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Evaluation and Prediction of Water Quality in Coastal Areas of China

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Abstract. The quality of Chinese coastal waters is crucial for maintaining environmental health, supporting economic activities, and ensuring public safety. Due to China's extensive coastal area, researchers typically focus on analyzing specific regions. In this study, we have gathered data published by the Chinese government and evaluated the water quality of the entire Chinese coastal area. By geographically analyzing changes in water quality over the past six years, we assess the overall trend in Chinese coastal water quality. Additionally, we identify several locations with severe contamination and highlight the reasons behind such pollution. In this research, we concentrate on analyzing six diverse parameters (pH, dissolved oxygen (DO), chemical oxygen demand (COD), inorganic nitrogen, active phosphate, and petroleum), which are the most significant indicators used in assessing water quality. Furthermore, we employed advanced statistical analysis to evaluate current water quality based on these six chemical factors. Nevertheless, we utilize linear regression to determine the weight of each factor to categorize water into different levels defined by the government. In the end, we provide several suggestions for the Chinese government for their future work in protecting water in Chinese coastal areas.

Keywords: Water quality, Statistical analysis, Coastal areas, China

1. Introduction

Water resources are of paramount importance for environmental sustainability, public health, and economic development. Water quality is vital for all creatures, affecting marine ecosystems, human survival, and activities. In China, the coastal area occupies 4.7 million square kilometers, which covers diverse industries, including the conservation of the ocean, fishing, ecotourism, and farming. However, rapid industrialization, urbanization, and agricultural practices have led to a significant impact on water quality, even leading to the risks of being subjected to environmental degradation. For instance, the issue of eutrophication was substantially intensified as a result of industrial development between the 1980s and 2000s in China [1]. In most circumstances, rapid economic and social development has consequences, especially environmental problems, and China is no

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exception. In the last four decades, substantial changes have occurred in the coastal ecosystems of the China Seas as a result of multiple stresses [2]. The water quality is determined by its physical, chemical, and biological parameters [3], including pH, dissolved oxygen (DO), chemical oxygen demand (COD), inorganic nitrogen, active phosphate, and petroleum content. Aiming to reveal and track the overall water quality trend, this research was carried out on the basis of the database involving 11 coastal provinces in China, while each data point was categorized into five levels (Level 1 represents the highest quality, whereas Level 4+ represents the worst quality). By analyzing such tendencies in a more comprehensive method, effective measures can be adopted by local governments to improve the current situation to the largest extent.

2. Literature review

In past studies, scholars have done research on water quality evaluation and prediction in many river sites and around magazines [4-5]. This research has helped scientists to understand how pollutants can damage the environment and what are efficient ways to solve such problems.

In Water Quality Trend Assessment in Jakarta: A Rapidly Growing Asian Megacity [4], Weill Duane has discussed the impact of sagacity in Jakarta by monitoring river sites. During the research, he used the Mann-Kendall test to analyze the trend of changes in water quality. Moreover, Weill analyzes the changing trends in different chemical elements, including DO, BOD, and TASS. Such analysis of water quality is believed to be very comprehensive, so we are also going to analyze the water quality level in a similar way. Despite this, Weill has collected the geographical locations of data sites. By analyzing these locations, people can see how other factors can affect the water quality. Such a method is also going to be used in our research process.

Similar to what Md Galal Uddin did in Robust machine learning algorithms for predicting coastal water quality index [5], we make a boxplot to analyze the overall trend of water quality. Also, we use machine learning to find the best-fit line and analyze how each chemical element can affect the overall water quality trend. By doing linear regression, we can find the weight of each chemical factor and predict the water quality based on the inputs of chemical factors.

3. Sample

3.1. Sampling sites and time

China is a vast and diverse country located in East Asia, containing approximately 9.6 million square kilometers. Its landscape includes mountains, plateaus, deserts, river deltas, and large marine areas. Also, China is the most populous country on Earth, with a population exceeding 1.4 billion people. Though the area beside the Chinese seashore only possesses 14% of the country's land area, it contains up to 40.9% of the whole Chinese population.

Thus, we present research to investigate the changes in nearshore marine quality from 2017 to 2023. We obtain the data from the official documents that are published by the Chinese government, which includes around 2500 water sample collection sites around the Chinese seashore.

3.2. Relevant factors

3.2.1. pH

pH stands as a paramount physicochemical parameter in aquatic environments, profoundly influencing the behavior of other water quality indicators and the concentration of metals. Measured

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on a scale ranging from 1 to 14, pH reflects the acidity or alkalinity of water. Values below 7 indicate acidity, 7 denotes neutrality, and values above 7 denote alkalinity. As a crucial determinant of water quality, pH significantly impacts both chemical processes and biological activities within aquatic ecosystems. Accurate pH assessment is essential for diverse water uses, encompassing drinking water, aquatic life sustenance, and industrial applications. Extreme deviations in pH, whether excessively high or low, can exert substantial and distinct impacts on water quality.

3.2.2. Dissolved Oxygen (DO)

Dissolved oxygen (DO), a crucial indicator of aquatic ecosystem health, refers to the amount of oxygen present in water. While DO is routinely measured in diverse aqueous studies, including marine, terrestrial, and wastewater investigations, the sources and sinks contributing to its variability, such as atmospheric exchange, photosynthesis, and respiration, often remain elusive [6].DO concentrations are among the most critical field parameters, providing insights into the overall water quality and supporting diverse biological communities. Several factors influence DO levels, including temperature, salinity, pressure, and pollution.

3.2.3. Chemical Oxygen Demand (COD)

Oxygen demand is a vital factor that can be observed to determine and assess the water contamination content. The biochemical degradation is an important process of seawater self-purification [7], and oxygen plays an important role in biochemically degrading organic compounds, as oxygen was massively consumed to break down organic substances, indicating that high COD represents severe pollution. Therefore, oxygenic indexes such as biological oxygen demand (BOD), chemical oxygen demand (COD), and total organic carbon (TOC) can be utilized to evaluate the extent of organic pollution in aqueous systems [8]. However, among these methods, COD is more advantageous and valid due to its simplicity and less sophisticated manipulating process. This can be attributed to the trait that it measures all organic matter that has been chemically oxidized due to oxygen consumption [9], whereas BOD covers a less broad range of organic substances.

3.2.4. Inorganic nitrogen

Inevitably, Inorganic Nitrogen plays the role as an essential nutrient source for aquatic organisms. The abundance of inorganic nitrogen facilitates the growth and development of microscopic algae, the base of the aquatic food chain. The appropriate nitrogen content sustains the balance of the ecosystem, whereas excess nitrogen content is indeed harmful. A boost in the population of phytoplankton and periphytes, known as eutrophication, may be directly associated with the elevated input of inorganic nitrogen [10]. An aquatic ecosystem would be subjected to a weaker biocapacity and eventually degradation when suffering eutrophication. Undeniably, eutrophication caused by excess nitrogen emission has also had a dramatic influence on local freshwater resources and fisheries.

3.2.5. Active phosphate

Likewise, phosphorus (P) is also an essential element for all forms of life and the phosphorus cycle is one of the most important biogeochemical processes. With the advancement of human industries, large amounts of phosphorus have been released during human activities, including phosphate rock mining, fertilizer application, livestock and food production [11]. In the past, phosphorus was

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mainly researched with Phosphate (PO4), which is a widely existing chemical compound in nature, and phosphate is a naturally occurring compound found in all aquariums. Though phosphate plays an undeniably important role in nature, excess amounts of it still create problems for marine ecosystems. For instance, the elevated phosphate content is often the main driving force of the issue of eutrophication, which results in a significant decline in biodiversity. Thus, it is necessary to be aware of the amount of phosphate in the marine environment.

3.2.6. Petroleum

Petroleum is a very crucial energy resource in human society, and it provides a significant proportion of energy that is consummated. Still, during the process of gaining petroleum, there are always some oil leaks. The contamination of leakage of petroleum can cause serious damage to the environment. The resulting layer of oil on the water's surface blocks sunlight and thus disrupts photosynthesis. As plants fail to do photosynthesis, they cannot produce oxygen, which leads to eutrophication and impacts the oxygen cycle that is essential for aquatic life. Moreover, the harmful compounds in waste oil pose a potential threat to marine animals, causing health risks for aquatic creatures and may even affect humans as these toxins move up the food chain [12].

4. Methodology

In this study, we have used various ways to analyze the change in water quality over time differently and how different factors contribute to the final level of water quality. The methods we use include standardizing data by using a z-score, making box plots for each factor by dividing them into different categories, and using linear regression to determine each factor’s weight to categorize water into different levels.

4.1. Z-score

Due to the reason that each factor has a different scale and unit, it is hard to analyze different data together. Also, as we have a very large amount of data, we assume the values of these data are normally distributed. Thus, what we do is to standardize these factors by using z-score. As z-scores don’t have any units and they have the same scale, it is really easy to compare them.

For the sample mean, suppose there is a variable X in a sample of size n, from a real-valued variable. The sample mean is the arithmetic average of the sample values.

$$Mean: \quad \bar{X} = \frac{\sum_{i=1}^{n} x_i}{N} \tag{1}$$

$\{X_i,\ i = 1,\ 2,\ \ldots,\ n\}$

For the variance, it is a measure of variability. Variance tells you the degree of spread in your data set. The more spread the data, the larger the variance is.

$$Var = \frac{\sum_{i=1}^{n} (x_i - \bar{X})^2}{N} \tag{2}$$

The standard deviation is also a measure of variability, it is calculated from the variance.

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$$S = \sqrt{Var} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{X})^2}{N}} \tag{3}$$

A z-score (also called a standard score) gives you an idea of how far from the mean a data point is. More technically, it's a measure of how many standard deviations below or above the mean a raw score is.

$$Z_i = \frac{\left(x_i - \bar{X}\right)}{S} \tag{4}$$

4.2. Linear regression

In the classification of water quality, each factor (pH, dissolved oxygen, chemical oxygen demand, inorganic nitrogen, active phosphate, petroleum) has its weight in determining the final quality value. Based on the numerical values of each factor and the final water quality level. We make a regression line to evaluate the water quality level of each site based on its factors.

Through linear regression, we can find a linear model that fits the dataset with coefficients w = (w1, …, wp) to minimize the residual sum of squares between the observed targets and the targets predicted by the linear approximation. By doing this, we can also receive each factor's weight.

$$\hat{y} = \epsilon + \sum_{i=1}^{n} w_i \times x_i \tag{5}$$

Through the process of finding the best-fit line, we want to make the residual sum of the square of the regression line as small as possible. Then, we can find the regression line that works the best.

$$RSS = \sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{6}$$

$$\text{Min (RSS)}$$

As the y-axis of the graph shows the predicted level of water quality and the x-axis shows the actual water quality level, the predicted value cannot be directly used to show the water quality level, because the prediction is a numerical value and the real value is categorical. Thus, we round the value we get from prediction and change them into discreet water quality levels.

$$round\left(x\right) = \begin{cases} \lceil x \rceil, \ if \ x - \lfloor x \rfloor \geq 0.5 \\ \lfloor x \rfloor, \ if \ x - \lfloor x \rfloor \leq 0.5 \end{cases} \tag{7}$$

By using the regression line, we can calculate a predicted value by inputting all factors in. For the prediction, a higher value represents worse water quality, and a lower value means better water quality.

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5. Statistical analysis

5.1. Statistical analysis about Z-score

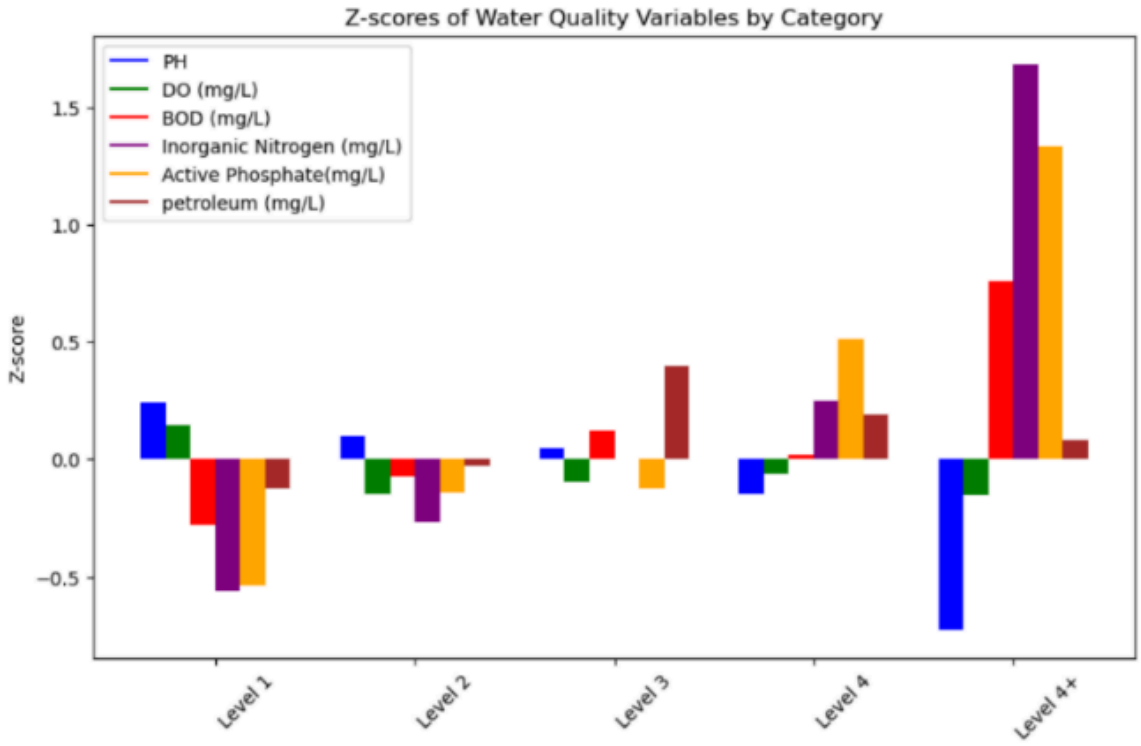

Figure 1. Z-scores for the water quality parameters, classified according to level

As shown in Figure1, the z-score indicates the distance between the data point and the mean, signifying the deviation and divergence of the datasets, making it more convenient to identify outliers. Moreover, it is crucial to acknowledge that direct comparison is misleading as the different factors (PH, DO, BOD, etc.) do not share the same scale, whereas adopting z-scores can standardize these values which supports a more conclusive comparison. To be more specific, a high absolute z-score for a particular parameter indicates it's significantly different from its typical range, suggesting it might have a greater impact on water quality compared to parameters with lower z-scores. From Figure 1, it is clear that some factors, including PH value, inorganic Nitrogen, and active phosphate, play very crucial role in determining the water quality level. On a contrary, some factors like DO and Petroleum don't show a significant difference between each water quality level, indicating that they may not be the determining factors in classification of water quality.

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5.2. Analysis of factors

5.2.1. PH

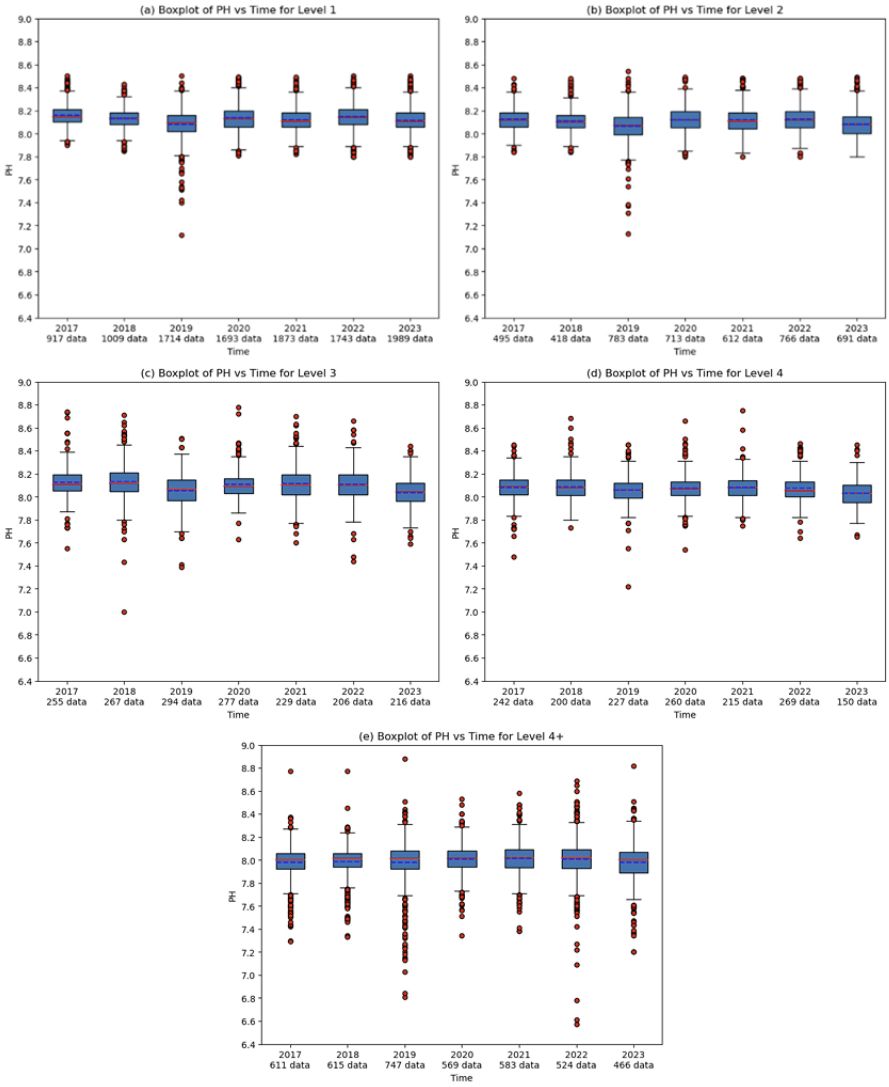

Figure 2. The boxplot of PH over time according to water quality level

The box plots in Figure 2 depict the temporal trends of pH across varying water quality levels. The analysis reveals a consistent range of average water quality values, fluctuating slightly between 8 and 8.2 across the years. Notably, across levels 1 to 4, the pH values exhibit a stable distribution, consistently ranging between 7 and 9. In contrast, the box plot for level 4+, representing the most compromised water quality, displays a significant outlier with a minimum pH value below 7, indicative of acidic conditions. These findings underscore the detrimental impact of low pH on water quality, reinforcing the notion that pH is a critical factor influencing overall water quality. Furthermore, it is crucial to acknowledge that pH can be affected by both natural and anthropogenic factors, including atmospheric deposition, industrial activities, and agricultural practices [13].

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5.2.2. Dissolved oxygen

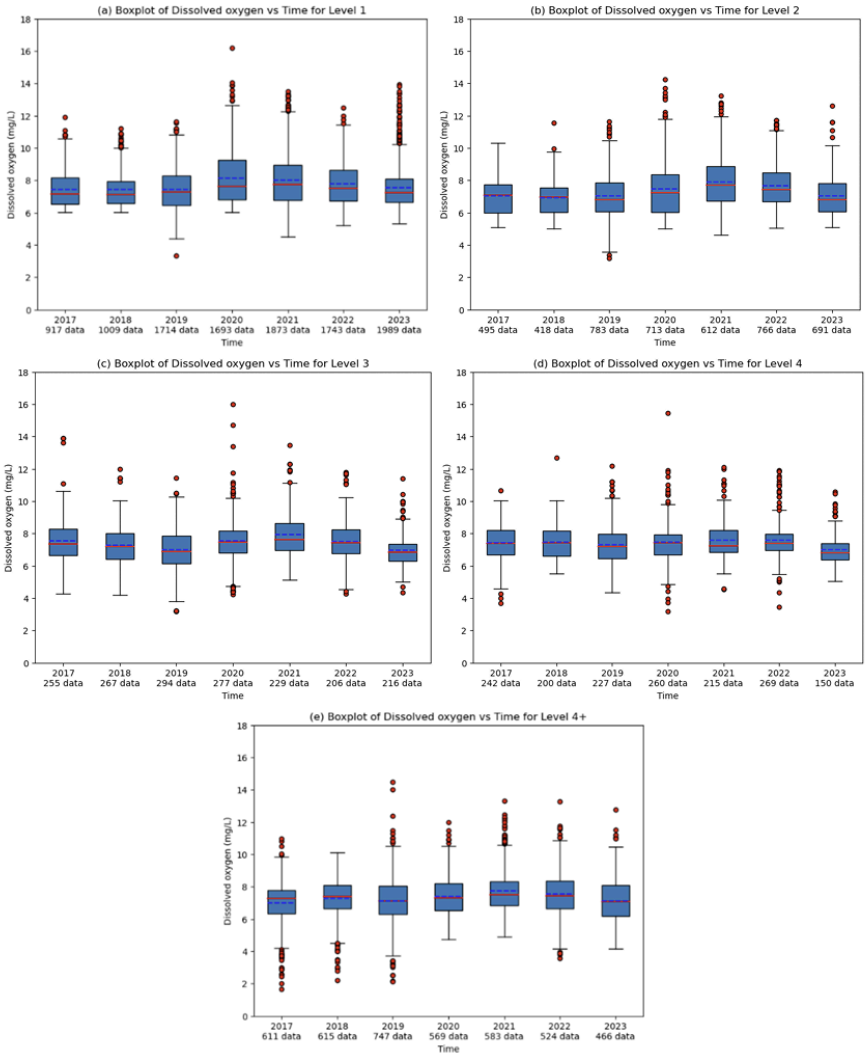

Figure 3. The boxplot of dissolved oxygen over time according to water quality level

The boxplots in Figure 3 illustrate the temporal trends of dissolved oxygen (DO) across different water quality levels. While the mean DO concentration remains relatively consistent at approximately 7 milligrams per liter, the maximum DO value in Level 1 appears to exceed those observed in other levels. Notably, the outliers in the Level 4+ plot predominantly fall below 5 milligrams per liter, suggesting a potential relationship between lower DO levels and poorer water quality. The concentration and spatial-temporal distribution of dissolved oxygen are influenced by a complex interplay of atmospheric exchange, photosynthetic activity, respiration, and mineral interactions [14].

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5.2.3. Chemical oxygen demand

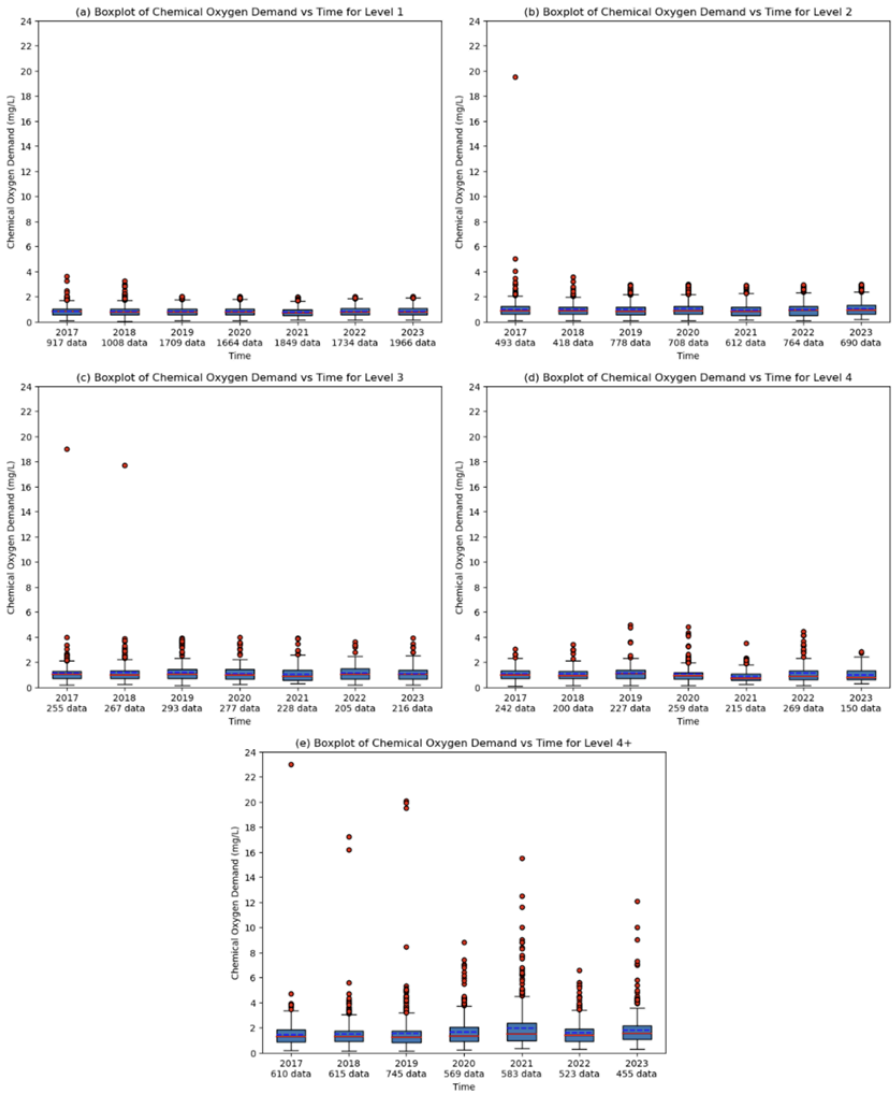

Figure 4. The boxplot of chemical oxygen demand over time according to water quality level

Box plots of chemical oxygen demand for each level were constructed to evaluate water quality over time and assess the impact of COD variation in Figure 4. According to the plots, we can figure out that more diverged outliers indicate worse water quality. In the worst water quality plot (Level 4+), its outliers were even distributed from 0 mg/L to 20 mg/L. Water with high COD typically contains high levels of decaying plant matter, human waste, or industrial effluent. This represents a stark contrast to Level 1, where the outlier with the highest value only reached 3.6. Additionally, the mean of COD increased slightly with the deterioration of water quality, but it is not very obvious.

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5.2.4. Inorganic nitrogen

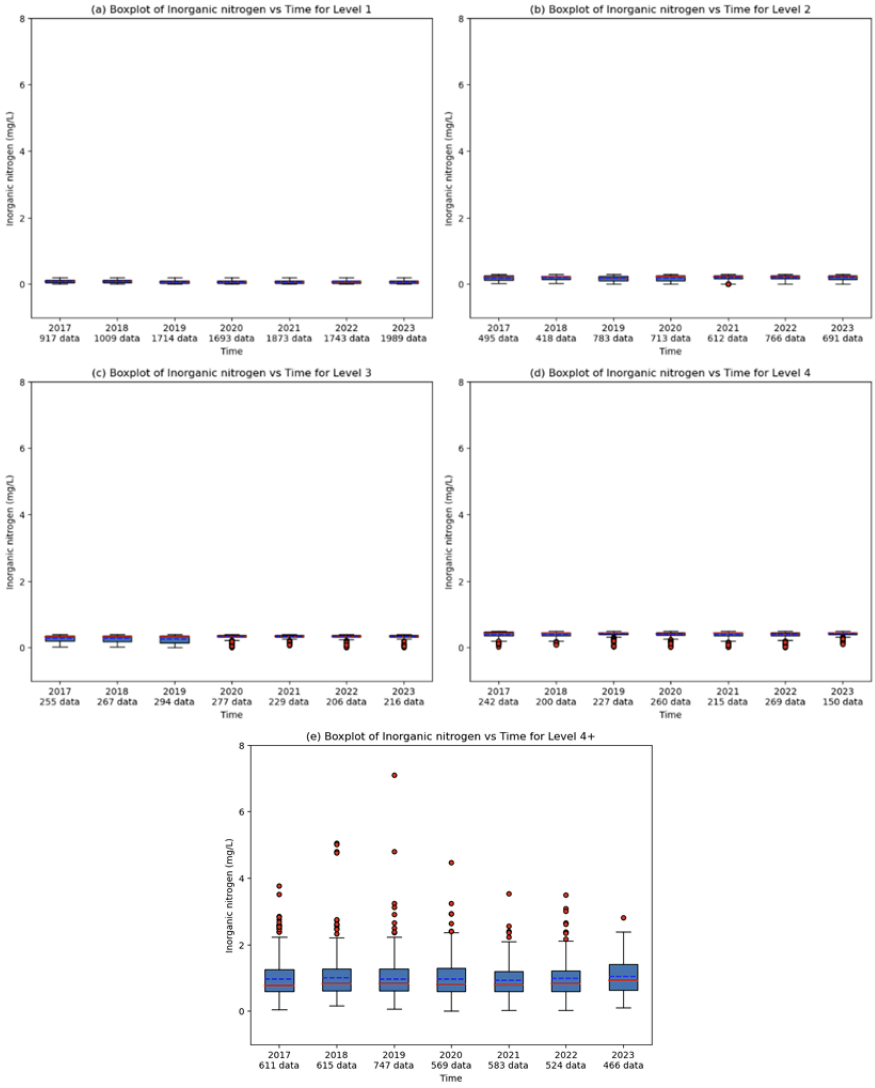

Figure 5. The boxplot of inorganic nitrogen over time according to water quality level

As illustrated in Figure 5, the box plots demonstrated the obvious inorganic nitrogen trends at different levels. From level 1 to level 4+, a notable increase in the mean value of Inorganic nitrogen was observed. Since Excessive amounts of nitrogen and phosphorus speed up the eutrophication process. When eutrophication occurs, algal and plant growth is stimulated, which results in a decline in water quality [15]. It can be concluded that with higher the inorganic nitrogen in the area, the worse the water quality is. Furthermore, when the water quality was at a good level, like Level 1 and Level 2, there is almost no outliers in the plot. On the contrary, in inferior water quality, the dispersion of outliers is markedly pronounced, like the outlier shown in level 4+. Thus, the inorganic nitrogen plays a crucial role in determining the water quality category.

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5.2.5. Phosphate

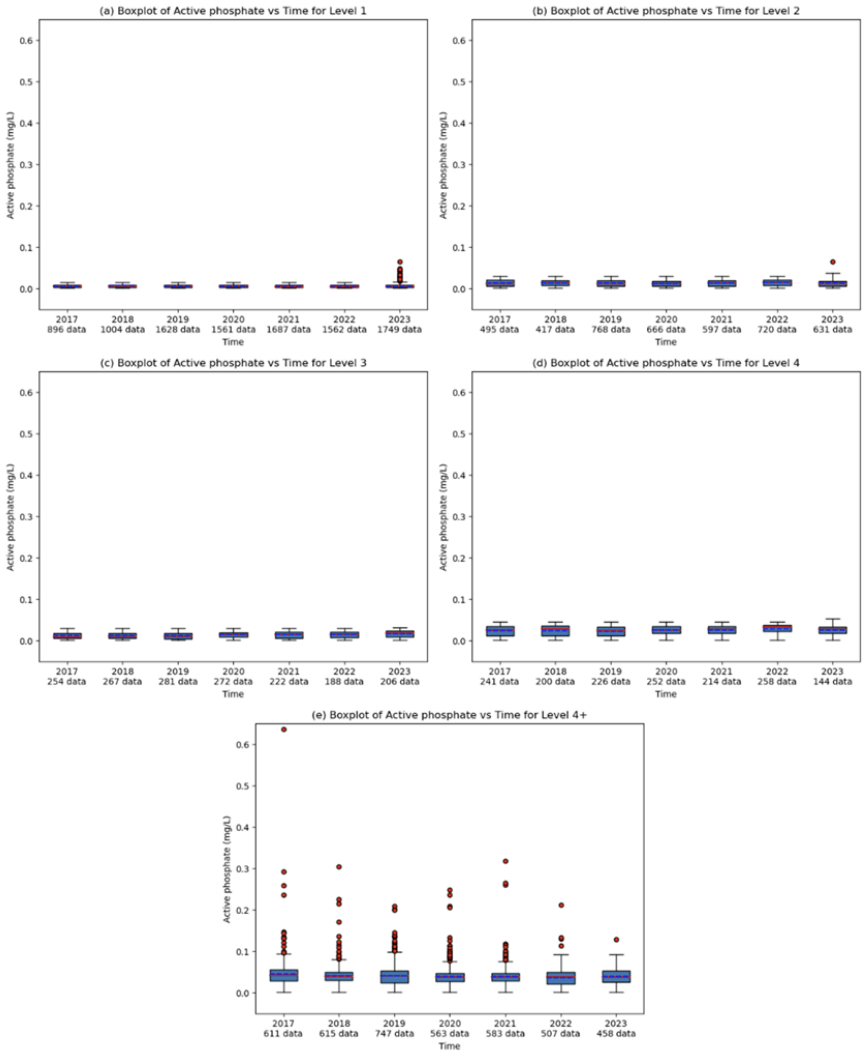

Figure 6. The boxplot of active phosphate over time according to water quality level

In Figure 6, as the level increases from 1 to 4+, the median active phosphate level generally increases, which is shown by the increasing red median lines. Moreover, higher levels tend to have greater variability in active phosphate levels, as indicated by the wider IQR in higher levels. Also, outliers are present at all levels, with a tendency to appear more frequently at higher levels and at specific time points. As the outliers in level 4+ are shown, the outlier with the highest value can reach 0.6, which is significantly higher than the outliers in level 1. Such appearance of phosphate indicates that this factor may play a very crucial role in determining the level of water quality since the value of Phosphate varies greatly among different water quality levels.

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5.2.6. Petroleum

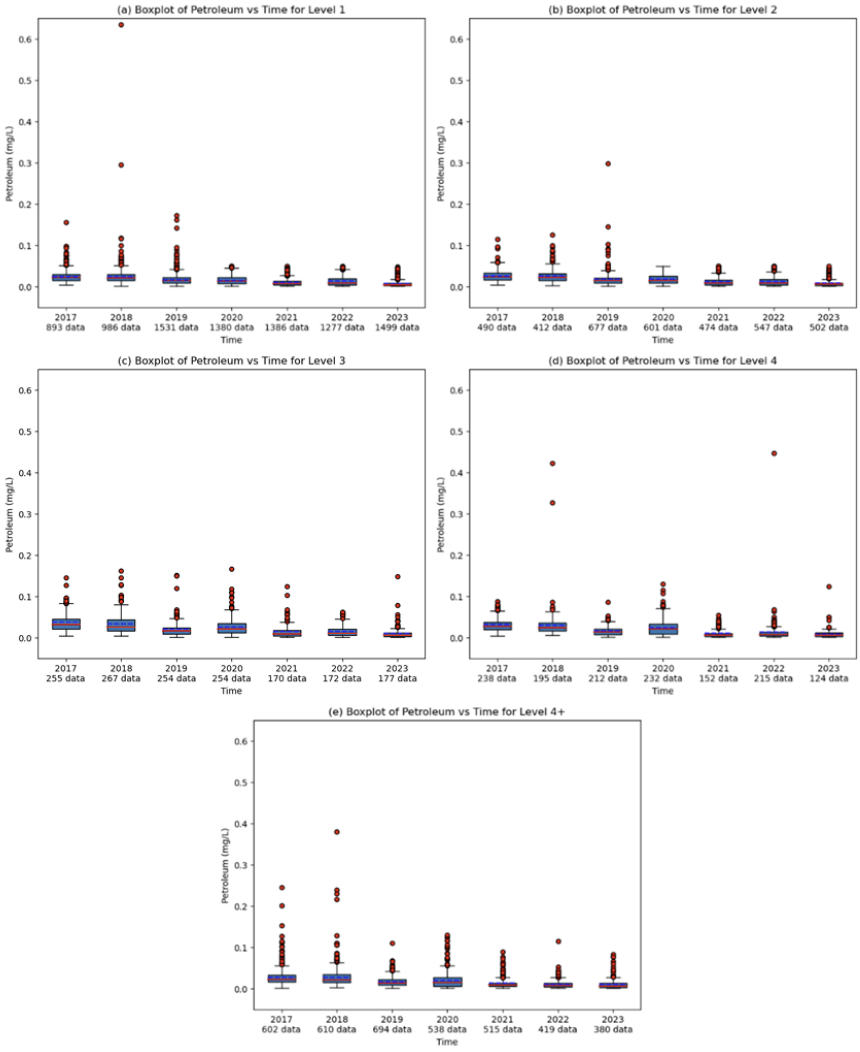

Figure 7. The boxplot of petroleum over time according to water quality level

Among these box plots from different water quality levels shown in Figure 7, levels 1 and 2 show consistently low petroleum levels with minimal variability and outliers. Levels 3, 4, and 4+ exhibit higher petroleum levels with significant variability and numerous outliers, indicating higher pollution levels. However, there is no clear increasing or decreasing trend in petroleum levels over the years for any level. The presence of outliers is more pronounced in certain years, for instance, 2018, 2019, and 2020, suggesting sporadic pollution events rather than a consistent trend. Still, certain years exhibit more outliers, indicating occasional high pollution events, just like in 2018.

6. Result

6.1. Spatial variations of water quality

In order to signify how the degree of pollution correlates with the specific location, we extracted data and combined them with the locations (longitudes and altitudes) provided by the database.

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Moreover, different colors were adopted to represent the five categorized levels. In this way, the overall tendencies of the variation in water quality, and the areas that are most severely afflicted by pollution can be shown visually and thus become more obvious.

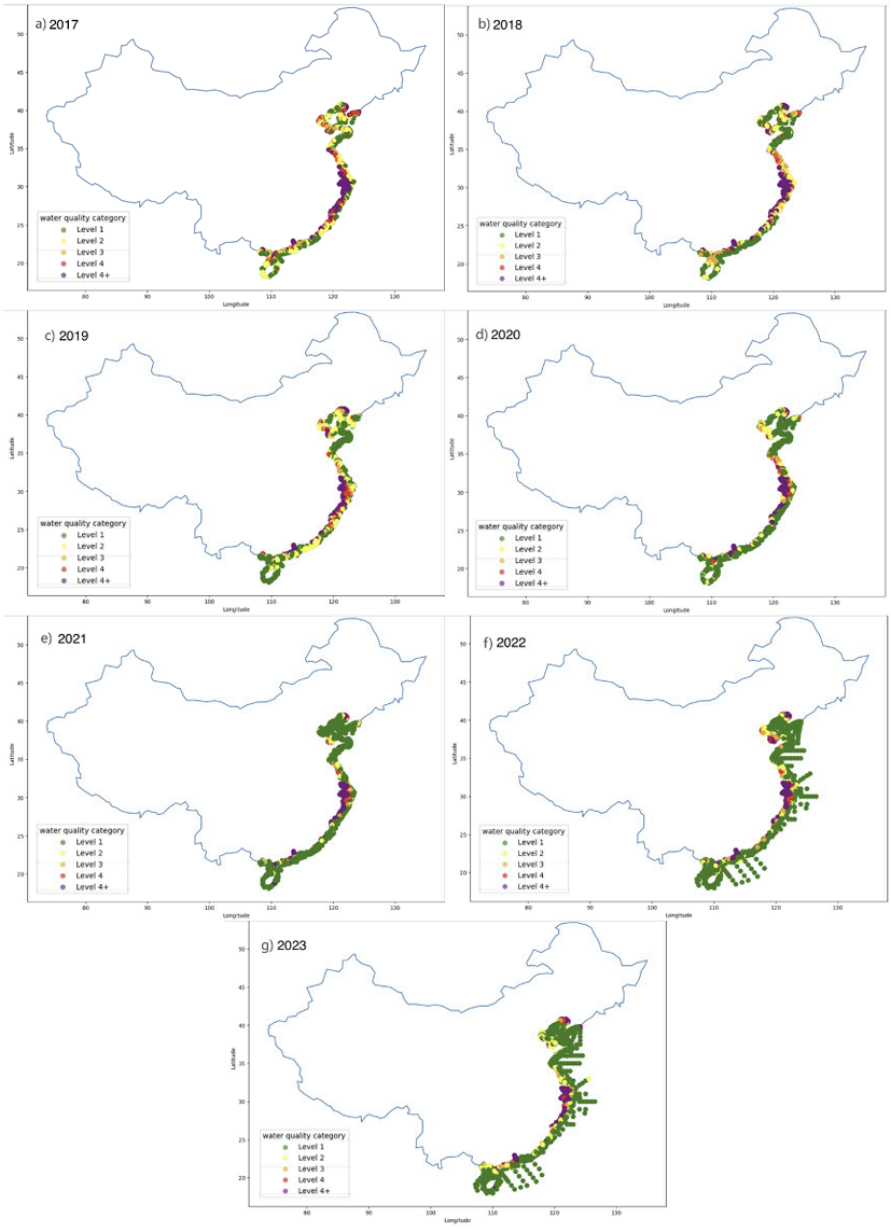

Figure 8. Spatial distributions of the water quality in coastal areas of China

As represented by Figure 8, it is obvious that the most industrially developed regions exhibit severe pollution since data points categorized as lower qualities mainly concentrate in regions such as the Yangtze River Delta and Pearl River Delta. To be more specific, the industries along the Yangtze River were highly developed; thus, the industrial contamination was eventually carried to the East China Sea. Moreover, the excess amount of water contamination often exceeds the treatment capacity, leading to even more complicated conditions such as ecosystem degradation.

In order to further demonstrate the factors affecting the quality of water, the average of the seven years' data were collected. In the diagrams shown in Figure 10, the darker colors were adopted to

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represent more severe pollution based on the appropriate quantities of each variable. To be more specific, dissolved oxygen, which can be simplified as DO, is crucial for the survival of all aquatic organisms. An abnormally low value of DO value is evidence of severe pollution, as the decomposition of organic matter undoubtedly consumes oxygen. Take Biochemical Oxygen Demand as another example. The BOD measures the amount of oxygen absorbed by microorganisms as a substance to decompose organic matter, which can be regarded as pollutants. In this way, an ideal aquatic ecosystem exhibits a lower BOD.

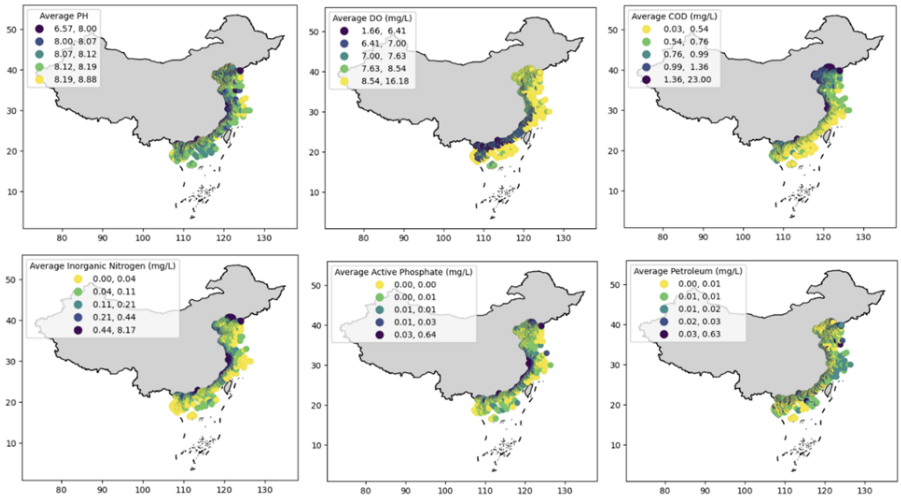

Figure 9. Spatial distribution of the average value (By time) of six aspects

Based on the results shown in figure 9, the darker-colored points consistently cluster to the most industrially developed regions, which mainly consist of the Yangtze River Delta and other major industrial estates. Among the six factors, DO levels, and the Inorganic Nitrogen levels demonstrated the most considerable variations with respect to regions.

However, it must also be acknowledged that an improving tendency in the overall water quality in the China Sea was revealed by the database, which can be explained by an increasing proportion of the data points categorized as “Level 1”. Well, this observation can be attributed to the significant increase in the government’s investment in water quality protection actions. A substantial increase in the investments in total environment restoration occurred, from almost nothing in the 1990s to 1000 billion RMB in 2014, and the investments aiming to address industrial pollution revealed a considerable change from 20 billion RMB in 1999 to 100 billion RMB in 2014[16]. Ineligibly, several challenges and obstacles may exist when carrying out the actual implementation of the water conservation policies. For instance, the rapid pace of urbanization and industrialization exerts pressure on conservation policies, while stricter regulations may interfere with industrial development. Therefore, it is necessary for the government to balance the various factors.

6.2. Regression line

As different regions may have confounding variables that alter the prediction of the regression line, we chose a specific location to do the regression, Jiangsu. We separated part of the data from Jiangsu as training data and used the rest as test data.

$$Regression Function: water\ quality = 1.8200 - 0.4107 * PH + 0.0568 * DO(mg/L) + 0.2927 * Chemical\ Oxy$$

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After computing out the regression line by using the training set. We have received the weight of each chemical factor in determining the final water quality level. Among all of the factors, the one that has the greatest weight is active phosphate, which is consistent with what we hypothesized before by observing the box plots. Despite phosphate, inorganic nitrogen, and petroleum also play very crucial roles in deciding the final water quality level, even though they are not as important as phosphate. The higher the phosphate, inorganic nitrogen, and petroleum levels, the water quality level becomes worse.

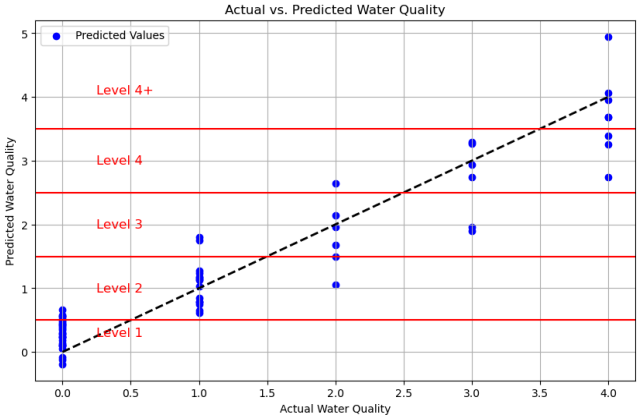

Figure 10. Scatter plot for the regression line

In Figure 10, we visualize the graph of the regression line. The x-axis includes the actual water quality level, and the y-axis includes the predicted water quality level. The red horizontal lines separate the graph into different categories and show how the points are determined by different water quality levels. In this graph, we can observe that a lower predicted value means better water quality level and a higher predicted value means worse water quality.

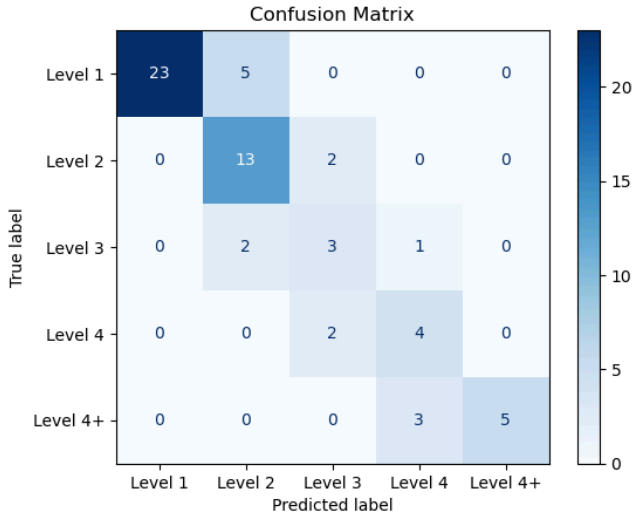

Figure 11. Confusion matrix for the prediction and true value

In this confusion matrix shown in Figure 11, there are predicted labels and true labels. The predicted label indicates the forecast made by the regression line based on the factors, while the true label reflects the actual water quality level. For example, if the predicted label is level 1, it signifies that the regression line predicts that these data sites have water quality level 1. If the true label also

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indicates level 1, it means that the linear model has correctly classified the data. The matrix, shows there are 23 data sites with actual water quality level 1 that are correctly classified into level 1 in the predicted label.

7. Discussion

Based on Figure 10, it is evident that we are unable to accurately classify the predicted values into distinct categories. Some data points from level 1 are misclassified as level 2, some from level 2 as level 3, and so on. A basic rounding approach is insufficient for achieving precise classification of water quality, as the predicted values for the same level can differ significantly. Therefore, there is room for enhancement in utilizing linear regression for improved classification tasks.

Also, in Figure 11 the confusion matrix again shows some limitations we have encountered in our classification of water quality. Still, we can successfully classify most water into the correct quality level. For future studies, we can try to use a non-linear way to do classification, which may increase the accuracy of classification.

8. Conclusions

In our work, the water quality of 11 coastal provinces in China was evaluated using z-score and six indices: pH, dissolved oxygen, chemical oxygen demand, inorganic nitrogen, phosphate, and active phosphate at varying levels. The results suggest that the PH value, inorganic nitrogen, and active phosphate are the most significant indexes for assessing the water quality. In a given area, as the concentration of inorganic nitrogen and active phosphate increase and PH value decrease, the quality of the water will deteriorate. Additionally, by analyzing the spatial variations of water quality, we reached the conclusion that the regions with the highest levels of industrial development exhibited the worst water quality, like the industries along the Yangtze River. Also, it indicated that only in conditions of low dissolved oxygen and chemical oxygen demand, we can reach to an ideal aquatic ecosystem. However, as coastal regions face increasing pressures from industrialization and urbanization, it is imperative to enhance our predictive capabilities. Thus, we predicted the future water quality using linear regression and a confusion matrix. The finding showed that in Jiangsu, there are 23 data sites with actual water quality level 1 that are correctly classified into level 1 in the predicted label, and only 5 data sites are correctly classified as level 4+ by our model, which means there is a discernible improvement in the overall water quality in coastal areas of China. After all, the collaborative efforts between government agencies, research institutions, and local communities are essential for the successful improvement of the water quality in China. The following recommendations could be taken into consideration for improving water quality: The total amount of pollutants discharged by factories along rivers and seas should be limited. Also, the government should balance the pace of urbanization and industrialization with water protection. In the future study, we could try to use a non-linear way to do classification with the objective of increasing the accuracy of the classification.

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Yaocheng Wang is the first author, Xinyi Wang, Shuhan Jiang and Yinyuan Li contributed equally to this work and should be considered co-second authors.

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