOD, and fecal coliform.

Current research indicates that domestic waste is the primary contributor to the river's contamination, accounting for over 60% of the total [12]. Informal settlements and inadequate sanitation systems along the riverbanks are a significant source of untreated sewage [13]. Industrial pollution, primarily from various mills and production plants, accounts for approximately 33% of the contamination. These factors contribute to high levels of BOD, ammonia, and total suspended solids (TSS), which harm aquatic ecosystems [14]. High fecal coliform levels in urban areas like Guadalupe also indicate that the river is unsafe for human contact [15]. Therefore, the integration of WQI and machine learning is a critical step toward proactive water governance and a data-driven approach to river rehabilitation.

2. Methodology

This study employs a quantitative design, using the CCME WQI to assess the Pasig River's water quality from 2010–2024 and forecast future trends through deep learning models. The research focuses on six DENR-identified monitoring stations along the Pasig River Main Line, namely Napindan Bridge (NB), Bambang Bridge (BB), Guadalupe Ferry (GF), Lambingan Bridge (LB), Nagtahan Bridge (NGB), and Jones Bridge (JB). Historical water quality data were obtained from the Pasig River Coordinating and Management Office.

2.1. Acquiring CCME WQI Values

The data compiled in the master Excel file were preprocessed to ensure consistency by standardizing units and normalizing datasets. Following CCME manual, eight parameters were selected due to their relevance to sewage and combined sewer overflow (CSO) discharges, which require both microbiological and physicochemical indicators to assess contamination and potential environmental impacts. The computation of CCME WQI values was based on the parameters and corresponding DENR guideline standards summarized in Table 1.

Table 1. Parameters and their Units

Parameters	DAO 2016-08
pH	6.5 - 9.0
Dissolved Oxygen (mg/L)	5
Total Suspended Solids (mg/L)	80
Biochemical Oxygen Demand (mg/L)	7
Nitrate (mg/L)	7
Phosphate (mg/L)	0.5
Fecal Coliform (MPN/100mL)	200
Ammonia (mg/L)	0.05

The CCME WQI was then applied to compute annual water quality scores for the six monitoring stations along the Pasig River main line. The CCME WQI is based on three factors: **F1 (Scope)**, the percentage of variables exceeding guideline values (Eq. 1)

$$\mathrm{F}_1 = \frac{Number\ of\ failed\ variables}{Total\ number\ of\ variables} \times 10 \tag{1}$$

F2 (Frequency), the percentage of failed tests (Eq. 2);

$$\mathrm{F}_2 = \frac{Number\ of\ failed\ tests}{Total\ number\ of\ tests} \times 100 \tag{2}$$

and **F3 (Amplitude),** the extent of exceedance, computed through excursions (Eq. 3–4), normalized sum of excursions (Eq. 5), and an asymptotic function (Eq. 6).

$$\text{excursion} = \frac{Failed\ test\ value}{Objective} - 1 \tag{3}$$

$$\text{excursion} = \frac{Objective}{Failed\ test\ value} - 1 \tag{4}$$

$$\text{nse} = \frac{\sum_{i=1}^{n}\ excursion}{Total\ number\ of\ tests} \tag{5}$$

$$\mathrm{F}_3 = \frac{nse}{0.01nse\ +\ 0.01} \times 100 \tag{6}$$

These are combined in the CCME WQI formula (Eq. 7), which produces values between 0–100, classified into five water quality categories (Table 2).

$$\text{CCME WQI} = 100 - \left(\frac{\sqrt{F1^2+F2^2+F3^2}}{1.732}\right) \tag{7}$$

Table 2. CCME WQI Water Quality Category (CCME, 2017)

Range	Quality Categories	Water Quality Description
95 - 100	Excellent	Virtually natural or pristine, all measurements consistently reach the recommended guidelines
80 - 94	Good	Protected with minimal threat, conditions usually deviate from normal levels
65 - 79	Fair	Normally preserved but is occasionally threatened or impaired, with conditions sometimes deviating from natural or desirable levels
45 - 64	Marginal	Regularly threatened or impaired, with conditions often deviating from natural or desirable levels
0 - 44	Poor	Consistently threatened or impaired, conditions usually deviate from desirable levels

2.2. Machine Learning Model

2.2.1. Artificial Neural Network

In this study, the ANN was used to model and forecast time-series water quality data with the Keras/TensorFlow framework. Preprocessing involved feature engineering (rolling statistics, interaction terms, seasonal and lagged variables), imputation of missing values, and scaling (Standard Scaler for inputs, MinMaxScaler for targets). The ANN comprised an input layer, two hidden layers (64 and 32 ReLU neurons with L2 regularization, batch normalization, and dropout rates of 0.4 and 0.3), and a linear output layer for regression. The model was trained using the Adam optimizer (learning rate = 0.01), with Mean Squared Error (MSE) as the loss function and Mean Absolute Error (MAE) as an additional metric. TimeSeriesSplit cross-validation and early stopping (patience = 30) were applied to enhance robustness. Performance was evaluated through RMSE, R^2, and relative RMSE.

2.2.2. Long-Short Term Memory (LSTM)

The LSTM model, built with Keras/TensorFlow, was used to forecast CCME WQI values from time-series data. Preprocessing included feature engineering, handling outliers with Robust Scaler, and applying a sliding window of three time steps across three features. The architecture consisted of an LSTM layer with 32 tanh units and L1-L2 regularization, followed by batch normalization, dropout (0.3), a dense ReLU layer with 32 units, and a linear output layer. The model was trained using Adam (learning rate = 0.001) with MSE loss and MAE as an additional metric, supported by early stopping (patience = 30) and ReduceLROnPlateau for convergence. Data were split chronologically into 80% training and 20% testing, and performance was evaluated using MAE, RMSE, and R^2 after rescaling predictions.

2.2.3 Extreme Gradient Boosting (XGBoost)

The XGBoost regression model was employed to forecast WQI from time-series data, supported by advanced feature engineering and dynamic forecasting techniques [9]. Preprocessing involved imputing missing values and chronologically sorting records to preserve temporal integrity, while feature engineering generated lag variables (1- and 2-year lags for CCME WQI, F1, and F2), three-year rolling averages, and interaction terms (e.g., F1/F2 and F2/F3) to capture complex dependencies among water quality indicators. All features were scaled using the Robust Scaler to mitigate the influence of outliers. Hyperparameters, including tree depth (3–9), learning rate (0.01–1.0), and subsampling ratios (0.6–1.0), were optimized through grid search cross-validation, with early stopping (10 boosting rounds) applied to prevent overfitting. A chronological train-test split (80% training, 20% testing) was used, and performance was evaluated using RMSE, MAE, and R^2. Additional validation strategies, such as temporal cross-validation and grid-based hyperparameter tuning, further strengthened robustness, while station-specific performance evaluation provided insights into spatial variability of model predictions across river monitoring points.

2.3. Statistical Method

2.3.1. Root Mean Squared Error (RMSE)

To evaluate the developed prediction model, linear regression analysis will be employed to examine the relationship between predicted and actual values. Model accuracy will be assessed using the RMSE, which measures the average magnitude of error by taking the square root of the mean squared differences between predicted and observed values [16]. RMSE penalizes large errors more heavily, making it useful for detecting significant deviations such as pollution spikes, which are critical in environmental monitoring. It also reflects how closely predictions align with actual values, with higher RMSE indicating less reliable performance.

$$\text{RMSE} = \sqrt{\frac{I}{n}\sum_{j=1}^{n} \quad (Pj - Aj)^2} \tag{8}$$

2.3.2. Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) will also be used to evaluate the model. MAE calculates the average absolute differences between predicted and actual values, treating all deviations equally without squaring errors, which makes it less sensitive to outliers and easier to interpret [17].

Expressed in the same units as the target variable, MAE provides a straightforward measure of accuracy and grows linearly with error magnitude. Its formula is given in Equation (9):

$$\mathrm{MAE} = \frac{I}{n}\sum_{j=1}^{n} \left| Pj - Aj \right| \qquad (9)$$

By averaging absolute differences, MAE reflects overall prediction consistency without disproportionately penalizing larger errors. This approach demonstrates a significant value in environmental applications [16].

2.3.3. R-Squared (R^2)

Regression analysis is applied to examine the relationship between the model's predicted values and the actual observations, with the strength of this association measured through the coefficient of determination (R^2). An R^2 value of 1 represents a perfect fit, indicating complete alignment between predictions and targets [18]. The metric is computed as:

$$R^2 = 1 - \frac{SS'_Y}{SS_Y} \qquad (10)$$

where SS′Y denotes the sum of squares of predicted values and SSY represents the total sum of squares of actual values. A high R^2 reflects strong predictive accuracy and agreement with observed data, thereby supporting the model's practical reliability. However, R^2 does not account for temporal alignment in time-series forecasting; a model may achieve a high R^2 while producing predictions that are systematically delayed or advanced [10]. Nonetheless, R^2 remains a valuable indicator of overall model performance in WQI prediction, as it provides evidence of the model's capacity to capture both spatial and temporal variability. It is critical for producing forecasts that not only approximate central tendencies but also reproduce the variability necessary to support robust environmental decision-making [19].

3. Presentation, Analysis, and Interpretation of the Data

3.1. CCME WQI Values

A review of the PRCMO dataset showed that 2009 records were incomplete, with key parameters missing; thus, the study period began in 2010 to ensure reliability. Data from 2010–2024 were compiled, converted to CSV, and processed using the CCME WQI to compute F1, F2, F3, and WQI values for six Pasig River stations (Table 3). Derived from eight parameters consolidated into one index, all results fell within the "Poor" category, reflecting consistently impaired water quality. These values will serve as input for three machine learning models to analyze trends and identify the most suitable algorithm for predicting water quality from 2025–2030.

Table 3. CCME WQI Values 2010-2024

	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
NB	14.56	26.08	21.45	25.6	33.22	26.2	24.8	30.31	20.38	23.88	25.5	27.16	26.03	25.48
BB	17.87	24.61	20.99	24.16	18.35	24.58	19.77	26.93	19.84	23.51	24.23	24.8	23.54	24.3
GF	12.92	24.98	21.33	23.78	26.74	24.15	23.33	23.76	19.48	19.38	23.36	23.45	21.86	21.55
LB	18.43	20.54	20.4	24.01	26.57	20.34	23.03	23.5	18.93	19.11	22.23	23.01	21.44	22.61
NGB	18.09	17.95	20.62	23.28	15.17	19.5	23.03	23.06	22.76	22.95	19.4	21.42	21.2	19.07
JB	16.67	24.99	20.88	23.73	24.78	19.41	19.11	23.14	22.8	24.07	22.14	22.6	21.19	22.38

3.2. Model Training

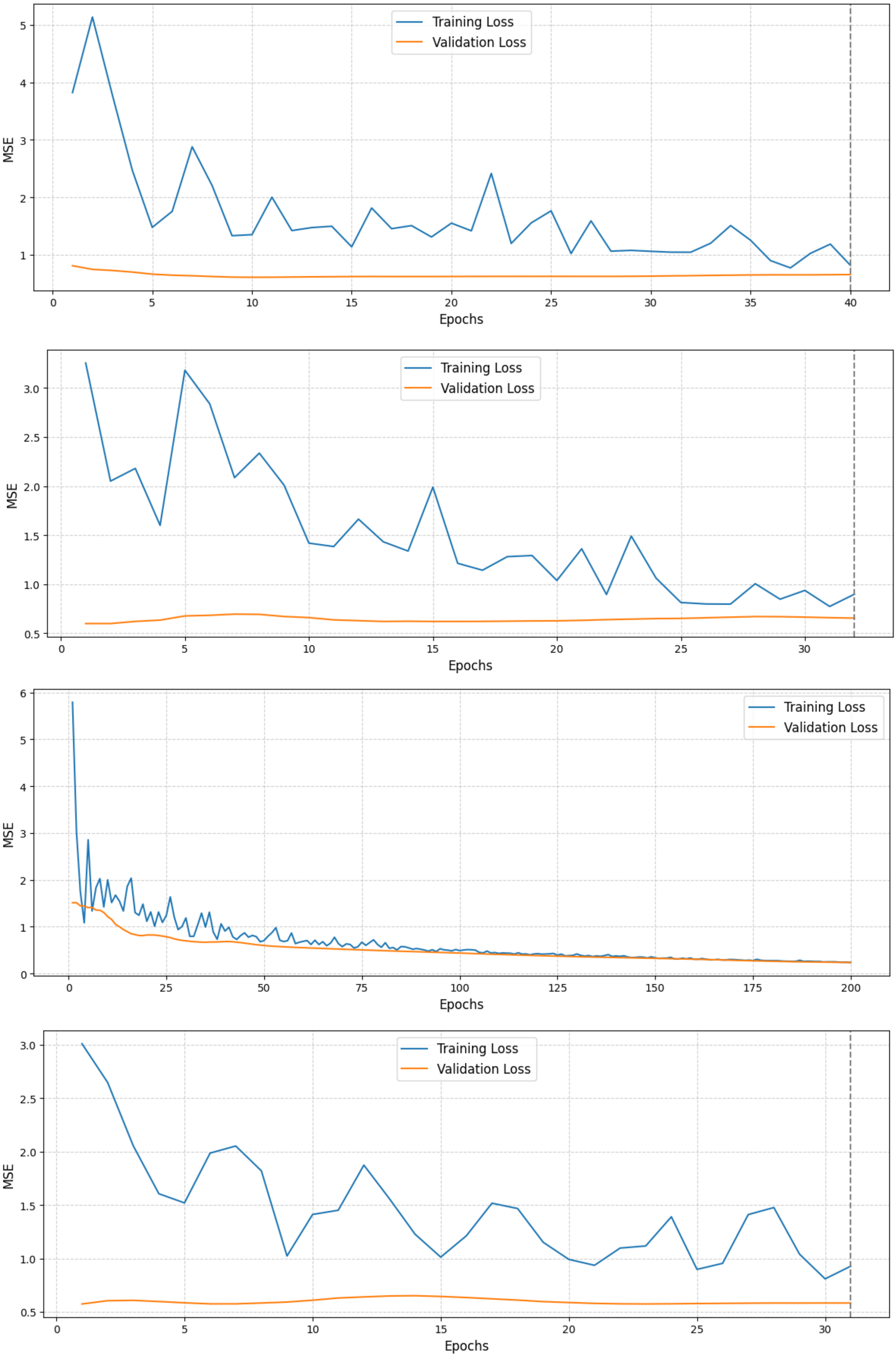
Model training involved monitoring training and validation losses, where training loss measures fit to the dataset and validation loss reflects generalization to unseen data. An optimized model is achieved when both losses are low and converge closely.

3.2.1. Artificial Neural Network (ANN)

Early stopping was triggered in most stations: NB (epoch 40), BB (epochs 30–35), LB (epoch 30), NGB (before epoch 40), and JB (epoch 35). In these cases, training loss decreased while validation loss plateaued, indicating no further improvement and preventing overfitting. At GB, both losses steadily declined without early stopping, suggesting effective learning. Overall, five of six stations showed stable validation losses despite decreasing training losses, implying limited generalization and possible overfitting due to validation data constraints (Figure 1).

3.2.2. Long-Short Term Memory (LSTM)

The training and validation loss curves of the LSTM models for NB, BB, GF, LB, NGB, and JB stations demonstrated that losses generally decreased and converged, reflecting stable learning and effective optimization. While some stations, such as LB, plateaued early, and others like GB and NGB mirrored consistent trends across datasets, the models overall showed balanced fits without clear signs of overfitting. Adjustments in learning rate, epochs, batch size, and early stopping helped achieve stability, though the relatively small dataset led to quick convergence and limited learning capacity. Despite this, the LSTM models captured meaningful patterns and general trends in CCME WQI values, highlighting their potential for improved forecasting performance with larger and more diverse datasets (Figure 2).


Training Loss
Validation Loss
MSE
Epochs
0
5
10
15
20
25
30
35
40
1
2
3
4
5
Training Loss
Validation Loss
MSE
Epochs
0
5
10
15
20
25
30
0.5
1.0
1.5
2.0
2.5
3.0
Training Loss
Validation Loss
MSE
Epochs
0
25
50
75
100
125
150
175
200
0
1
2
3
4
5
6
Training Loss
Validation Loss
MSE
Epochs
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1.0
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2.5
3.0

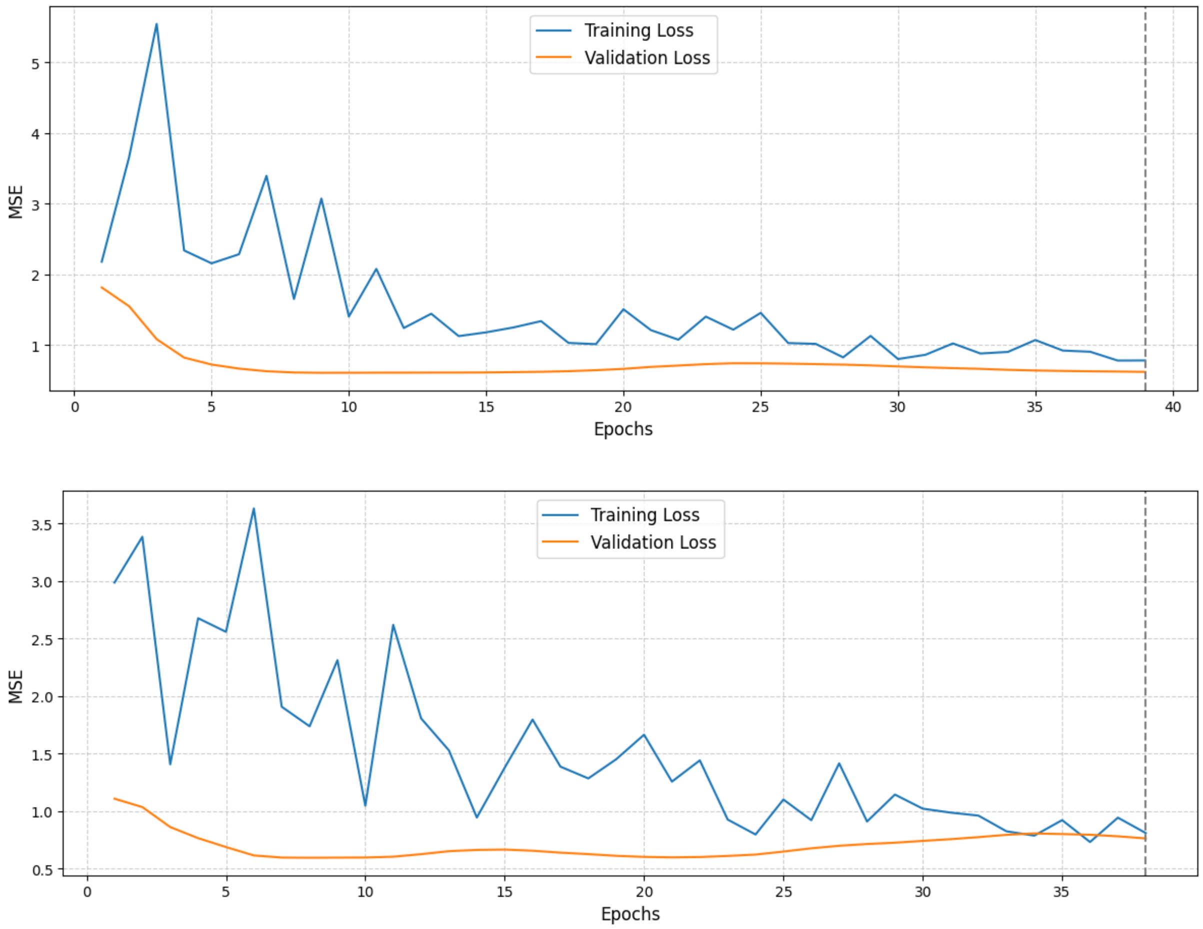
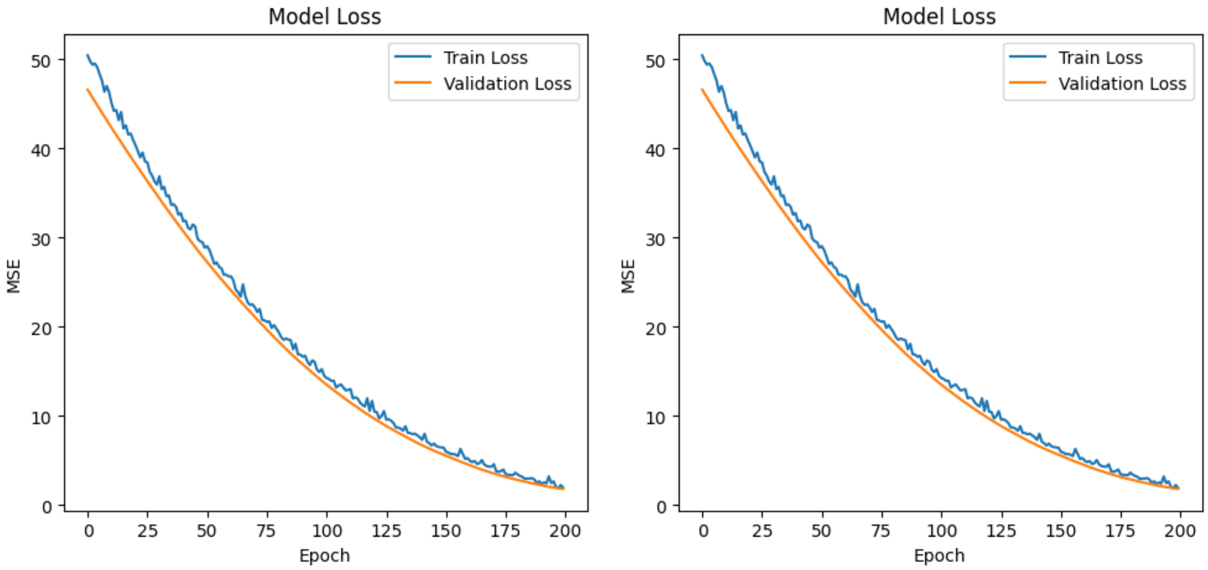


Figure 1. ANN training and validation loss curves for NB, BB, GF, LB, NGB, and JB stations, respectively



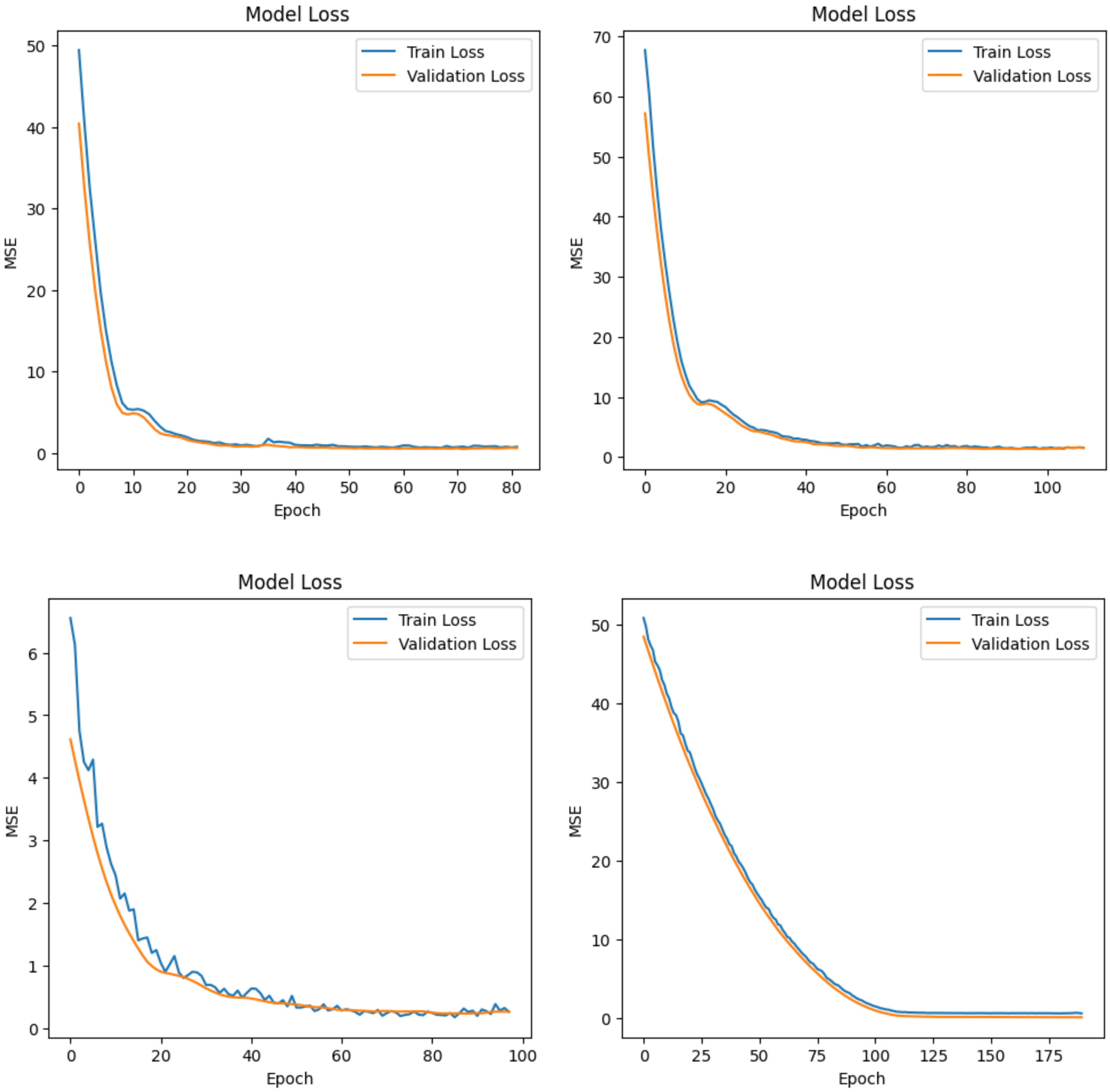


Figure 2. LSTM training and validation loss curves for NB, BB, GF, LB, NGB, and JB stations, respectively

3.2.3. Boosted Gradient Regression (GBR)

The GBR models showed mixed performance across stations. At NB, GB, NGB, and JB, decreasing training losses paired with rising test losses indicated signs of overfitting, with GB and JB showing early divergence. BB demonstrated better generalization with both losses decreasing, while LB performed best, with training and validation losses converging and early stopping at epoch 35. Overall, four stations showed overfitting tendencies, while Bambang and Lambingan achieved more stable performance, suggesting that further station-specific tuning could enhance model optimization (Figure 3).

3.3. Data Validation

3.3.1. Artificial Neural Network

The ANN-trained model for CCME WQI prediction demonstrated favorable performance at the LB and JB, where the predicted values closely aligned with the actual observations. The close alignment at LB and JB may be due to more consistent data and stable conditions. In contrast, the larger discrepancies observed at the other sites could be due to greater variability in water quality parameters, data gaps, or external factors such as localized pollution events, tidal influences, or upstream discharges that introduce complexities not fully captured by the ANN model (Figure 4).

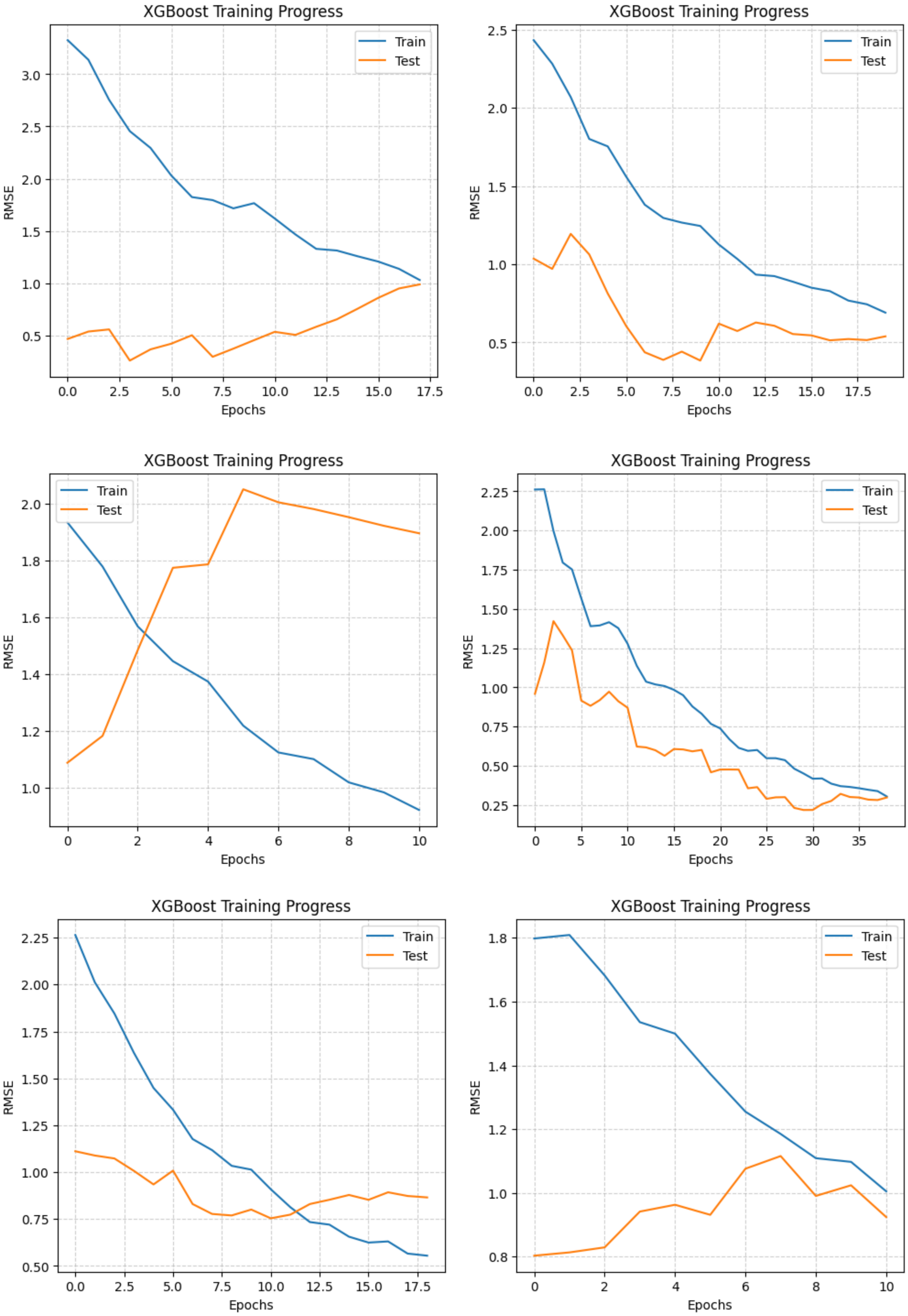
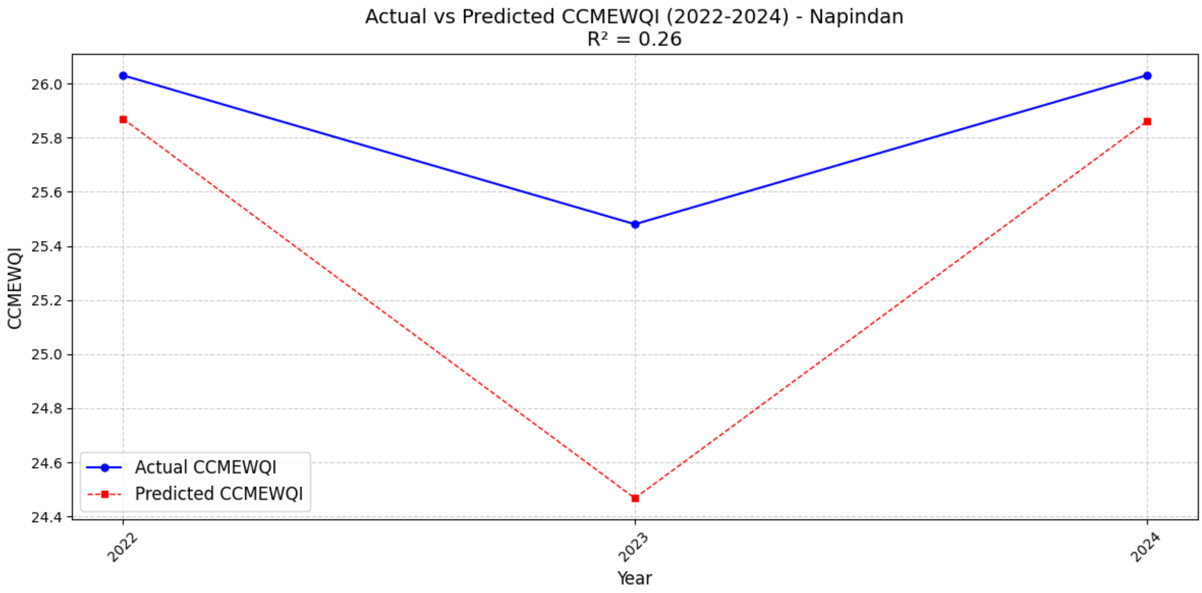
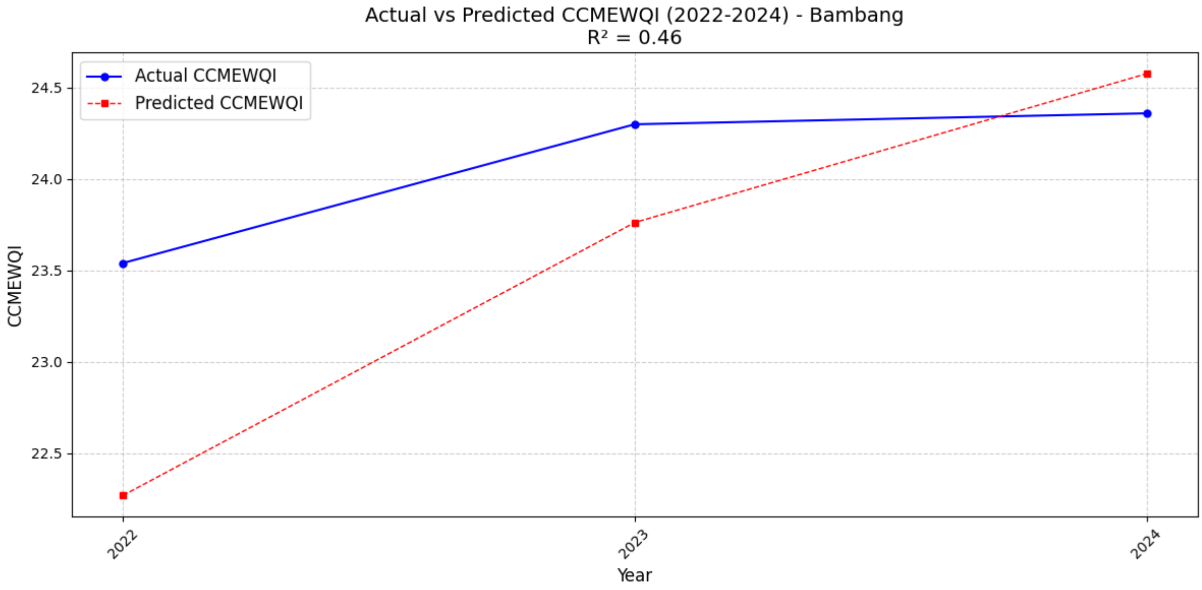
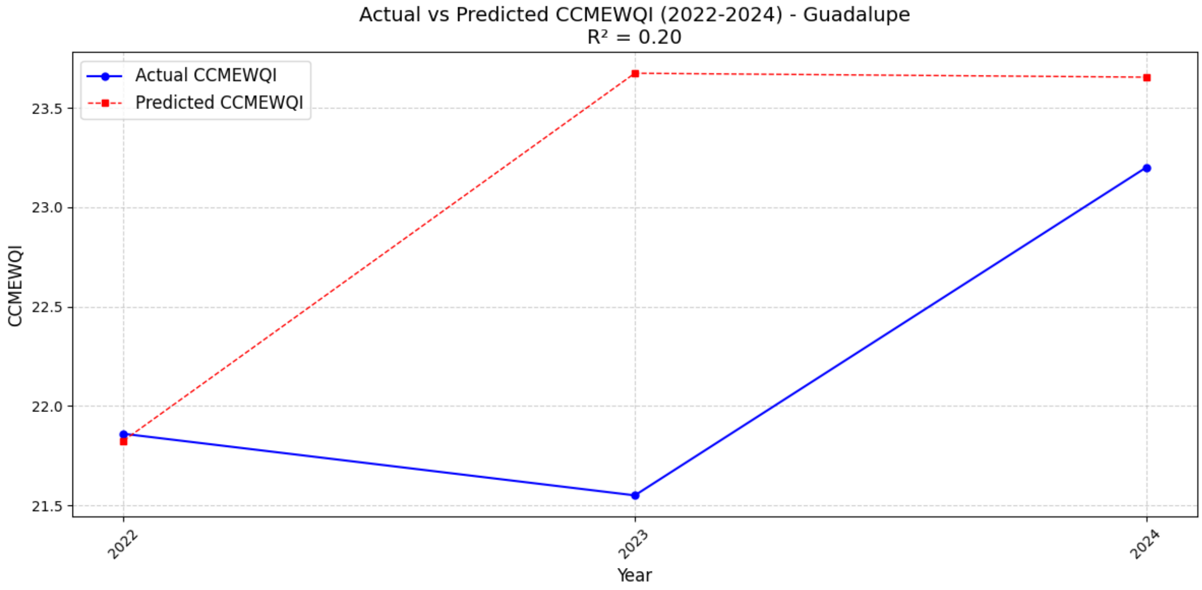


Figure 3. XGBR training and validation loss curves for NB, BB, GF, LB, NGB, and JB stations, respectively


Actual vs Predicted CCMEWQI (2022-2024) - Napindan
R² = 0.26


Actual vs Predicted CCMEWQI (2022-2024) - Bambang
R² = 0.46


Actual vs Predicted CCMEWQI (2022-2024) - Guadalupe
R² = 0.20

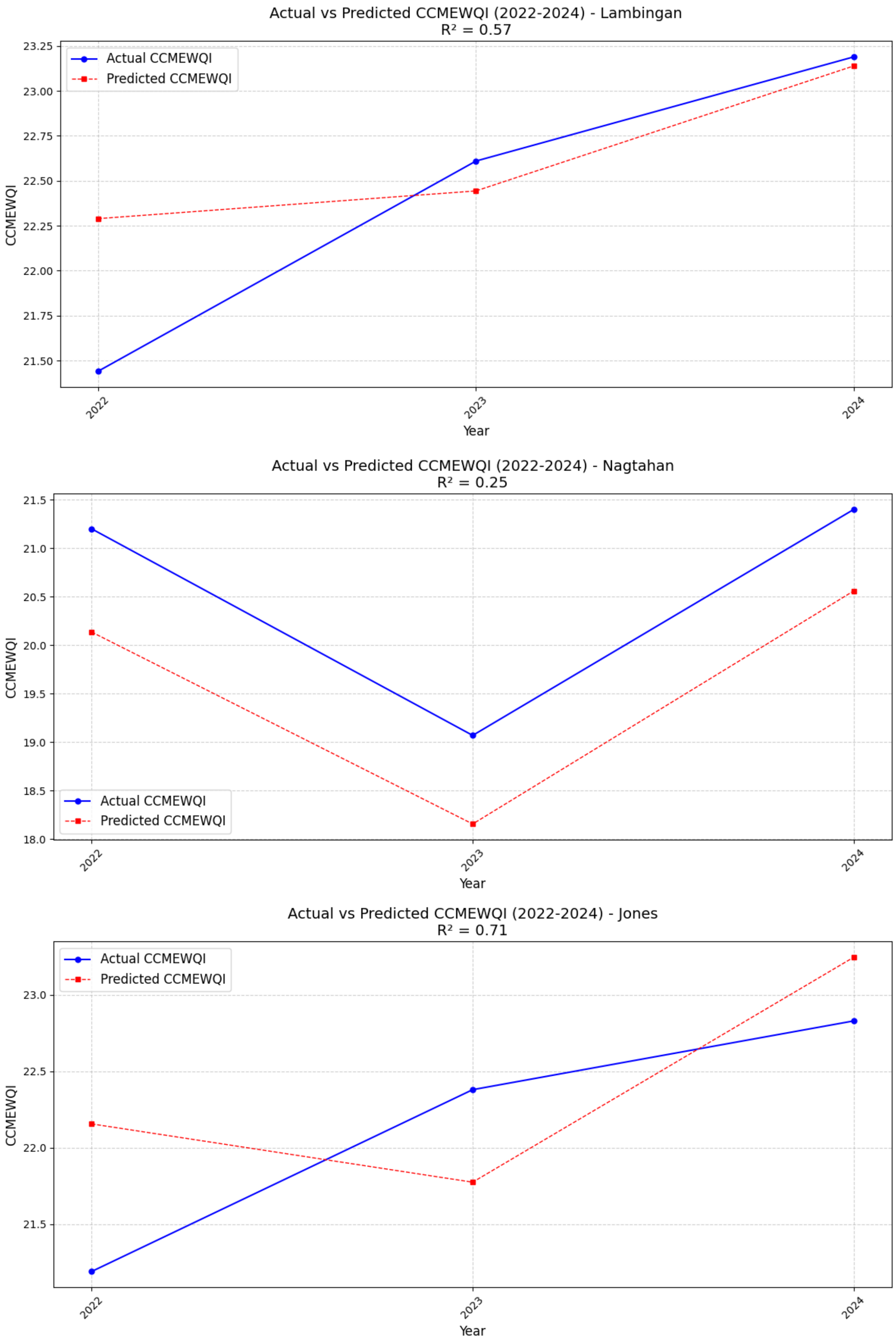


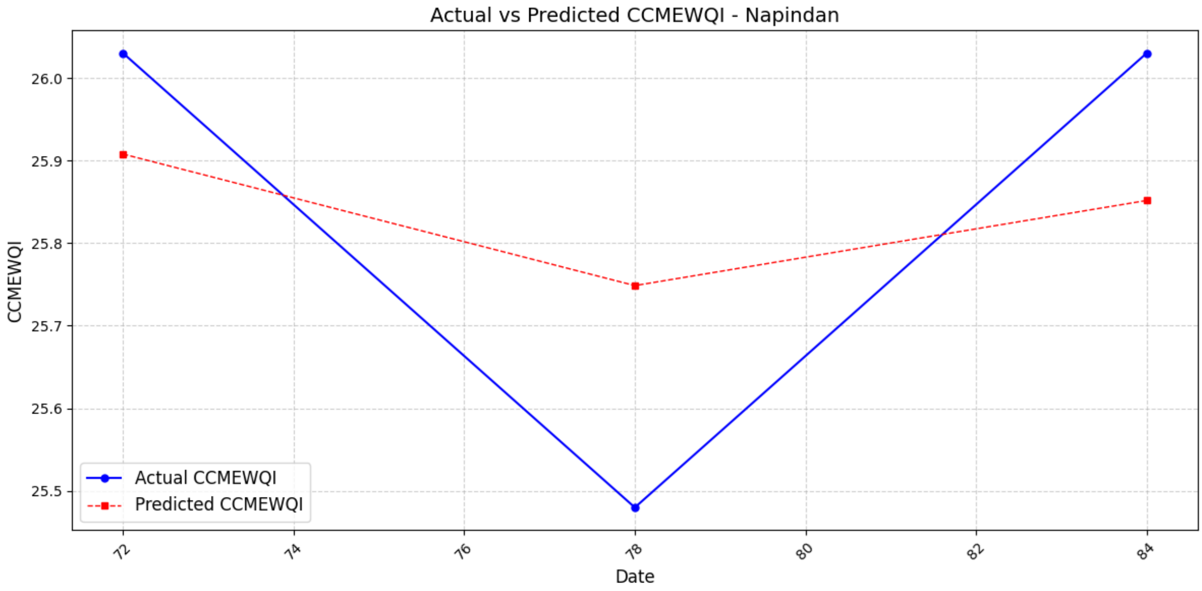
Figure 4. ANN Model: Actual vs. Predicted CCME WQI for NB, BB, GF, LB, NGB, and JB stations, respectively

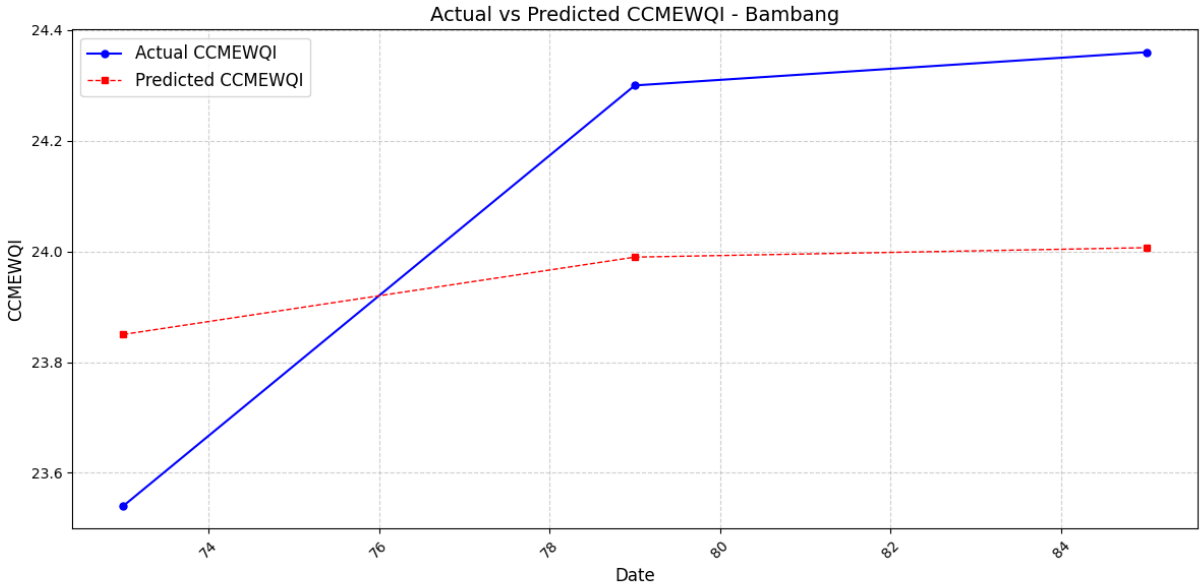
3.3.2. Long Short Term Memory

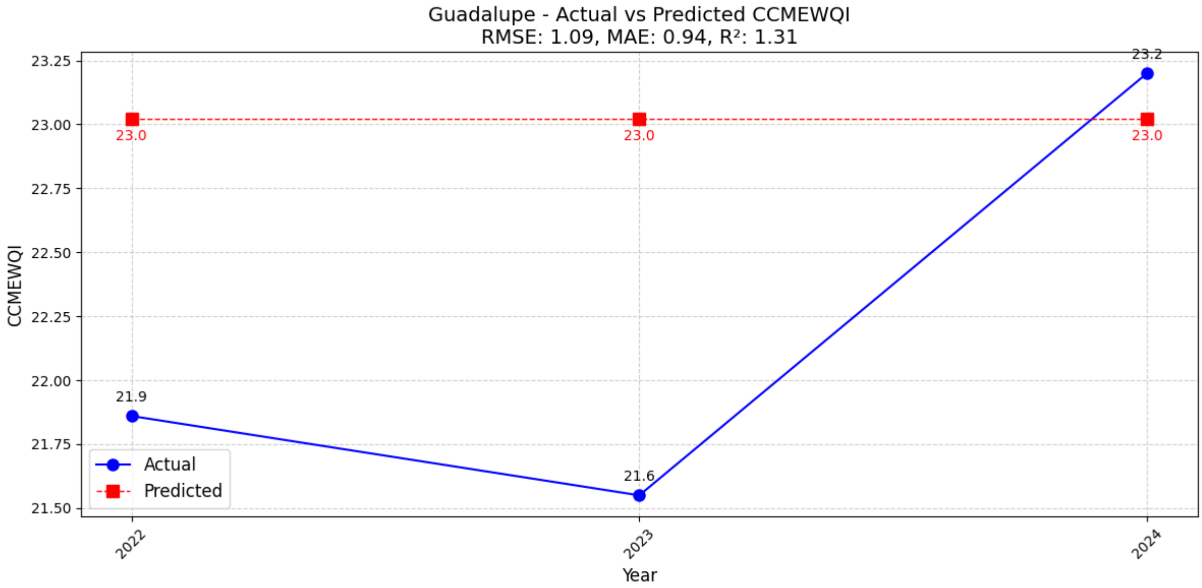
For the LSTM model, the stations of NB, BB, GB, and NGB exhibited predicted CCME WQI values that closely followed the overall direction or trend of the actual values, such as increases or decreases over time. This suggests that the model was generally effective in capturing the temporal dynamics of water quality at these locations, even if exact values were not always matched. In contrast, the predictions for the JB and LB stations showed greater deviations from the actual values, with differences exceeding 1 unit of CCME WQI. Additionally, the model's ability to track the direction or trend of the data at these two stations was weaker compared to the others. This may indicate that the LSTM model had more difficulty learning from the patterns specific to these locations, potentially due to variations in data quality, station characteristics, or limitations in model tuning (Figure 5).

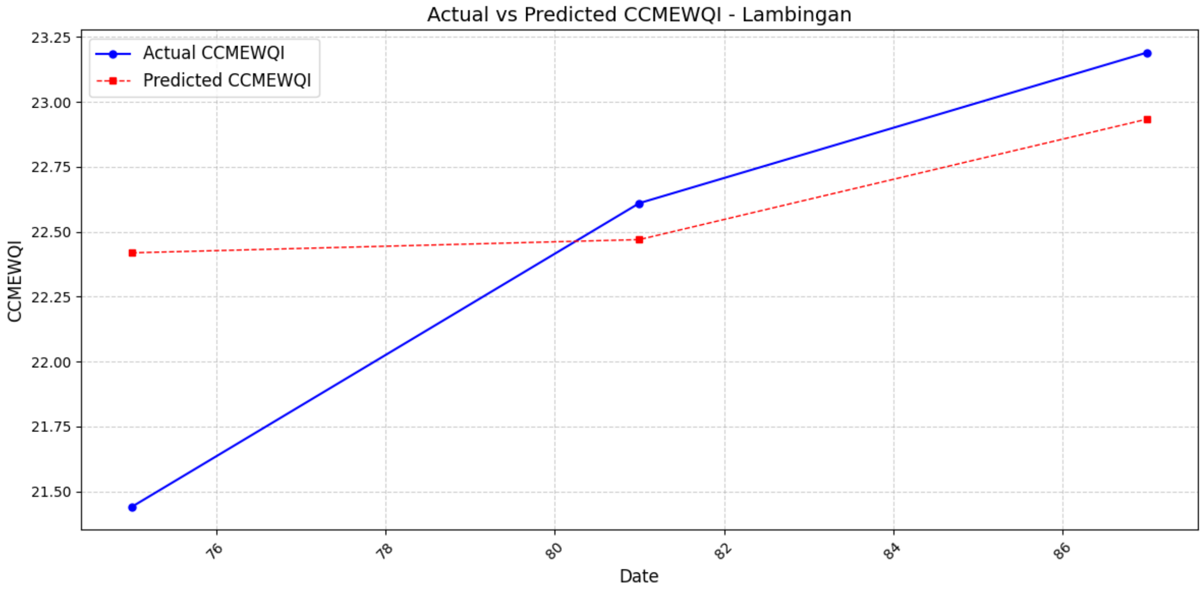
3.3.3. Gradient Boosted Regression

The Gradient Boosted Regression (GBR) model exhibited evident signs of underfitting, particularly at the NB and GB monitoring stations. This outcome can be attributed to the model's sensitivity to hyperparameter configurations, including the learning rate, maximum tree depth, and the number of boosting iterations. The adoption of shallow tree structures and conservative learning rates, while effective in mitigating overfitting, may have constrained the model's capacity to capture the complex nonlinear relationships inherent in the data. Additionally, the limited sample size and the presence of localized noise likely diminished the diversity of training instances, further restricting the model's representational ability. This limitation was reflected in the near-uniform predictions generated across all data points at the NB and GB stations, signifying a deficient learning process. The lack of variability in the outputs indicates that the model was overly simplistic to approximate the underlying data patterns, a condition that may have been exacerbated by the uniform application of hyperparameter settings across all monitoring sites. Given the high sensitivity of GBR performance to hyperparameter tuning, this standardized approach may have hindered the model's adaptability to station-specific characteristics. In contrast, the models developed for the BB and LB stations produced predictions that closely approximated the observed CCME WQI values, demonstrating more effective learning and improved generalization. To enhance model performance in future implementations, it is recommended to employ Bayesian hyperparameter optimization, incorporate additional input features to increase data richness, and utilize cross-validation strategies specifically designed for small-sample time-series datasets (Figure 6).




Actual vs Predicted CCMEWQI - Bambang
Actual CCMEWQI
Predicted CCMEWQI
CCMEWQI
24.4
24.2
24.0
23.8
23.6
74
76
78
80
82
84
Date


Guadalupe - Actual vs Predicted CCMEWQI
RMSE: 1.09, MAE: 0.94, R²: 1.31
CCMEWQI
23.25
23.00
22.75
22.50
22.25
22.00
21.75
21.50
23.2
23.0
23.0
23.0
21.9
21.6
Actual
Predicted
2022
2023
2024
Year


Actual vs Predicted CCMEWQI - Lambingan
Actual CCMEWQI
Predicted CCMEWQI
CCMEWQI
23.25
23.00
22.75
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22.25
22.00
21.75
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80
82
84
86
Date

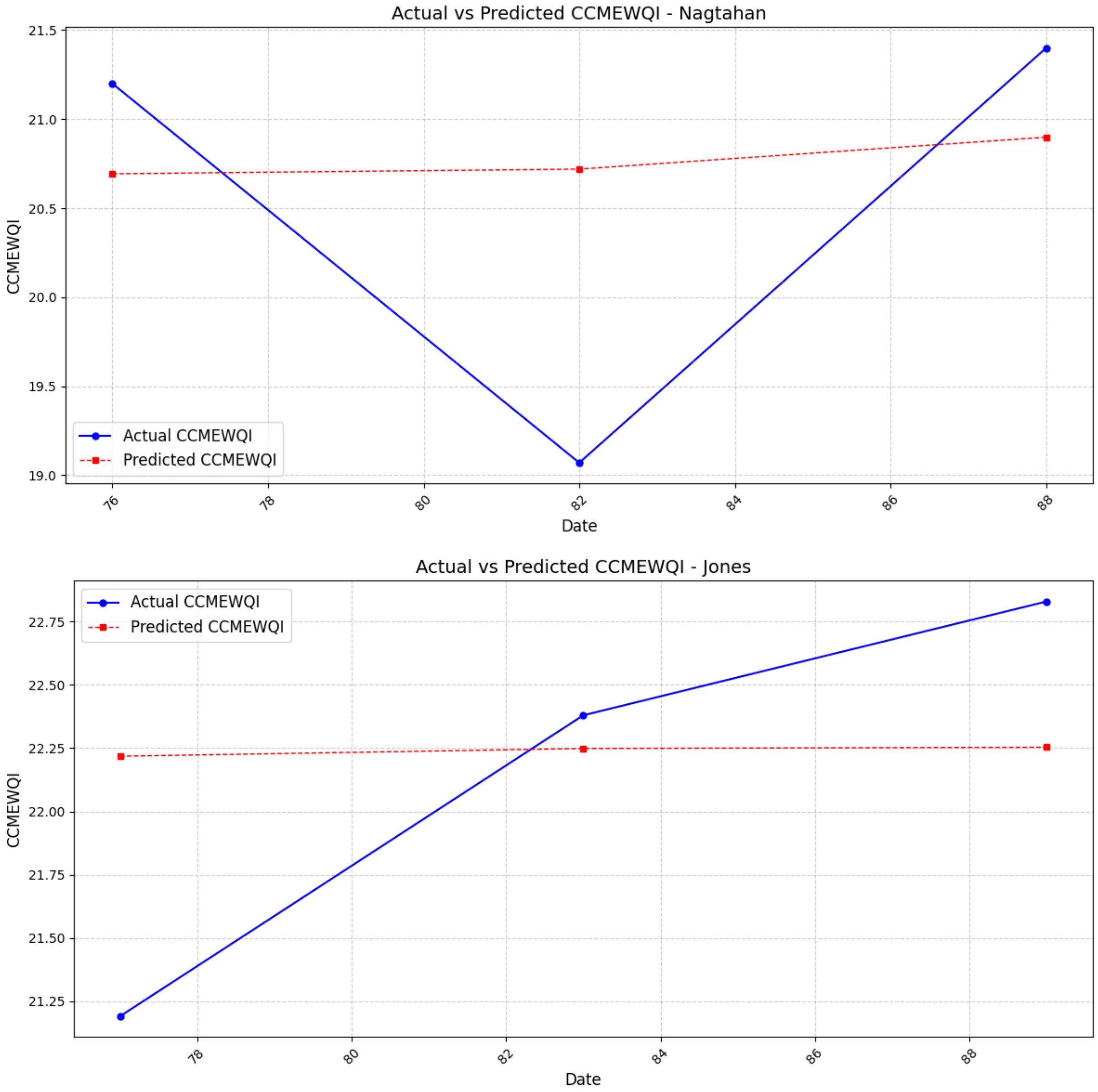
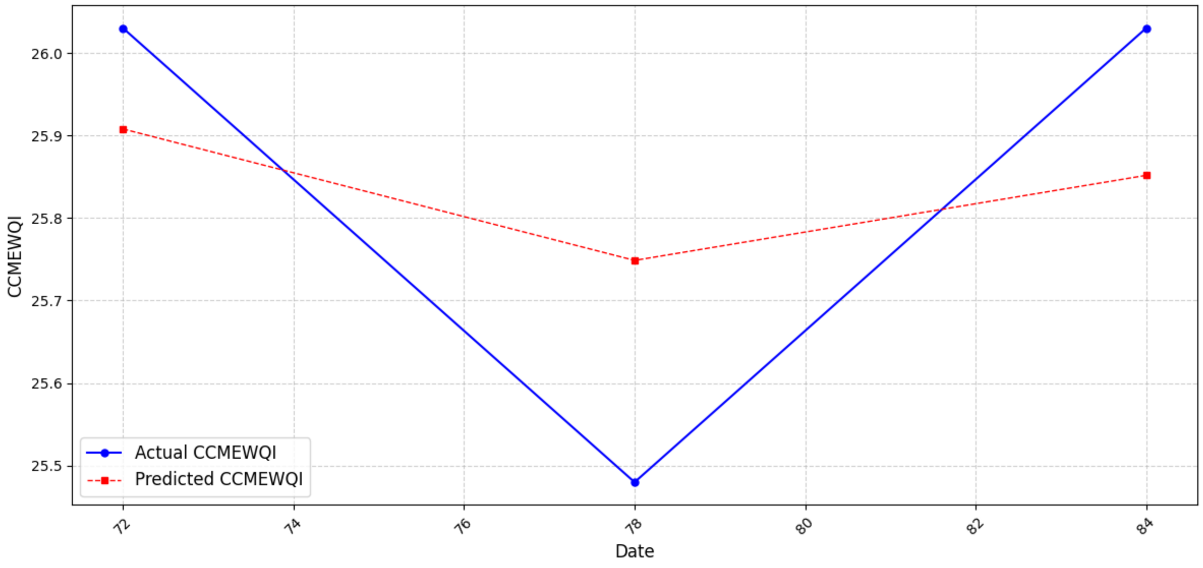
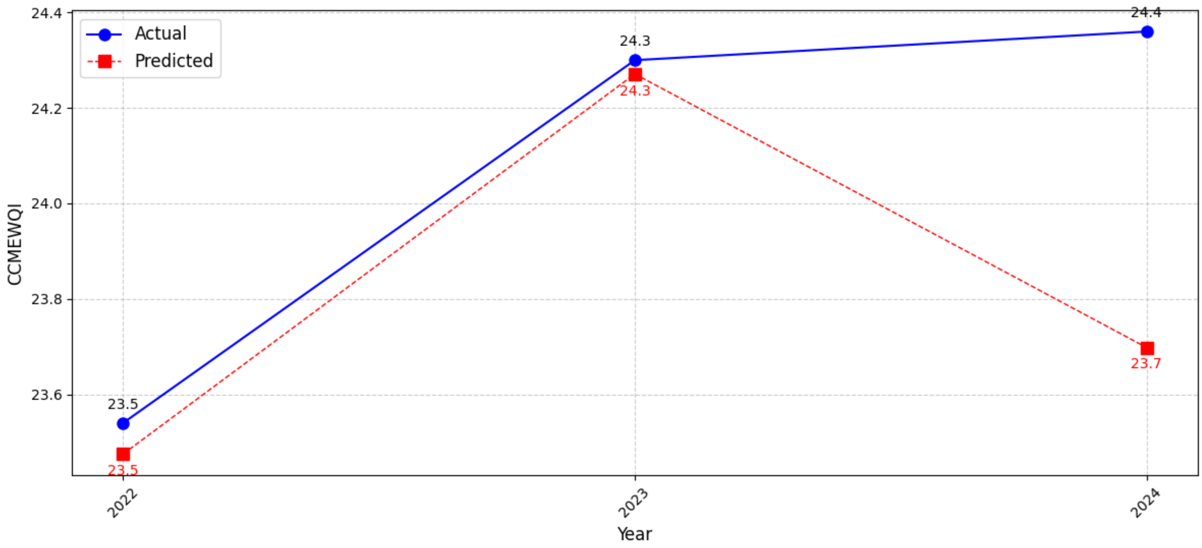
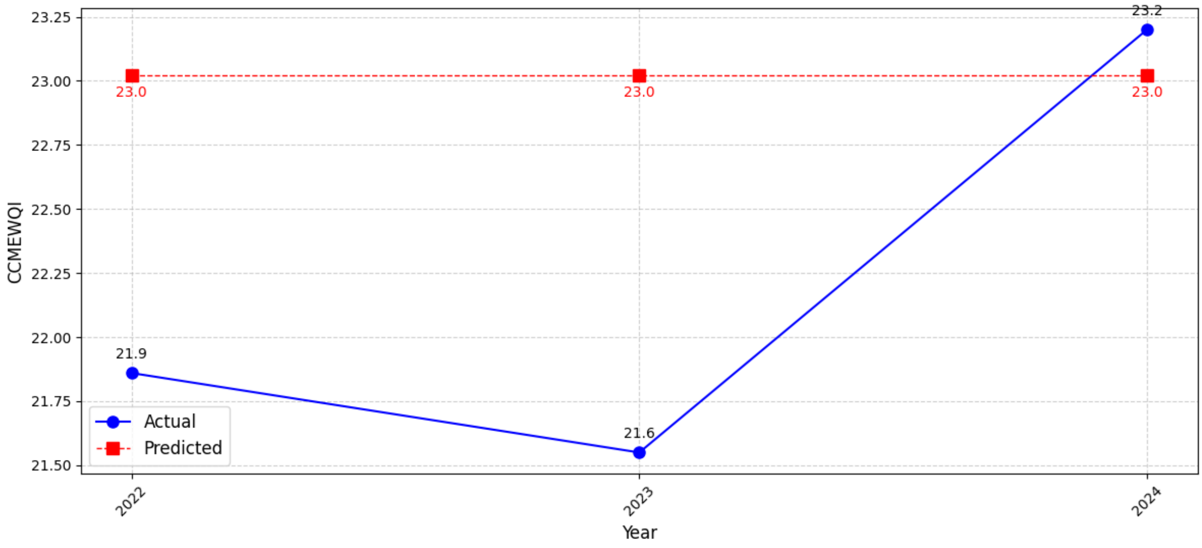
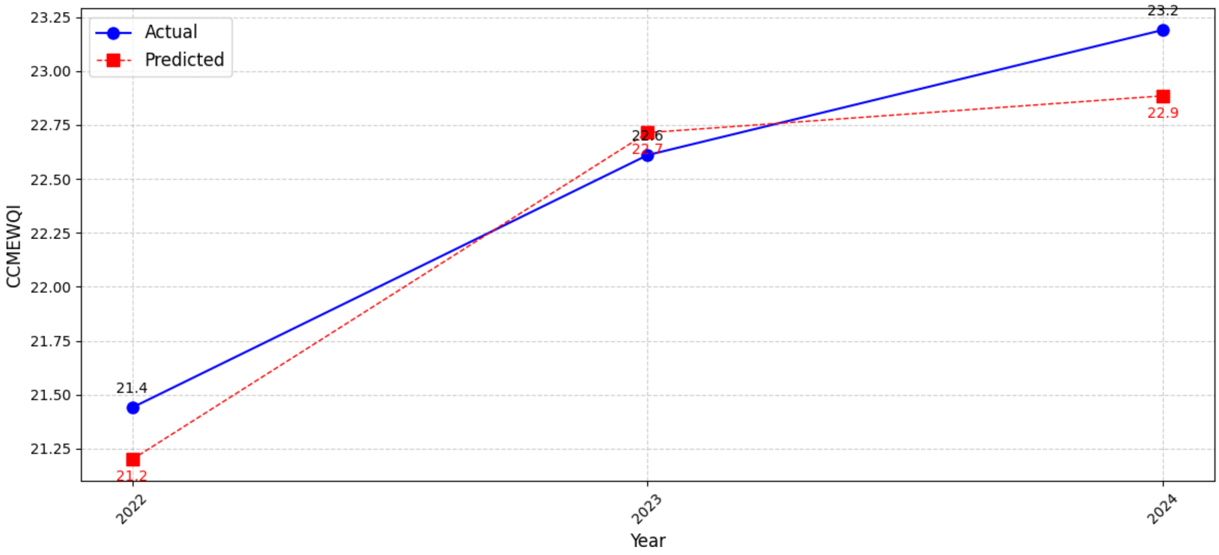


Figure 5. LSTM Model: Actual vs. Predicted CCME WQI at NB, BB, GF, LB, NGB, and JB stations, respectively




Actual
Predicted
CCMEWQI
24.4
24.2
24.0
23.8
23.6
23.5
23.5
24.3
24.3
24.4
23.7
2022
2023
2024
Year


23.2
23.0
23.0
23.0
21.9
21.6
Actual
Predicted
CCMEWQI
23.25
23.00
22.75
22.50
22.25
22.00
21.75
21.50
2022
2023
2024
Year


Actual
Predicted
23.2
22.9
22.6
22.7
21.4
21.2
CCMEWQI
23.25
23.00
22.75
22.50
22.25
22.00
21.75
21.50
21.25
2022
2023
2024
Year

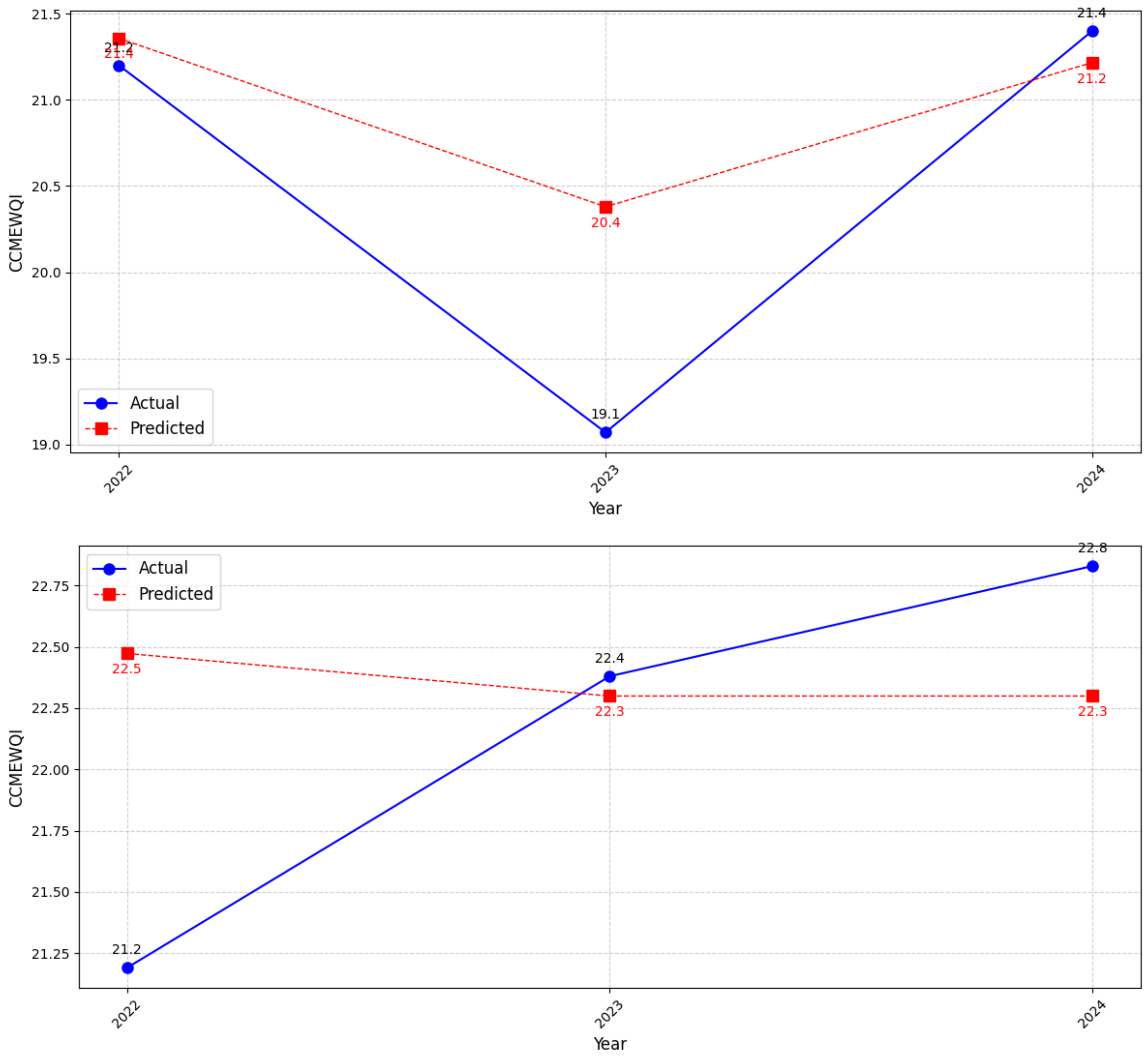


Figure 6. GBR Model: Actual vs. Predicted CCME WQI at NB, BB, GF, LB, NGB, and JB stations, respectively

3.4. Performance Metrics

To support the Model Training results, this study also evaluated the performance of ANN, GBR, and LSTM, in forecasting water quality at six monitoring stations along the Pasig River using RMSE, MAE, and R^2analysis.

3.4.1. Root Mean Square Error

The RMSE values for the ANN model range from 0.82 to 2.03, which are considered relatively low within the context of CCME WQI scoring, especially given the wide value ranges associated with each water quality classification. However, the broader variation in RMSE across stations suggests that the ANN model's performance may be less consistent and potentially more influenced by station-specific characteristics.

In contrast, the GBR model records RMSE values between 0.23 and 1.09, representing the smallest range among the three models. This indicates a more uniform level of error across different stations and that GBR's performance is stable. However, it does not consistently yield the lowest RMSE values. Lastly, the LSTM model yields RMSE values ranging from 0.19 to 1.14 and achieves the lowest error in 4 out of the 6 stations. This suggests a strong ability to model temporal dependencies in the data, which is particularly relevant in this study for forecasting water quality index. The relatively low minimum values and consistent performance across multiple stations indicate that the LSTM model generalizes well and maintains a high level of predictive accuracy (Table 4).

Table 4. RMSE Values

Stations	ANN	GBR	LSTM
NB	2.03	0.30	0.19
BB	1.54	0.38	0.32
GF	1.48	1.09	0.85
LB	1.06	0.23	1.14
NGB	1.31	0.77	1.04
JB	0.82	0.80	0.68

3.4.2. Mean Absolute Error (MAE)

To further assess model performance, the MAE was also examined as a complementary evaluation metric, offering a straightforward measure of the average magnitude of prediction errors (Table 5).

Table 5. MAE Values

Stations	ANN	GBR	LSTM
NB	1.41	0.20	0.19
BB	1.54	0.25	0.32
GF	1.48	0.94	0.56
LB	1.06	0.22	0.93
NGB	1.31	0.55	0.88
JB	0.82	0.63	0.58

The ANN model recorded the highest MAE values across all stations, indicating comparatively larger deviations from the actual CCME WQI values than the other models. Nonetheless, the errors in the ANN model remain relatively small in the context of the CCME WQI scoring range, suggesting that the predictions may still fall within acceptable interpretive thresholds for water quality classification.

The GBR model achieved the lowest MAE in 3 out of 6 stations, reflecting relatively accurate performance in those cases, likely due to its suitability for structured data when conditions align with its learning parameters. Similarly, the LSTM model showed the lowest MAE in 3 out of 6 stations as well which means that it is as effective in modeling temporal patterns, particularly in datasets with noticeable time-dependent behavior.

3.4.3. R-squared (r^2) Analysis

The R^2 analysis highlights variations in model performance across the six Pasig River stations, reflecting the influence of site-specific factors (Table 6).

Table 6. R-squared Values

Stations	ANN	GBR	LSTM
NB	0.26	0.30	0.41
BB	0.46	0.06	0.24
GF	0.20	1.31	0.43
LB	0.57	0.90	0.34
NGB	0.25	0.47	0.03
JB	0.71	0.35	0.02

For the ANN model, R^2scores were generally low across stations. Jones Bridge showed the highest R^2, suggesting a relatively strong fit, while Lambingan demonstrated a moderate level of explanatory power. Bambang yielded an R^2value of 0.46, indicating a weak but still acceptable fit.

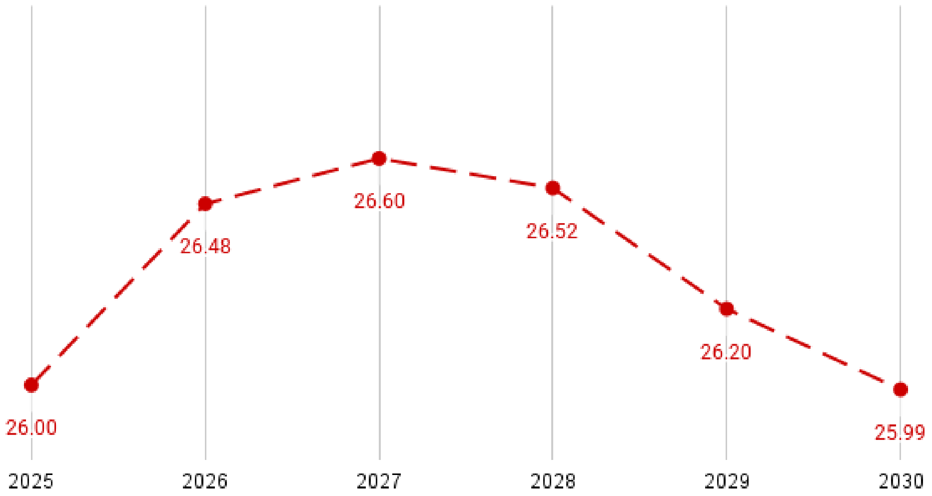
In contrast, the models for Napindan and Guadalupe displayed low R^2values which means that there is limited ability to capture variability in those stations. On the other hand, the GBR model achieved the highest R^2scores for Lambingan and Nagtahan, with particularly strong performance at Lambingan ($R^2 = 0.90$), indicating a very good fit. Meanwhile, the LSTM model recorded relatively low R^2 values for Jones and Nagtahan, suggesting less effective performance in these locations.

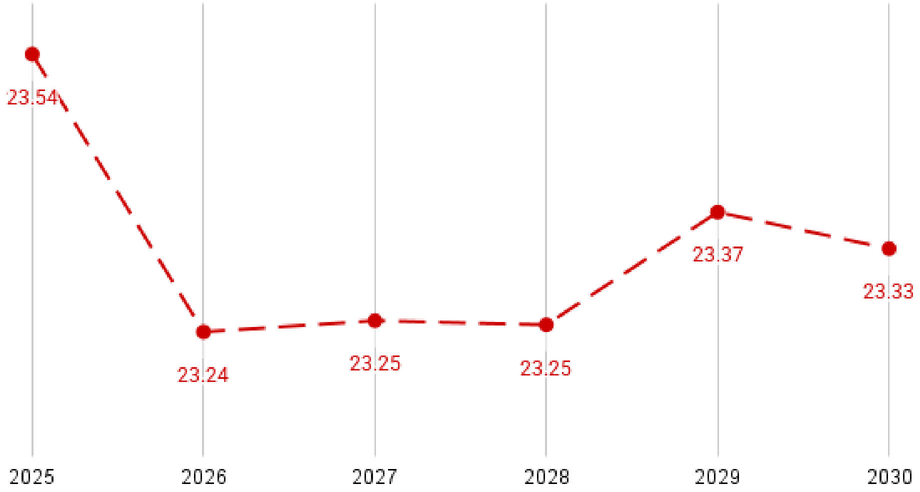
3.5. Model Deployment

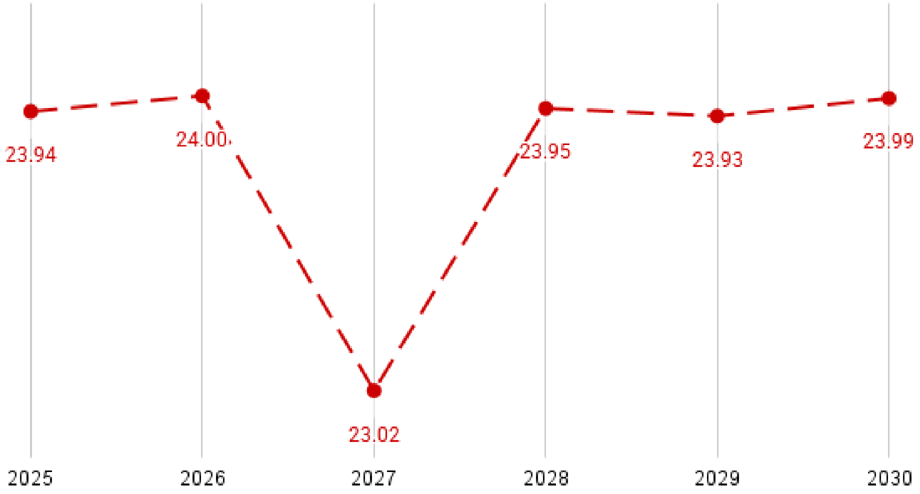
The consistently low R^2 values observed across most monitoring stations highlight the inherent difficulty of modeling complex and irregular hydrological processes using limited annual datasets. Despite this statistical limitation, all models, particularly the LSTM, demonstrated the capability to capture the directional trends of change in water quality. This finding suggests that while the models may not accurately reproduce the exact magnitude of CCME WQI fluctuations, they effectively identified the general trajectory of improvement or decline. In environmental forecasting, such trend-based insights remain valuable for supporting long-term management decisions, especially in data-scarce contexts where recognizing patterns of degradation or recovery is more critical than achieving precise numerical accuracy.

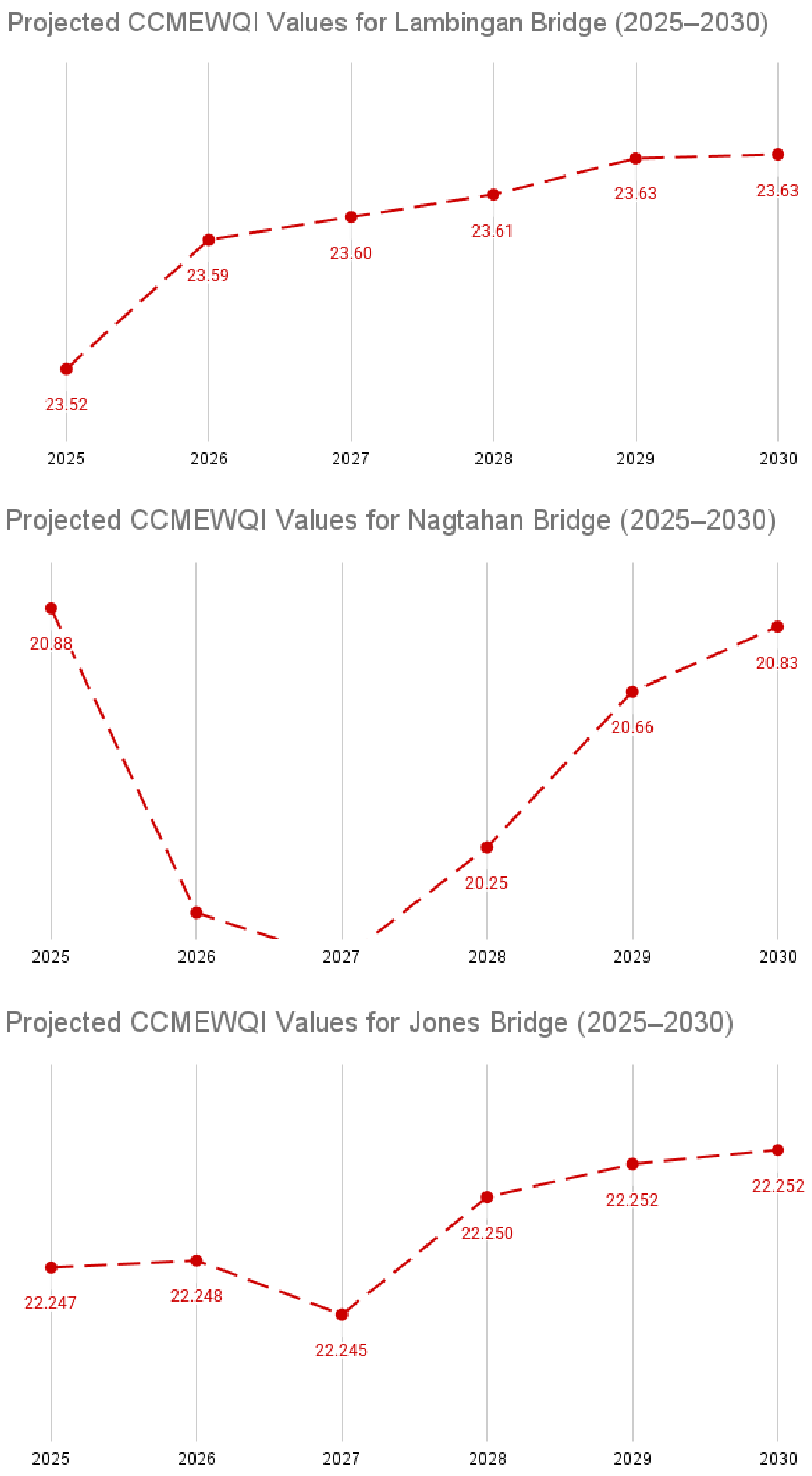
Among the evaluated models, the ANN exhibited generally low R^2scores across stations, with the highest value recorded at Jones Bridge, indicating a relatively strong fit. Lambingan demonstrated moderate explanatory power, while Bambang produced a weak yet acceptable R^2 value of 0.46. Conversely, the Napindan and Guadalupe models displayed limited ability to capture variability in their respective datasets. The GBR model achieved the highest R^2values at Lambingan ($R^2= 0.90$) and Nagtahan, reflecting strong model performance at these sites. Although the LSTM recorded relatively low R^2values for Jones and Nagtahan, it consistently exhibited better capability in capturing temporal dependencies compared to the other approaches.

Quantitatively, the LSTM model achieved the lowest RMSE in 4 out of 6 stations and shared the lowest MAE in 3 out of 6 stations, similar to the GBR model, indicating favorable predictive accuracy across most locations. However, it attained a high R^2score (approaching 1) in only one station, suggesting that while the model effectively minimized prediction error and captured trends, its explanatory power remained limited in some cases. Hence, considering its overall performance across multiple evaluation metrics, the LSTM model is selected to forecast CCME WQI values for the period 2025 to 2030 (Figure 7).


Projected CCMEWQI Values for Napindan Bridge (2025–2030)


Projected CCMEWQI Values for Bambang Bridge (2025–2030)


Projected CCMEWQI Values for Guadalupe Ferry (2025–2030)


Projected CCMEWQI Values for Lambingan Bridge (2025–2030)

Projected CCMEWQI Values for Nagtahan Bridge (2025–2030)

Projected CCMEWQI Values for Jones Bridge (2025–2030)

Figure 7. Projected CCME WQI values for NB, BB, GF, LB, NGB, and JB stations, respectively

4. Conclusion and Recommendations

In conclusion, the results of this study show that the water quality of the Pasig River, based on CCME WQI values from 2010 to 2024, consistently falls within the “Poor” category, confirming the continuing environmental challenges facing the river system [1].

The findings claim that the overall WQI of the Pasig River Main Line follows a pattern and can be modeled for future years through the application of machine learning techniques. Among the implemented machine learning models, the LSTM model exhibited the most robust performance relative to the dataset. It demonstrated stable training behavior and no apparent signs of overfitting. While the model was more effective in identifying directional trends in water quality, general increases or decreases, it was less accurate in predicting exact WQI values. Nonetheless, performance metrics indicated that the LSTM model achieved the lowest Root Mean Square Error in four out of six stations and shared the lowest Mean Absolute Error in three stations with GBR, suggesting comparatively strong predictive accuracy. However, only one station yielded a high coefficient of determination (R^2), indicating limited generalizability, which may be attributed to the restricted size and variability of the dataset.

The LSTM model’s forecast from 2025 to 2030 indicated only marginal, decimal-level changes in CCME WQI values across all monitoring stations. This suggests that, without significant intervention, the water quality of the Pasig River is unlikely to improve or decline substantially in the near term and will likely remain within the "Poor" classification. However, a comparative analysis of WQI values from 2010 and projected values for 2030 shows an almost 10-point improvement across the six stations. Although this trend may be affected by data limitations, it suggests a gradual improvement in water quality over the 20-year period. The projected stagnation in short-term water quality highlights the possibility that current rehabilitation efforts may be inadequate to achieve measurable improvements within the next five years.

From a policy standpoint, rehabilitation efforts for the Pasig River have already required substantial financial commitments from both government and private sectors, aimed at enhancing its aesthetics, usability, and ecological condition. Nonetheless, the five-year forecast reveals no statistically significant improvement in water quality. This discrepancy between large-scale expenditures and limited environmental gains indicates the need for a critical re-evaluation of existing rehabilitation frameworks. Continuing along the current trajectory risks sustaining a financially straining program with minimal environmental return. Given the river’s persistent “poor” classification, the results underscore the necessity of integrating evidence-based, outcome-oriented strategies to achieve meaningful and measurable improvements.

Despite these findings, the study faced limitations due to missing and inconsistent data, which may have affected the accuracy and generalizability of the models. It is therefore recommended that future research should expand and standardize the dataset, explore alternative or modified WQI methods suitable for tropical urban rivers [20], and integrate additional environmental and anthropogenic variables to better capture water quality dynamics. Beyond reporting overall WQI scores, retrospective analysis of the F1, F2, and F3 components is recommended to identify parameter-level drivers of poor water quality and link them to known pollution sources. Implementing more rigorous time-series validation and applying model-explainability techniques would further enhance the interpretability and reliability of machine learning predictions. Collectively, these improvements will strengthen forecasting and advance the use of machine learning for environmental monitoring and policy-oriented water resource management.

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