Development of a Regression Model to Estimate Water Quality in Riverine Wetlands Using Sentinel-2 Satellite Imagery

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Abstract: *Accurately estimating water quality in riverine wetlands is essential for preserving biodiversity, maintaining ecosystem services, protecting public health, and promoting sustainable environmental management. Chlorophyll-a concentration is a critical indicator of water quality, reflecting phytoplankton biomass and nutrient levels, and is commonly used to assess ecosystem health and biological productivity. This study aimed to develop and evaluate a linear regression model to estimate Chlorophyll-a concentrations in the Seojae-ri riverine wetland using Sentinel-2 satellite imagery and in-situ data collected from 2019 to 2023. The study methodology involved dividing the data into training and testing sets, with multispectral bands from Sentinel-2 satellite imagery and corresponding in-situ Chlorophyll-a concentration data. To improve model accuracy, correlation coefficients between the in-situ Chlorophyll-a concentrations and the intensity values of each Sentinel-2 band were calculated. Based on these coefficients, two linear regression models were developed: the first used all available multispectral bands, while the second employed only the selected bands that showed higher correlations with in-situ Chlorophyll-a concentrations. The performance of both models was evaluated using statistical metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and the R^2 score. The second model, which used the selected bands, demonstrated superior performance with an R^2 score of 0.5898, MAE of 2.9793, and MSE of 11.5249. In contrast, the first model, which incorporated all bands, had a lower R^2 score of 0.0806, along with higher MAE (4.1110) and MSE (25.8338). These results indicate that focusing on the bands with stronger correlations to in-situ Chlorophyll-a concentrations improves the predictive accuracy of the regression model. While the second model outperformed the first, the study recognizes that linear regression may not fully capture the complexity of relationships between spectral data and Chlorophyll-a concentrations. Future research should consider non-linear regression models, such as random forests or neural networks, which can better handle the non-linear interactions in such datasets. Additionally, incorporating data from other remote sensing platforms, including hyperspectral imagery, could further enhance the accuracy of Chlorophyll-a concentration estimation in riverine wetlands.*

Keywords: *Water Quality, Sentinel-2 Satellite Imagery, Linear Regression Model, Chlorophyll-a*

Introduction

Assessing water quality in riverine wetlands is critical for conserving biodiversity, supporting ecosystem services, protecting public health, and fostering sustainable environmental management practices (Dudgeon *et al*., 2006; Mitsch and Gosselink, 2015; Verhoeven *et al*., 2006). Riverine wetlands are dynamic systems, and in-situ water quality monitoring can be challenging due to their remote locations, which often limit accessibility, as well as the potential for human presence to disturb sensitive habitats. Additionally, water quality in these wetlands can fluctuate significantly due to seasonal and environmental changes, making regular monitoring labor-intensive and time-consuming (Kadlec and Wallace, 2008). In recent years, satellite remote sensing has emerged as a valuable tool for estimating water quality parameters in such environments. Satellite imagery provides large-scale spatial coverage, frequent temporal data, and the ability to monitor water conditions without physical interference, thereby reducing the risks associated with traditional field sampling (Klemas, 2013; Tyler *et al.*, 2016). Sentinel-2 satellite imagery, in particular, with its high resolution and multispectral capabilities, offers enhanced accuracy for detecting key water quality indicators like chlorophyll-a (Chl-a), suspended solids, and turbidity. This technology allows for continuous, efficient, and non-invasive monitoring of water quality in wetlands, contributing to more effective management and conservation strategies (Duan *et al.*, 2019; Villa *et al.*, 2014).

Chlorophyll-a is a crucial photosynthetic pigment found in phytoplankton and is widely recognized as an important indicator of water quality, particularly concerning nutrient levels and algal biomass (Bresciani *et al.*, 2011; USEPA (United States Environmental Protection Agency), 2003; Wetzel, 2001). In riverine wetlands, monitoring Chlorophyll-a is essential as it serves as a direct measure of phytoplankton biomass, which in turn reflects the nutrient status and overall ecological health of the ecosystem (Wetzel, 2001). Elevated levels of Chlorophyll-a often indicate nutrient enrichment or eutrophication, a process driven by excessive inputs of nitrogen and phosphorus that promote algal blooms. This can result in diminished water quality through a reduction in dissolved oxygen levels, which negatively impacts aquatic life and can lead to habitat degradation (Smith *et al.*, 1999). Tracking Chlorophyll-a concentrations is not only critical for understanding nutrient dynamics but also for predicting potential shifts in ecosystem function and services. High concentrations of this pigment can lead to hypoxia (low oxygen conditions), which poses serious risks to fish, macroinvertebrates, and other aquatic organisms (Carpenter *et al.*, 1998). Additionally, eutrophication linked to excessive Chlorophyll-a can disrupt biodiversity, reduce water clarity, and harm the provisioning of ecosystem services such as water filtration, flood control, and carbon sequestration (Dodds *et al.*, 2008; Paerl *et al.*, 2014). Therefore, regular monitoring of Chlorophyll-a in riverine wetlands is key to managing nutrient loads and maintaining ecological balance in these vulnerable environments.

Remote sensing technologies have proven to be highly effective for estimating Chlorophyll-a concentrations in riverine wetlands and other inland water bodies due to their ability to provide large-scale, frequent, and non-invasive monitoring (Gitelson and Merzlyak, 1998). This is especially advantageous in wetlands, where accessibility is often limited and traditional water quality assessments can be logistically challenging (Matthews, 2011). Early studies utilized Landsat Thematic Mapper (TM) data for estimating Chlorophyll-a concentrations in inland waters, demonstrating the potential of satellite data for large-area water quality monitoring (Mishra *et al*., 2005). However, atmospheric interference and other factors initially posed challenges to achieving high accuracy. To address these limitations, subsequent research focused on refining atmospheric correction techniques. For example, Wang *et al*. (2007) used MODIS (Moderate Resolution Imaging Spectroradiometer) data to improve Chlorophyll-a estimation in both coastal and inland waters, enhancing accuracy by resolving atmospheric interference. Hyperion hyperspectral imagery, with its ability to capture detailed spectral information, was later used by Giardino *et al*. (2007) to assess water quality, offering a higher resolution for distinguishing between different water quality parameters, including Chlorophyll-a concentrations. In more recent years, the Sentinel-2 satellite has emerged as a valuable tool for monitoring Chlorophyll-a, thanks to its high spatial and spectral resolution. Du *et al*. (2012) highlighted the effectiveness of Sentinel-2 imagery for estimating Chlorophyll-a concentrations in large water bodies like rivers and lakes, making it a key resource for water quality management. Additionally, the integration of drone-based remote sensing has introduced new possibilities for monitoring smaller, more complex ecosystems. Zhou *et al*. (2012) demonstrated the use of drone-based multispectral imagery to estimate Chlorophyll-a in wetlands, providing accurate and efficient data collection. Similarly, Kuhn *et al*. (2019) showcased the potential of Unmanned Aerial Vehicle (UAV) multispectral and hyperspectral imagery for estimating Chlorophyll-a in smaller inland water bodies, underscoring the growing role of UAVs in environmental monitoring. These advancements in remote sensing technologies have significantly improved the ability to monitor Chlorophyll-a in riverine wetlands and other inland waters, enabling more effective management of water quality and ecosystem health.

In this study, a linear regression model was created to estimate Chlorophyll-a concentrations in riverine wetlands using the multiple scenes of Sentinel-2 satellite imagery and in-situ data. The process involved dividing the data into training and testing sets, calculating correlation coefficients between in-situ Chlorophyll-a concentrations and the intensity values of each Sentinel-2 multispectral band, and selecting the most relevant bands. Two linear regression models were developed: one using all bands and another using only the selected bands with higher correlation coefficients to improve estimation accuracy.

Study Area and Datasets

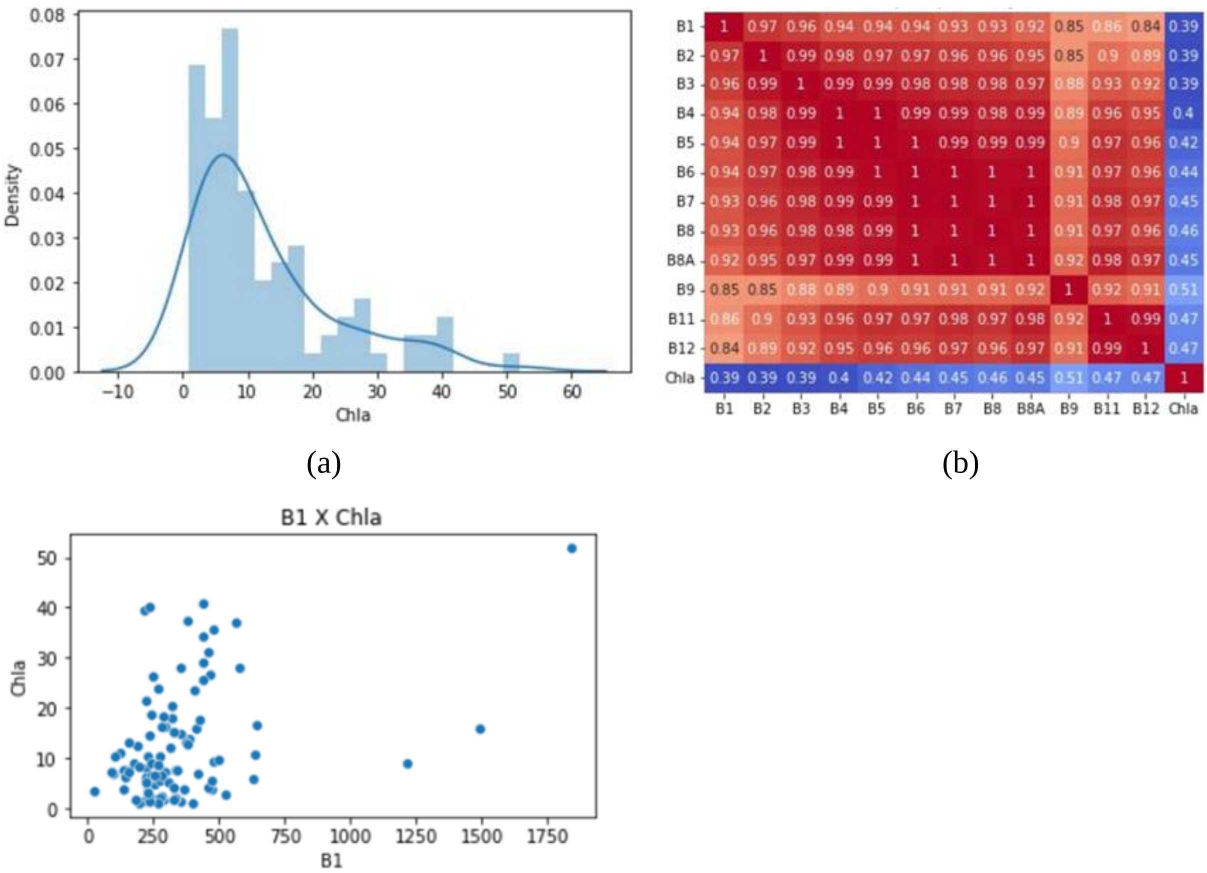
In this study, the Seojae-ri riverine wetland (total area: 445,217.88 m²), located along the Gumho River, was selected as the study area because there is a water quality monitoring station (latitude: 35.885°, longitude: 128.503°) near the wetland that can continuously provide daily in-situ Chlorophyll-a concentration data (see Figure 1).

Figure 1: Location of the Sejae-ri riverine wetland shown in Google™ map

The 97 scenes of Sentinel-2 satellite imagery acquired in the study area from 2019 to 2023 were used for obtaining the intensity values of all multispectral bands including Bands 1, 2, 3, 4, 5, 6, 7, 8, 8A, 9, 11 and 12.

Methodology

In the first step of the proposed methodology, the in-situ Chlorophyll-a concentration data and the intensity values of all multispectral Sentinel-2 satellite imagery acquired in the study area were divided into training and testing sets. Then, exploratory data analysis was conducted to examine the relationship between the in-situ Chlorophyll-a concentrations and the intensity values of the Sentinel-2 multispectral bands. Figure 2(a) shows the distribution of in-situ Chlorophyll-a concentrations, Figure 2(b) presents the correlation heatmap between the Chlorophyll-a concentrations and all multispectral bands, and Figure 2(c) displays an example scatterplot of Chlorophyll-a concentrations and a single band (Band 1) of the Sentinel-2 imagery.



(a) (b)

(c)

Figure 2: Results of the exploratory data analysis: (a) Distribution of in-situ Chlorophyll-a concentration density, (b) Correlation heatmap between in-situ Chlorophyll-a concentrations and the intensity values of the multispectral bands of the Sentinel-2 satellite imagery, and (c) Example scatterplot of Chlorophyll-a concentrations and a single band (Band 1) of the Sentinel-2 satellite imagery.

Figure 2(a) represents the distribution of in-situ Chlorophyll-a concentrations in a riverine wetland, depicted as a histogram with a corresponding density curve. The x-axis shows the Chlorophyll-a concentrations (Chla), measured in mg/m³, while the y-axis represents the density, which corresponds to the frequency of these concentrations within the dataset.

From the figure, we observe a right-skewed distribution, indicating that the majority of Chlorophyll-a concentration values fall between 0 and 15 mg/m³, with the peak occurring near 10 mg/m³. This suggests that lower concentrations of Chlorophyll-a are more common in the dataset. The distribution tails off gradually, with some higher Chlorophyll-a concentrations extending beyond 40 mg/m³, but these are relatively infrequent. The shape of the density curve indicates that the data is not normally distributed; instead, it has a positive skew. This skewness could be indicative of occasional instances of nutrient enrichment or eutrophication, where higher Chlorophyll-a levels are present due to increased phytoplankton activity. The relatively rare high concentrations suggest that these conditions may not be frequent in the sampled region but can occur under specific environmental conditions.

Figure 2(b) epresents a correlation heatmap that shows the relationships between in-situ Chlorophyll-a concentrations (denoted as "Chla") and the various bands of Sentinel-2 satellite imagery (B1, B2, B3, etc.). The correlation values are shown in the heatmap, where the color intensity reflects the strength of the correlation: red indicates strong positive correlations, and blue indicates weaker or moderate correlations. The values range from 0 to 1, where 1 represents a perfect positive correlation, 0 indicates no correlation, and negative values would reflect inverse correlations (though none are shown here). In Figure 2(b), Bands 4 (Red), 5 (Red-edge 1), 6 (Red-edge 2), 7 (Red-edge 3), 8 (Near-infrared), 8a (Near-infrared narrow), 9 (Water vapor), 11 (Shortwave infrared 1), and 12 (Shortwave infrared 2) have higher correlation coefficients (0.4 or more) with Bands 1 (Coastal aerosol), 2 (Blue), and 3 (Green), respectively.

Figure 2(c) depicts a scatterplot showing the relationship between in-situ Chlorophyll-a concentrations (Chla, represented on the y-axis) and the intensity values of Band 1 (Coastal aerosol) of Sentinel-2 satellite imagery (B1, represented on the x-axis). The scatterplot provides a visual representation of how Chlorophyll-a concentrations vary with changes in the reflectance values captured by Band 1.

The next step involved developing a linear regression model to estimate Chlorophyll-a concentrations, with in-situ Chlorophyll-a data as the dependent variable and the intensity values of the multispectral bands from 97 scenes of Sentinel-2 satellite imagery as the independent variables. Linear regression is one of the simplest and most widely used predictive models for analyzing relationships between a dependent variable and one or more independent variables (Freedman, 2009; Montgomery *et al*., 2021). It assumes a linear relationship between the variables and fits a straight line to model this relationship.

By applying this approach, the model can predict Chlorophyll-a concentrations based on the observed values from the multispectral satellite bands. This method's simplicity and interpretability make it highly suitable for environmental applications, where understanding the relationships between different variables is critical for effective water quality management. Moreover, linear regression has been successfully applied in remote sensing studies, especially for estimating water quality parameters like Chlorophyll-a (Zhou *et al.*, 2012; Kuhn *et al.*, 2019), offering an effective solution for monitoring ecological health in riverine wetlands.

The linear regression model for estimating Chlorophyll-a concentrations in riverine wetlands using Sentinel-2 satellite imagery can be expressed in Equation 1 as follows:

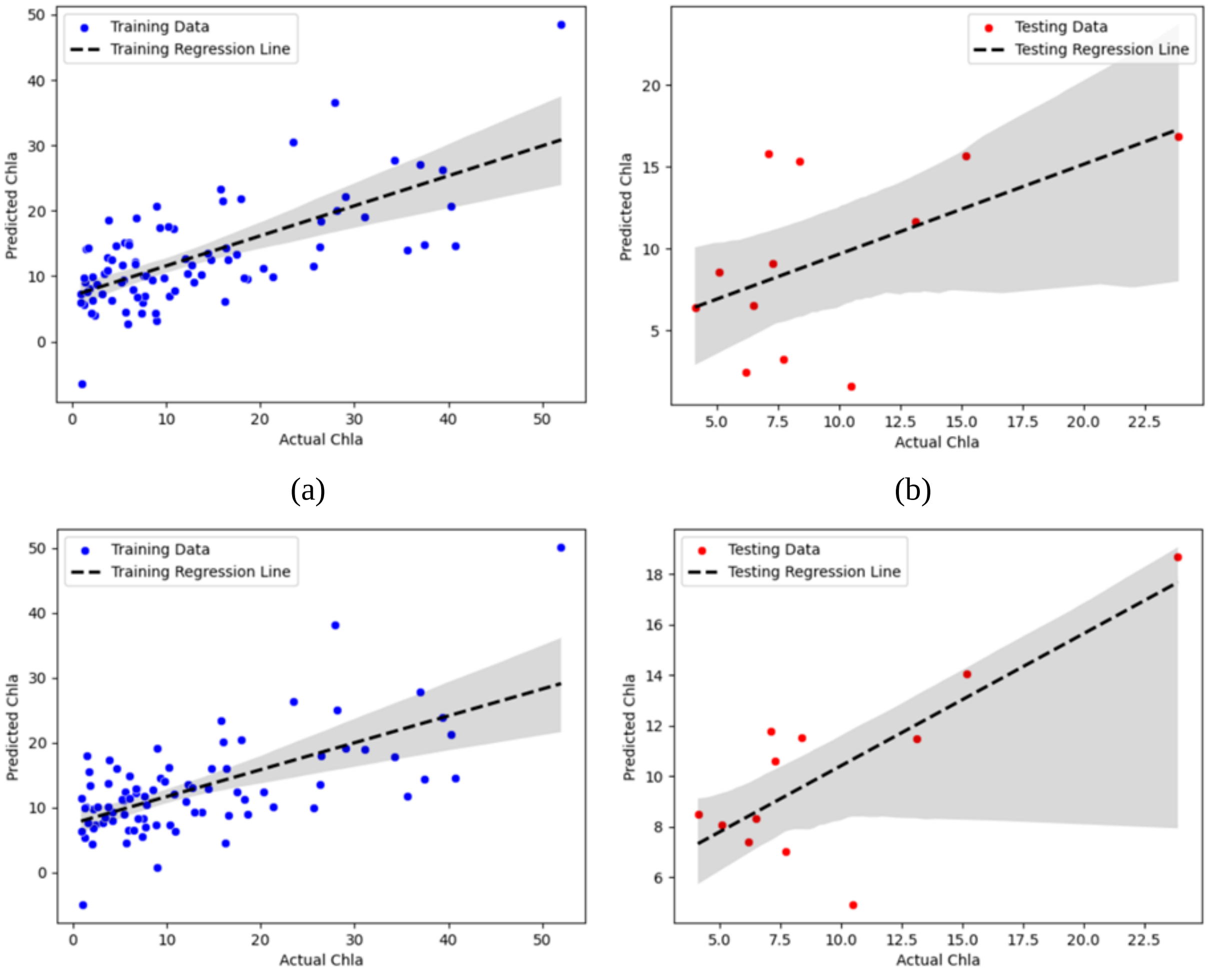
$$CHA = a_0 + a_1B_1 + a_2B_2 + \ldots.. + a_nB_m + \varepsilon \quad (1)$$

Where CHA (dependent variable) represents the estimated Chlorophyll-a concentration (mg/m³) in the riverine wetlands, which serves as the outcome or target variable, a_0 (intercept) represents the constant term in the regression model, representing the estimated Chlorophyll-a concentration when all reflectance values from the selected bands are zero. In addition, $a_1,..,a_n$ (regression coefficients) represents the coefficients associated with each Sentinel-2 multispectral band, $B_1,\ldots,B_m$ (independent variables) represents the reflectance values (intensity) from the multispectral bands of Sentinel-2, and ε represents the residual or error term that captures the variation in Chlorophyll-a concentrations not explained by the model, and the residual accounts for the random error or noise in the data, as well as any un-modeled relationships between the variables (Montgomery *et al*., 2021).

In this step, two linear regression models were developed to estimate Chlorophyll-a concentrations using Sentinel-2 satellite imagery. The first model utilized all the multispectral bands from the Sentinel-2 imagery as independent variables to predict the in-situ Chlorophyll-a concentrations. In contrast, the second model was based on a subset of bands, specifically Bands 3 (Green), 4 (Red), 5 (Red-edge 1), 6 (Red-edge 2), 8 (Near-Infrared), 9 (Water vapor), and 11 (Shortwave Infrared 1), which showed stronger correlations with in-situ Chlorophyll-a concentrations. The selection of these bands was informed by the correlation analysis conducted in the exploratory phase, where these bands exhibited higher correlation coefficients, making them more reliable predictors for estimating Chlorophyll-a levels (Matthews, 2011; Kuhn *et al*., 2019). Using these two models allowed for comparison of the predictive performance between using all available spectral bands and a refined subset of bands, providing insight into the most efficient methods for water quality estimation in riverine wetlands.

Results and Discussion

Figure 3 showed the two linear regression model graphs with the training and testing sets, respectively. Figure 3(a) showed the first model graph with the training set, Figure 3(b) showed the first model graph with the testing set, Figure 3(c) showed the second model graph with the training set, and Figure 3(d) showed the second model graph with the testing set.



(c) (d)

Figure 3: Linear regression model graphs: (a) First model graph with the training set, (b) First model graph with the testing set, (c) Second model graph with the training set, and (d) Second model graph with the testing set

To evaluate the performance of a linear regression model, several key metrics are commonly used, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and the R^2 score (coefficient of determination) (Kutner *et al.*, 2004; Montgomery *et al.*, 2021).

These metrics provide a comprehensive assessment of the model's predictive accuracy. Mean Squared Error (MSE) is the average of the squared differences between the actual values and the predicted values of Chlorophyll-a concentrations. This metric gives more weight to larger errors, making it sensitive to outliers. A lower MSE indicates better model performance, as it reflects smaller prediction errors. Mean Absolute Error (MAE), on the other hand, is the average of the absolute differences between actual and predicted values. Unlike MSE, it treats all errors equally, providing a more straightforward interpretation of the average prediction error without amplifying larger deviations. A lower MAE suggests that the model predictions are closer to the actual values. The R^2 score, also known as the coefficient of determination, measures the proportion of variance in the dependent variable (Chlorophyll-a concentrations) that can be explained by the independent variables (Sentinel-2 multispectral bands). R^2 ranges from 0 to 1, where a higher score indicates a better fit of the model. An R^2 score of 1 represents a perfect fit, while a score closer to 0 indicates that the model fails to explain the variance in the data (Kutner *et al*., 2004). In this study, Table 1 presents the statistical results of MAE, MSE, and R^2 scores for the two developed linear regression models using both the training and testing datasets. These metrics provide valuable insight into the accuracy and reliability of the models.

Table 1: Statistical results of the two linear regression model with the training and testing sets

Types of Linear a Regression Model	**MAE**	**MSE**	**R^2 Score**
First model with the training set	6.8373	71.8562	0.4591
First model with the testing set	4.1110	25.8338	0.0806
Second model with the training set	6.9635	77.7798	0.4145
Second model with the testing set	2.9793	11.5249	0.5898

The table presents the statistical results of two linear regression models used to estimate Chlorophyll-a concentrations, evaluated using the Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score for both the training and testing datasets. These metrics provide insight into the models' performance and predictive accuracy. Starting with the first model, the MAE and MSE for the training set are 6.8373 and 71.8562, respectively, with an R^2 score of 0.4591. This suggests that the model explains approximately 46% of the variance in the training data, indicating a moderate fit. However, when applied to the testing set, the model's performance significantly deteriorates. The MAE drops to 4.1110, and the MSE decreases to 25.8338, but the R^2 score plummets to 0.0806. This low R^2 indicates that the model explains only about 8% of the variance in the testing set, revealing poor generalization to new data. The relatively low MSE in the testing set suggests that while prediction errors are lower, the model may be overfitting the training data, failing to capture the underlying patterns effectively for the testing set (Kutner *et al*., 2004). In contrast, the second model, which uses a subset of selected bands, performs more consistently. For the training set, the MAE and MSE are slightly higher than the first model, at 6.9635 and 77.7798, respectively, with an R^2 score of 0.4145. Although this indicates a slightly worse fit compared to the first model, the second model shows a much stronger performance when tested on the testing set. The MAE significantly improves to 2.9793, and the MSE drops to 11.5249. Most notably, the R^2 score increases to 0.5898, meaning that the second model explains approximately 59% of the variance in the testing set, a substantial improvement over the first model. These results indicate that the second model generalizes better to new, unseen data. Despite slightly higher errors in the training set, the second model's ability to capture the relationship between Chlorophyll-a concentrations and the Sentinel-2 bands in the testing set demonstrates its robustness. The improved performance on the testing set suggests that selecting bands with higher correlations to Chlorophyll-a concentrations results in a more reliable predictive model. This highlights the importance of feature selection in regression models to avoid overfitting and improve generalization (Montgomery *et al*., 2021).

Conclusion and Recommendation

In this research, two linear regression models were developed to estimate Chlorophyll-a concentrations in the Seojae-ri riverine wetland using Sentinel-2 satellite imagery. The first model used all available multispectral bands, while the second model was based on selected bands that demonstrated higher correlation coefficients with in-situ Chlorophyll-a concentrations. The statistical results showed that the model utilizing the selected bands significantly outperformed the model using all bands. Specifically, the second model demonstrated better predictive accuracy, as indicated by lower Mean Absolute Error (MAE) and Mean Squared Error (MSE), along with a higher R^2 score, particularly when tested on unseen data. These results suggest that selecting bands with stronger correlations to Chlorophyll-a concentrations improves the model's ability to generalize and estimate water quality more effectively (Montgomery *et al*., 2021). This research contributes to the field of water quality monitoring by demonstrating the feasibility of estimating Chlorophyll-a concentrations in riverine wetlands using remote sensing data from

Sentinel-2. The ability to estimate these concentrations without human access to the wetland offers significant advantages, particularly for large or inaccessible areas. Sentinel-2 imagery provides non-invasive, frequent, and wide-scale monitoring, which is essential for tracking dynamic ecosystems like wetlands (Matthews, 2011). However, the results also revealed limitations in the linear regression models. As depicted in Figure 3, the models were limited in their ability to capture the complex, non-linear relationships between Chlorophyll-a concentrations and the multispectral band intensities. Linear regression assumes a simple, linear relationship, which may not fully account for the intricate interactions between the variables, particularly in natural ecosystems where environmental factors can influence spectral readings. Moreover, the model's sensitivity to outliers and noise suggests that more advanced techniques may be required to improve accuracy and robustness (Kutner *et al*., 2004). To address these limitations, future research should explore more sophisticated machine learning algorithms such as random forests, support vector machines, or neural networks, which are better suited for capturing non-linear relationships. Additionally, incorporating other remote sensing data, such as higher resolution imagery or integrating data from different sensors, could further improve the accuracy of Chlorophyll-a estimation. Finally, future work could focus on expanding the study area to include various types of wetlands and water bodies, enhancing the model's generalizability and application in diverse environmental contexts (Montgomery *et al*., 2021).

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