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Dynamics of the Estuarine Zone of the Ebrié Lagoon (Abidjan - Ivory Coast) and Transparency Prediction

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Abstract: In order to contribute to the effective fight against eutrophication of the Ebrié lagoon estuarine waters, the present study proposed a mathematical model to predict water transparency based on five physico-chemical descriptors (temperature, dissolved oxygen, nitric nitrogen N-NO_3^-, nitrous nitrogen N-NO_2^- and ammoniacal nitrogen N-NH_4^+). On twenty-seven (27) water samples collected from 2014 to 2015, in situ measurements and physico-chemical analyses were carried out based on French standards. All the data collected was subjected to a multiple linear regression analysis. The proposed linear model is accredited with good statistical indicators. These statistical indicators revealed effective predictions with a coefficient of determination (R^2 = 0.9308) close to one; a standard deviation (RMSE = 0.1311) of less than 0.3; a cross-validation coefficient of determination (Q^2_{CV} = 0.9256) of more than 0.9; and a Fischer test p-value of less than 0.0001. Furthermore, the values of the ratio of theoretical to experimental transparency of the validation set tend towards one. The results obtained suggest that the combination of these 5 descriptors could be useful for predicting transparency. Moreover, dissolved oxygen is the priority descriptor for the prediction of the transparency of the Ebrié lagoon, although the influence of the other descriptors is not less important.

Keywords: Ebrié Lagoon, Eutrophication, Modelling, Multiple Linear Regression, Physico-Chemical Descriptors, Transparency

1. Introduction

Since the 1980s, the waters of the Ebrié lagoon have been declared by several studies as highly eutrophic. This eutrophication, one of the major problems identified in the Ebrié lagoon, is the result of the large quantity of nutrients, mainly nitrogen and phosphorus, and the input of organic matter [1-7]. The effects of this eutrophication are manifested by sulphurous odours, massive fish mortality, anoxia and hypoxia, and reservoirs of pathogenic microorganisms, with the corollary of epidemics. Excessive inputs of nitrogen and phosphorus nutrients lead to several types of environmental disturbances, including a decrease in the oxygen level in the water, which can lead to anoxia and a decrease in water transparency [8, 9]. The study conducted in the estuarine zone of the Ebrié Lagoon by Akilinon [7] revealed a state of advanced eutrophication. In addition, the trophic level of the waters in this area, given the low values of transparency, corresponds to a eutrophic to hypereutrophic state. Thus, transparency seems to be a parameter that reflects the impact of eutrophication on lagoon waters. The fight against eutrophication in the Ebrié lagoon is based on increased monitoring of the physical-chemical and biological quality of the lagoon. This monitoring, which is essential, appears to be costly in terms of equipment and reagents [10] and must be carried out over a sufficiently long period of time to take into account the temporal variability of the phenomenon [11]. It is therefore necessary, for the effectiveness of this control, to associate mathematical models which are real decision-making tools for managers by simulating the response of the environment to the various environmental measures. These models enable progress to be made in understanding the processes at work [12]. According to INRA [13], modelling is a means of explaining complexity in order to better understand the functioning of a system and to make decisions concerning it. Several mathematical models have been developed to understand and represent the dynamics of the eutrophication phenomenon. Some have been used to estimate eutrophication risks, while others have been used to assess the necessary reduction of nutrient inputs [14]. However, so-called statistical models seek to predict one or more descriptors of eutrophication as a function of causal variables measured on the research [15, 16]. This statistical approach makes it possible to use methods such as linear regression which, through mathematical equations involving parameters, makes it possible to explain or predict a variable which is a dependent variable by explanatory variables which are independent variables [17]. Since transparency seems to reflect the environmental response to ecological disturbances, its modelling appears necessary.

The general objective of this study is to develop a statistical model using multiple linear regression that can be used as a tool for forecasting, planning and decision-making in the fight against eutrophication of the waters of the Ebrié Lagoon. Specifically, the aim is to identify environmental variables capable of explaining and predicting the transparency of these waters.

2. Material and Methods

2.1. Presentation of the Study Area

Located in the central part of the Ivorian lagoon system and stretching from east to west over 130 km with a width of 7 km, the Ebrié Lagoon is situated between 3°40' and 4°50' west longitude and 5°02' and 5°42' north latitude. This lagoon comprises six more or less homogeneous sectors [18, 19], including an estuarine sector directly subject to oceanic influence and where the activities of the Abidjan agglomeration have the greatest impact. This sector, which constitutes our study area, has an average depth of 4.5 m [7], a surface area of 71 km^2 with a volume of 0.32 billion m^3, i.e. 12% of the total volume of the lagoon [18]. This area is highly anthropised with an estimated population of 4,395,243 inhabitants in 2014 compared to 2,877,948 in 1998 [20]. According to Ané [21], the Ebrié Lagoon estuary is exposed to discharges from industrial activities in the various communes of Abidjan that it borders. Figure 1 shows a map of the study area with the different sampling sites.

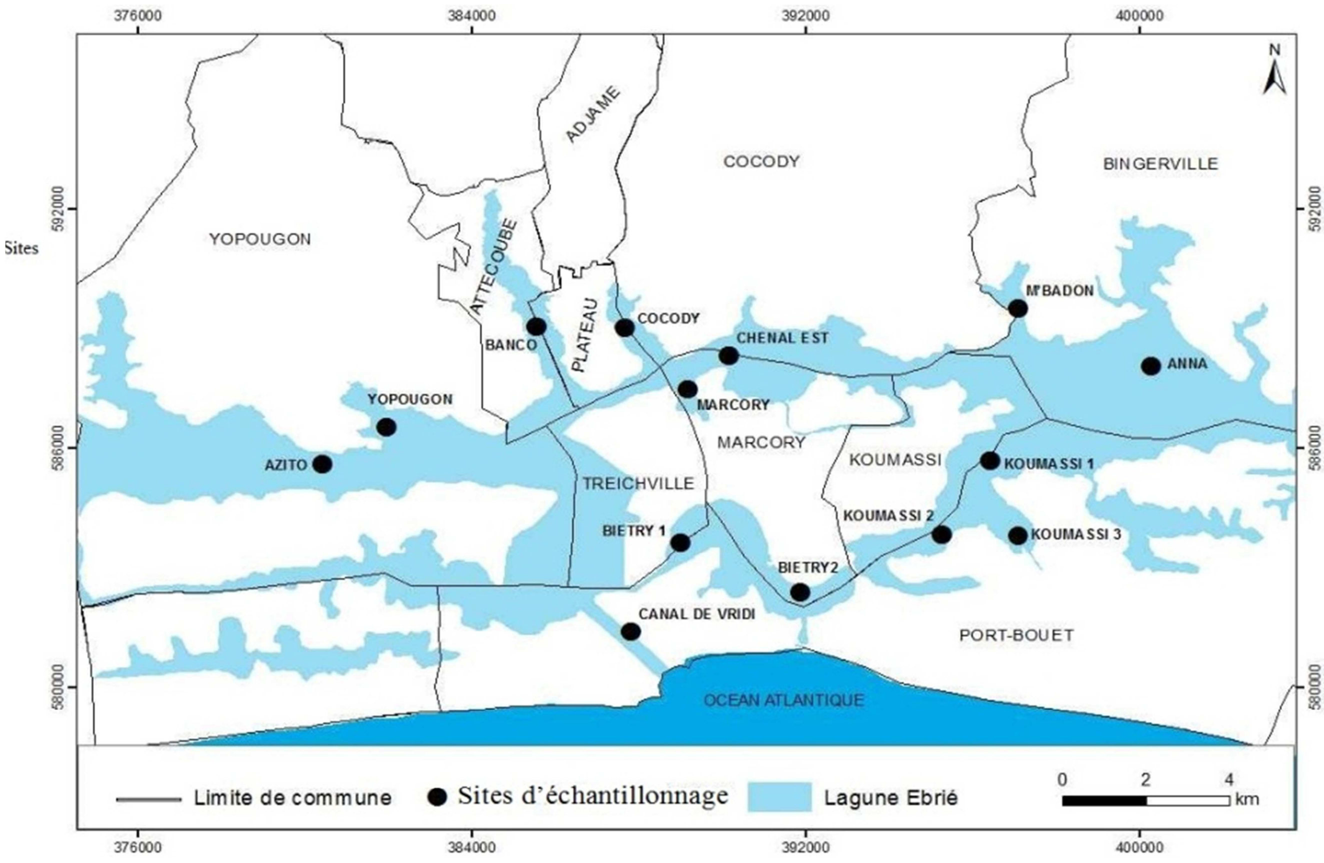

Figure 1. Map of the study area.

2.2. Physico-Chemical Descriptors

Water transparency was measured using a weighted metal Secchi disc attached to a graduated rope. The disc, immersed in the water until it disappeared, was then raised by means of its string until it was visible again. The distance at which it becomes visible again determines the depth of the sampling point. The measurements carried out three (03) times at each sampling point give an average value which is taken as the transparency value [7, 22]. The physico-chemical descriptors considered most relevant for the transparency model were selected using the step-by-step method [23]. This method consists of incorporating the variables into the model one by one, selecting at each stage the variable whose partial correlation with the modelled quantity allows the coefficient of determination (R^2) to be increased. At each stage, the significance of the partial correlations of the previously introduced variables is verified [24]. Thus, temperature, dissolved oxygen, nitric nitrogen ($N\text{-}NO_3^-$), nitrous nitrogen ($N\text{-}NO_2^-$) and ammoniacal nitrogen ($N\text{-}NH_4^+$) are the physico-chemical descriptors taken into account in the model. These descriptors are indicators of eutrophication in lagoon waters. According to Ifremer [11], temperature influences many physical and biological processes and its increase can cause sediment anoxia resulting in the release of nutrients. Dissolved oxygen is the result of physical, chemical and biological phenomena, particularly production by photosynthesis and consumption by respiration. As for the inorganic forms of nitrogen ($N\text{-}NO_3^-$, $N\text{-}NO_2^-$ and $N\text{-}NH_4^+$), their excess contributes to accelerating eutrophication processes depending on the conditions of the environment, with serious consequences for water quality and the life of aquatic species [25]. These different physico-chemical descriptors were determined by Akilinon *et al* [6]. The modelling was done using the multiple linear regression method implemented in Excel spreadsheet version 2016 and XLSTAT version 2014.

2.3. Estimating the Predictive Capacity of a Model

The quality of a model is determined by taking into account various statistical indicators such as the coefficient of determination (R^2), the standard error (RMSE), the Fischer test (F) and the cross-validation coefficient of determination (Q^2_{CV}). These indicators provide information on the fit between theoretical and experimental values. They allow the quality of the model to be assessed and its accuracy to be expressed [26]. The coefficient of determination R^2 is an index of the quality of the model's prediction; it gives an evaluation of the dispersion of the calculated values around the experimental values. The quality of the model is better when the points evaluated by R^2 are close to the fitting line. The closer the R^2 value is to one (1), the better the calculated and experimental values are correlated.

The coefficient of determination (R^2) is given by the expression:

$$R^2 = 1 - \frac{\Sigma\left(y_{i,exp} - \hat{y}_{i,théo}\right)^2}{\Sigma\left(y_{i,exp} - \bar{y}_{i,exp}\right)^2} \quad (1)$$

As for the standard error or standard deviation (RMSE), it is used to assess the reliability and accuracy of the model. It is expressed as follows:

$$RMSE = \sqrt{\frac{\Sigma\left(y_{i,exp} - y_{i,théo}\right)^2}{n-k-1}} \quad (2)$$

The Fischer F-test is useful for choosing the descriptors that make up the model and measures their statistical significance. The Fischer test is given by the mathematical equation.

$$F = \frac{\Sigma\left(y_{i,théo} - y_{i,exp}\right)^2}{\Sigma\left(y_{i,exp} - y_{i,théo}\right)^2} * \frac{n-k-1}{k} \quad (3)$$

The coefficient of determination of the cross-validation evaluates the accuracy of the prediction. It is obtained by the equation:

$$Q^2_{CV} = \frac{\Sigma\left(y_{i,théo} - \bar{y}_{i,exp}\right)^2 - \Sigma\left(y_{i,théo} - y_{i,exp}\right)^2}{\Sigma\left(y_{i,théo} - \bar{y}_{i,exp}\right)^2} \quad (4)$$

In these equations, k is the number of descriptors, n is the number of observations in the test set and n-k-1 is the degree of freedom [27].

$y_{i,exp}$ is the experimental transparency value, $\hat{y}_{i,théo}$ is the theoretical transparency value and $\bar{y}_{i,exp}$ is the experimental mean transparency value.

2.4. Statistical Analysis

The statistical analysis method used in this study is multiple linear regression (MLR). This regression is a statistical technique used to study the relationship between a dependent variable called property and several independent variables called descriptors. This statistical method minimises the differences between the experimental and predicted values [23, 14]. The MLR method is based on the assumption that the property y depends linearly on the different descriptors x_1, x_2, …. x_i, according to the relationship:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i \quad (5)$$

y is the dependent variable or variable to be explained or property; x_i are the independent variables or explanatory variables or descriptors; n is the number of explanatory variables; a_0 is the constant of the model equation; a_i are the coefficients of the descriptors in the model equation. The size of these coefficients indicates the degree of influence of the corresponding descriptors on the property. A positive coefficient indicates that the corresponding descriptor contributes positively to the property, while a negative coefficient suggests a negative contribution [28].

2.5. Model Acceptance Criterion

The closer the coefficient of determination R^2 is to one (1), the better the linear regression fits the collected data. A predictive model is acceptable when the root mean square error RMSE is less than 0.3 [23]. Furthermore, according to these authors, the number of descriptors in a model is declared acceptable if the difference $|R^2 - R^2_{adjusted}|$ is less than 0.3. The predictive accuracy of a model is said to be satisfactory for a value of the coefficient of determination of the cross-validation Q_{cv}^2 greater than 0.5 and excellent for a value of the coefficient greater than 0.9 [29]. Finally, a model will perform well if the acceptance criterion $|R^2 - Q^2_{CV}| < 0.3$ is met [30].

3. Results and Discussion

3.1. Results

3.1.1. Physico-Chemical Descriptors

Eighteen (18) water samples (observations) were used to calibrate the model (training set) and nine (09) others for its validation (validation set). All the values of the physico-chemical descriptors measured (temperature, dissolved oxygen O_2, nitric nitrogen $N\text{-}NO_3^-$, nitrous nitrogen $N\text{-}NO_2^-$ and ammoniacal nitrogen $N\text{-}NH_4^+$) and those of the variable to be explained (transparency) are recorded in Table 1. In this study, five (05) descriptors were retained and the transparency of the twenty-seven (27) observations shows a variation ranging from 0.50 m to 1.80 m.

Table 1. *Physico-chemical descriptors and transparency of the training and validation sets.*

Observations	Temperature (°C)	O_2 (mg/L)	$N\text{-}NO_3^-$ (mg/L)	$N\text{-}NO_2^-$ (mg/L)	$N\text{-}NH_4^+$ (mg/L)	Transparency (m)
Training Set						
1	27,620	4,750	0,023	0,335	1,711	1,000
2	27,210	0,070	0,090	0,243	1,556	1,800
3	28,540	0,330	0,429	0,213	2,567	1,200
4	27,650	7,460	0,158	0,274	0,311	0,900
5	27,270	7,500	0,903	0,457	0,311	0,500
6	27,850	3,950	0,903	0,274	0,622	0,500
7	27,970	4,980	0,023	0,304	2,333	1,000
8	28,820	3,710	0,294	0,002	0,233	1,000
9	28,880	2,170	0,610	0,006	0,156	1,000
10	28,990	1,920	0,158	0,020	0,062	1,600
11	29,710	4,470	0,203	0,013	0,933	0,800
12	31,590	1,650	0,181	0,002	0,700	1,800
13	31,070	2,190	0,271	0,002	0,156	1,700
14	31,630	5,860	0,248	0,005	0,117	0,900
15	31,520	6,150	0,158	0,008	0,031	0,900
16	31,770	1,470	0,316	0,002	0,272	1,700
17	32,290	3,150	0,203	0,002	1,128	1,300
18	30,180	2,110	0,203	0,007	1,322	0,900
Validation Set						
19	27,340	7,810	0,226	0,243	0,389	0,500
20	27,300	7,560	0,677	0,426	0,622	0,500
21	28,080	7,270	0,452	0,670	1,556	1,000
22	28,960	4,580	0,339	0,013	0,319	0,600
23	29,990	5,090	0,271	0,002	0,156	0,800
24	29,180	4,630	0,023	0,020	0,062	1,300
25	28,900	2,250	0,045	0,014	0,233	1,200
26	30,660	2,230	0,068	0,007	0,117	1,500
27	31,270	0,600	0,339	0,004	0,194	1,500

3.1.2. Multiple Linear Regression Model

The equation of the multiple linear regression model expressing the transparency of the water as a function of the different parameters measured is given below:

$$Transp. = -1.59281 + 0.12880*Temperature - 0.20948*O_2 - 1.11100*N\text{-}NO_3^- + 2.63224*N\text{-}NO_2^- - 0.38016*N\text{-}NH_4^+$$

In this equation, a positive coefficient indicates that the transparency evolves in the same direction as the descriptor; this is the case for temperature (+ 0.12880) and nitrous nitrogen (+ 2.63224). However, a negative coefficient indicates that transparency evolves in the opposite direction of the descriptor; this is the case for dissolved oxygen (- 0.20948), nitric nitrogen (- 1.11100) and ammoniacal nitrogen (- 0.38016).

Figure 2 shows the linear regression line between the experimental and theoretical values of water transparency for the training and validation sets. The scatterplot practically follows a straight line with the equation.

$$y = 0.9308\ x + 0.0788.$$

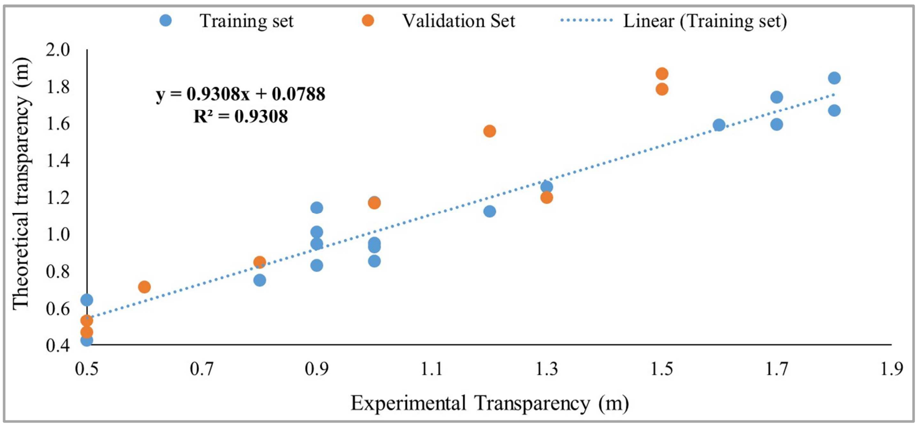

Figure 2. *Multiple linear regression line with test and validation sets.*

3.1.3. Predictive Ability of the Multiple Linear Regression Model

The values of the statistical indicators and the result of the Fisher test of the multiple linear regression are reported in Table 2. On analysis, the coefficient of determination R^2 (0.9308) is close to one (1), the root mean square error RMSE (0.1311) is less than 0.3 and the cross-validation correlation coefficient Q^2_{CV} (0.9256) is greater than 0.9. The model has a Fisher test p-value of less than 0.0001. We also note that: $|R^2 - Q^2_{CV}| = 0.0052$ and $|R^2 - R^2_{Adjusted}| = 0.0288$. Both differences are less than 0.3.

Table 2. *Statistical indicators and test of the multiple linear regression model.*

Statistical indicators				Fisher test	
R^2	$R^2_{Adjusted}$	RMSE	Q^2_{CV}	F	p-value
0,9308	0,9020	0,1311	0,9256	32,2835	< 0,0001

3.1.4. Validation of the Multiple Linear Regression Model

The validation test was verified by calculating the ratio of the theoretical to the experimental Transparency of the multiple linear regression model. The results of this calculation are given in Table 3. The calculated ratio values are approximately equal to one (1).

Table 3. *Values of the ratio between theoretical and experimental values of the transparency of the validation set.*

Observations	Transp exp	Transp theo	Transp theo / Transp exp
19	0,5000	0,5347	1,07
20	0,5000	0,4721	0,94
21	1,0000	1,1703	1,17
22	0,6000	0,7155	1,19
23	0,8000	0,8482	1,06
24	1,3000	1,1998	0,92
25	1,2000	1,5569	1,30
26	1,5000	1,7878	1,19
27	1,5000	1,8684	1,25

Figure 3 shows the similarity curves between the theoretical and experimental values of transparency. The two curves have almost the same shape despite some deviations observed.

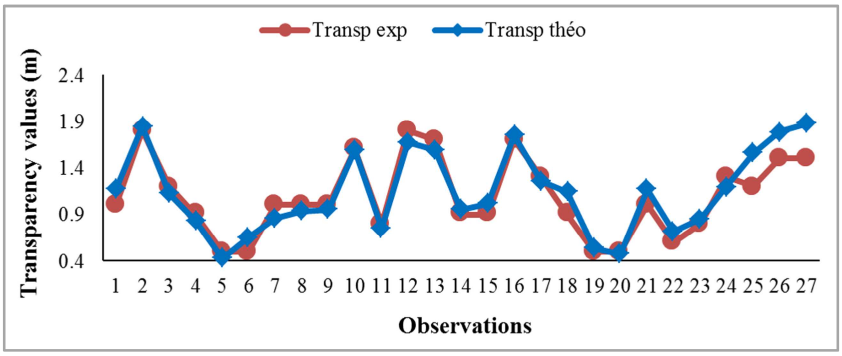

Figure 3. *Similarity curves of the multiple linear regression model.*

3.1.5. Contribution of Physico-Chemical Descriptors

The contributions of the five (05) physico-chemical descriptors in the prediction of water transparency are illustrated in Figure 4. This figure shows that temperature (+0.5437) and nitrous nitrogen $N\text{-}NO_2^-$ (+0.9725) contribute positively to transparency, while dissolved oxygen O_2 (-1.1285), nitric nitrogen $N\text{-}NO_3^-$ (-0.6883) and ammoniacal nitrogen $N\text{-}NH_4^+$ (-0.7241) contribute negatively. The figure also shows that dissolved oxygen contributes most to transparency, followed by nitrous nitrogen. The contributions of temperature, nitric nitrogen and ammoniacal nitrogen are non-negligible with normalised coefficients greater than 0.5 in absolute value. Thus, on the basis of the standardised coefficients, the physico-chemical descriptors are ranked from the most to the least contributory according to the following sequence: Dissolved oxygen > $N\text{-}N0_2^-$ > $N\text{-}NH_4^+$ > $N\text{-}N0_3^-$ > Temperature.

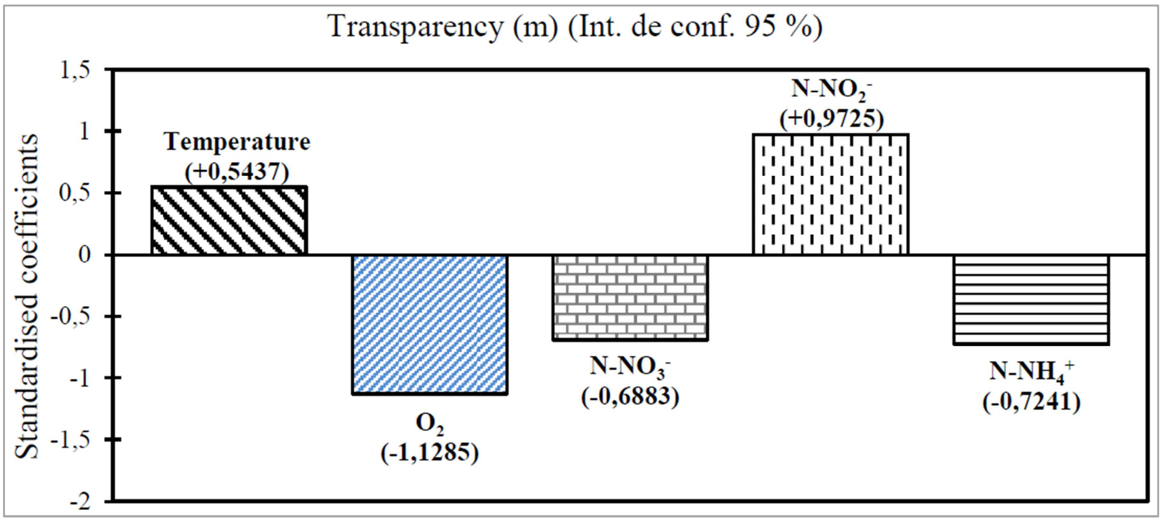

Figure 4. *Contribution of physico-chemical descriptors in the model.*

3.2. Discussion

The proposed model took into account five (05) physico-chemical descriptors. This number is in accordance with the rule of thumb which states that the number of descriptors should not exceed one fifth of the total number of observations used [24, 31-33]. Furthermore, we observe that $|R^2 - R^2_{adjusted}| = 0.0288$; this difference being less than 0.3, we can, according to Kombo *et al* [23], declare the number of descriptors taken into account acceptable. The high values of the coefficients of determination R^2 (0.9308) and adjusted determination $R^2_{adjusted}$ (0.9020) and the low value of the mean square error RMSE (0.1311) indicate that the proposed model is predictive and reliable. Indeed, the two coefficients of determination are close to one (1), which reflects a good correlation between the predicted values and the experimental values of the transparency; this shows that the established model is stable. This result is in agreement with that of the research of Diudea [34] which suggests that when the value of R^2 is greater than 0.9 and therefore close to 1, which is an ideal case, then the established model is better. Secondly, given the value of R^2 (0.9308), it can be observed that more than 93% of the variability in transparency is explained by the descriptors used. Finally, knowing that the root mean square error or standard error RMSE is to the multilinear regression coefficient what the standard deviation is to the mean of a variable, its estimation could be a measure of the dispersion of the observed transparency values on the regression line. The latter (RMSE = 0.1311), which is low for the established model, would reflect a good statistical fit of the model and a high reliability of the prediction, according to Guendouzi [35]. The statistical significance of the model was measured using the Fisher test. This test recorded a p-value of less than 0.0001. This means that the model established is globally significant. Thus, the selected physico-chemical descriptors (temperature, dissolved oxygen, nitric nitrogen, nitrous nitrogen and ammoniacal nitrogen) provide a highly significant amount of information to the model. The resulting model was validated internally using the Q^2_{CV} cross-validation correlation coefficient. The value of this coefficient, which is 0.9256, reveals that the predictive capacity of the model is excellent [29]. Moreover, the difference between the coefficients of determination and cross-validation is less than 0.3. According to Veerasamy *et al* [30], this observation highlights the robustness and performance of the established model. The external validation test was verified by calculating the ratio Transp theo / Transp exp. The values of this ratio tend towards one, reflecting a good correlation between theoretical and experimental transparency. The similar evolution of the latter has also been shown by the similarity curves, which show the same trend despite some deviations that may be due to measurement errors on observations [33]. The proposed model is therefore acceptable for the prediction of the transparency of the waters of the Ebrié lagoon. The exploitation of the equation of the established model makes it possible to observe that the transparency evolves in the same direction as the temperature and the nitrous nitrogen. However, it is inversely proportional to dissolved oxygen, nitric nitrogen and ammoniacal nitrogen. This observation is in agreement with the contributions of the different descriptors obtained in the prediction of transparency. It is also observed that dissolved oxygen is the most influential descriptor in this prediction. All descriptors have normalised coefficients greater than 0.5 in absolute value. This reveals the fact that these descriptors, which are eutrophication variables, have a considerable impact on water transparency. This situation is comparable to that described by Durand *et al* [8], Grizzetti *et al* [9] and Akilinon [7].

4. Conclusion

This study allowed the establishment of a mathematical model for the prediction of the transparency of the surface waters of the estuarine zone of the Ebrié lagoon from five (5) physico-chemical descriptors. These descriptors are temperature, dissolved oxygen, nitric nitrogen $N\text{-}NO_3^-$, nitrous nitrogen $N\text{-}NO_2^-$ and ammoniacal nitrogen $N\text{-}NH_4^+$. The analysis of the robustness and performance of the model showed the following results: the coefficient of determination R^2 (0.9308) is close to one (1), the standard deviation RMSE (0.1311) is less than 0.3, the Fischer test registers a p-value less than 0.0001 and the cross-validation correlation coefficient Q^2_{CV} (0.9256) is higher than 0.9. These results showed that the multiple linear regression model has good stability and excellent predictive power. Furthermore, the model revealed that the descriptors used have a good influence in the prediction of the transparency of the waters of the Ebrié lagoon and that dissolved oxygen is the priority descriptor in this prediction.

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