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Monitoring of the water quality of Lake Blidinje and examination of the prognostic model

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Abstract: The largest mountainous lake in Bosnia and Herzegovina, Lake Blidinje, is located 1,185 meters above sea level. Polymictic lakes are those in which the entire water column is frequently mixed. Shallow lakes function very differently than deep lakes in many ways because of the strong sediment–water interaction and the possibility for significant water impact on vegetation. In the multiple regression analysis, two models were developed with coefficients of multiple determination (R^2 = 0.720 and R^2 = 0.497) for the independent variable chlorophyll a. The resulting models are compared with water quality monitoring data from 2017 to 2019.

Keywords: physical-chemical indicators, multiple regression analysis

1. Introduction

The largest mountainous lake in Bosnia and Herzegovina, Lake Blidinje, is located 1,185 meters above sea level. According to Directive 2000/60/EC of the European Parliament and the Council [1] of the Western Balkans, Lake Blidinje is categorized as belonging to the fifth ecoregion for rivers and lakes in the Dinaric Alps. When Krasić and Zelenika [2] investigated ways to preserve the waters of Blidinje Nature Park in 1998, they came to the conclusion that the lake loses roughly 24,000 m^3 of water daily, or 4-5 mm during spring. The lake filters sediment and experiences an annual sediment growth of 1 mm. Large amounts of suspended particles in the lake water contribute to its high turbidity. The 15 cm clarity of the lake reflects this in a sizable way. The lake loses water from evaporation because of its wide surface, particularly in the summer. Most of the animals of this region and the surrounding area use this lake as a watering place.

Polymictic lakes are those that regularly have the entire water column intermingled in them. The functioning of shallow lakes differs significantly from that of deep lakes in many ways because of the intensive sediment–water interaction and the potentially significant influence of aquatic vegetation. Simple criteria, such as the traditional correlation between algal growth and nutrient load, do not apply to shallow lakes [3]. Shallow lakes frequently have "catastrophic" rather than "mild" responses to eutrophication. Many lakes have been seen to change repeatedly from having clear water to having cloudy water without any discernible external influences. This entirely distinct behaviour of shallow lakes has seemingly repelled rather than attracted researchers throughout time, given the relative neglect of shallow lakes in the limnological literature. The few available deep lakes have long been the sole subject of limnological research, even in nations where nearly all lakes are shallow such as Denmark and the Netherlands [4]. Due to a lake's delicate and complicated ecosystem, even a tiny amount of external stress (such as tourist activity) combined with biogenic element inflows might contribute to eutrophication [5]. High mountain lakes are characterized by great diversity and high sensitivity to external influences. Each lake in itself is an expression of interactions within the ecosystem, which in the scientific sense imposes special standards (e.g. water quality) but also special scientific approaches and methodologies. The experiences of researchers highlight the need to use chemical analysis methods with high sensitivity and high precision, that is, the strict application of the quality system, in order to determine, model, and correctly interpret possible changes. Almost every mountain in Bosnia and Herzegovina with peaks above 2,000 m has a "mountain eye" (Vranica, Čvrsnica, Maglić, Zelengora, Lelija, Treskavica) – lakes whose quality status is little known. Where humans are permanently present, there are indications of anthropogenic pollution (Blidinje, Lake Prokoško). In order to achieve or maintain a good ecological status of these waters in line with the EU's *Water Framework Directive*, the identification and assessment of the condition of these lakes serves as the first link in the management of these water resources. Remote mountain lakes are the most sensitive water ecosystems in Europe. They are the focal points of mountain landscapes, habitats for unique plants and animal communities. Such ecosystems, for example, in the areas of the Arctic and the Alps, represent the most preserved ecosystems in Europe. They are vulnerable and impacted by pollution and climate change. Due to their sensitivity, remote highland lakes are excellent environmental change sensors, and the excellent quality of their sediment can be used to calculate the rate, direction, and biological consequences of changes in climate and air quality [6, 7]. Shallow polymictic lakes are more prevalent than deep lakes in many regions of the world, and even when they are small, they are nevertheless important, especially in densely populated areas. In many aspects, their ecology is different from stratified lakes. The concept of "alternate stable equilibrium" describes how lakes might transition from a clear water condition where macrophytes are dominant to a state where algae are dominant during the eutrophication process [8]. Although the area of Lake Blidinje is not densely populated due to a large number of livestock grazing in the immediate surroundings during the summer months, an influence on the eutrophication process cannot be ruled out. In comparison to deep lakes, shallow basins are often smaller in volume and have a lower capacity for incoming nutrients. This makes shallow basins more susceptible to anthropogenic influences. Additionally, shallow lakes have more frequently strong water–sediment interactions and are more likely to have sediment resuspension, which increases internal nutrient loading and productivity [9].

The model of multiple regression analysis makes it possible to forecast system dynamics and future situations. Multiple regression analysis models are recommended by many advocates of empirical limnology for predictions [10–14]. The prognostic model created in previous studies with the help of the multiple regression analysis of the markers of water quality is looked at in this study. Data collected during water quality monitoring from 2017 to 2019 are compared with the resulting model.

2. Materials and methods

When creating the multiple regression analysis model, data from earlier research was used [15, 16]. In the multiple regression analysis, chlorophyll a was selected as the dependent variable, and the following independent factors were employed as the independent variables:

a) With chlorophyll a, transparency and total phosphorus are factors that characterize the trophic state of the lake.

b) Total phosphorus and electrical conductivity, variables that, according to the literature [12], showed a strong and statistically significant relationship with chlorophyll a.

c) SO_4^{2-}, Fe, NH_4^+, temperature, hardness, PO_4^{3-} of filtered samples, N/P ratio. All abiotic indicators were chosen as independent variables, and then the variables with the least statistical significance were gradually eliminated until these seven variables were found, all of which had an effect on chlorophyll a, which was statistically significant.

d) Temperature, Fe, SiO_2, pH, TN/TP of filtered samples. The variables that have a statistically significant correlation (p 0.05, p 0.01) with chlorophyll a in the first phase were first chosen as independent variables. Following that, the variables that did not show a statistically significant link were gradually removed. There was no relevant link with chlorophyll a until the multiple regression technique had reached these five parameters, all of which have a statistically significant impact on chlorophyll a. Data sources from earlier investigations were used [15].

The resulting models are compared with water quality monitoring data from 2017 to 2019 [17–19], which is regularly carried out by the Agency for Watershed of the Adriatic Sea. The monitored indicators are: water temperature, air temperature, pH, suspended matter, electrical conductivity (CND), dissolved oxygen, oxygen saturation, amount of oxygen required (BOD), permanganate index, NH_4^+, NO_3^-, total nitrogen (TN), total phosphorus (TP), TN/TP, PO_4^{3-}, Cl^-, SO_4^{2-}, total dissolved carbon (TOC), Cu, Cr, Zn, SiO_2, chlorophyll a [17–19]. For the monitored indicators, the Pearson correlation coefficient was determined. The monitoring was conducted in compliance with European Parliament and Council Directive 2000/60/EC [1].

3. Results and discussions

Multiple regression analysis was used to investigate the relationship between the concentration of chlorophyll a and SO_4^{2-}, Fe, NH_4^+, water temperature, hardness, dissolved reactive phosphorus, and Redfield's N/P ratio. The coefficient of multiple determination (R^2 = 0.720) demonstrated that up to 72% of the variance of the chlorophyll concentration during the observed time was explained by the link between the aforementioned parameters, which was determined to be quite strong (R = 0.849). As a result, this model can be regarded as typical.

Table 1. Multiple regression, dependent variable chlorophyll a, independent variables: SO_4^{2-}, Fe, NH_4^+, temperature, hardness, PO_4^{3-} of filtered samples (dissolved reactive phosphorus), N/P ratio (Redfield's)

Variables Entered/Removed			
Model	Variables entered	Variables removed	Method
1	N/P Fe Temperature Hardness NH_4^+ SO_4^{2-} PO_4^{3-} [a]		Enter
a. All requested variables entered b. Dependent variable: Chlorophyll a			

Model summary				
Model	R	R^2	Adjusted R^2	Std. error of the estimate
1	0.849[a]	0.720	0.670	0.36331
a. Predictors: (Constant), N/P, Fe, Temperature, Hardness, NH_4^+, SO_4^{2-}, PO_4^{3-}				

Anova[b]					
Model	Sum of squares	df	Mean square	F	Sig
1					
Regression	13.239	7	1.891	14.329	0.000[a]
Residual	5.148	39	0.132		
Total	18.387	46			

a. Predictors: (Constant), N/P, Fe, Temperature, Hardness, NH_4^+, SO_4^{2-}, PO_4^{3-}
b. Dependent variable: Chlorophyll a

Coefficients[a]					
Model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. Error	Beta		
1					
(Constant)	-0.179	0.466	-0.257	-0.384	0.703
SO_4^{2-}	-0.067	0.030	0.248	-2.224	0.032
Fe	0.418	0.169	0.327	2.470	0.018
NH_4^+	1.779	0.596	0.923	2.987	0.005
Temperature	0.084	0.010	-0.262	8.752	0.000
Hardness	-0.018	0.006	0.237	-2.770	0.009
PO_4^{3-}	23.354	11.486	0.272	2.033	0.049
N/P	0.003	0.001		2.602	0.013

a. Dependent variable: Chlorophyll a

The regression model's individual significance test revealed that each of the independent variables that were chosen had a statistically significant impact on the level of chlorophyll a. The link between sulphate and hardness as independent variables and chlorophyll a as a dependent variable is inversely proportional, but the relationship between the other independent parameters in this model and chlorophyll a is linearly proportional. Following the selection of all abiotic characteristics as independent variables, the variables with the least statistical significance were gradually eliminated until these 7 variables were reached, all of which having had a statistically significant impact on chlorophyll a. Because sulphate concentrations are higher in the spring months following snowmelt, independent of chlorophyll a, the inversely proportional link between sulphate and chlorophyll a does not necessarily imply that sulphates affect the concentration of chlorophyll a. The correlation between chlorophyll a and hardness can also be explained as a coincidence. It is hypothesised that orthophosphate and ammonia will have a direct proportional relationship with chlorophyll a.

Chlorophyll a concentration dependence on water temperature, Fe, SiO_2, pH, and TN/TP limit of filtered water samples found in the multiple regression analysis revealed a strong relationship between the mentioned parameters ($R = 0.705$), while the coefficient of multiple determination ($R^2 = 0.497$) revealed that up to 49.7% of the aforementioned independent variables contributed to the explanation of the variance of chlorophyll a concentration throughout the observed time. As a result, this model can be regarded as typical. Each of the selected independent variables had a statistically significant impact on the level of chlorophyll a according to the individual significance test of the regression model. The relationship between the TN/TP ratio of filtered samples as an independent variable and chlorophyll a as a dependent variable is inversely proportional, in contrast to the other independent variables in this model, which are all directly proportional to chlorophyll a. This selection of variables was made by first selecting as independent variables all those that have a statistically significant correlation (p 0.05, p 0.01) with chlorophyll a in the first phase. Following that, the variables that did not show a statistically significant link were gradually removed. There was no relevant link with chlorophyll a until the multiple regression technique had reached these five parameters, all of which have a statistically significant impact on chlorophyll a. Since SiO_2 and chlorophyll a have a direct proportional connection, SiO_2 can be a limiting nutrient for the growth of Bacillariophyceae class algae.

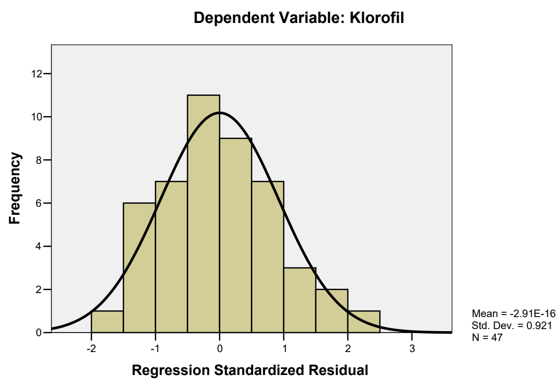

Figure 1. Multiple regression histogram, dependent variable chlorophyll a; independent variables: SO_4^{2-}, Fe, NH_4^+, Temperature, Hardness, PO_4^{3-} of filtered samples (dissolved reactive phosphorus), N/P ratio (Redfield's); dependent variable: Chlorophyll a

Temperature and chlorophyll a were shown to be directly proportional in both typical models of multiple regression analysis, as predicted. Given that iron is required for the synthesis of chlorophyll a as a micronutrient, Fe also shows a directly proportionate connection with chlorophyll a in both representative models of multiple regression.

Future studies can use these two representative multiple regression models to forecast chlorophyll a concentration. Some researchers have already described such models for forecasting the concentration of chlorophyll a [20].

Table 2. Multiple regression, dependent variable chlorophyll a, independent variables: Temperature, Fe, SiO2, pH, TN/TP of filtered samples

Variables Entered/Removed

Model	Variables entered	Variables removed	Method
1	TN/TP pH Fe SiO_2 Temperature[a]		Enter

c. All requested variables entered
d. Dependent variable: Chlorophyll a

Model summary

Model	R	R^2	Adjusted R^2	Std. error of the estimate
1	0.705[a]	0.497	0.453	0.47476

a. Predictors: (Constant), TN/TP, pH, Fe, SiO_2, Temperature

Anova[b]

Model	Sum of Squares	df	Mean Square	F	Sig
1					
Regression	12.839	5	2.579	11.440	0.000[a]
Residual	13.073	58	0.225		
Total	25.966	63			

a. Predictors: (Constant), TN/TP, pH, Fe, SiO_2, Temperature
b. Dependent variable: Chlorophyll a

Coefficients[a]

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. Error	Beta		
1					
(Constant)	-3.744	1.540	0.413	-2.431	0.018
Temperature	0.039	0.009	0.273	4.082	0.000
Fe	0.534	0.186	0.213	2.879	0.006
SiO_2	1.747	0.809	0.263	2.160	0.035
pH	0.527	0.194	-0.226	2.722	0.009
TN/TP	-0.003	0.001		-2.235	0.029

b. Dependent variable: Chlorophyll a

Pearson's correlation index was calculated to determine the significance of the relationship between certain physico-chemical indicators of water, with an emphasis on their connection with the concentration of chlorophyll a. Observing the water quality monitoring indicators for the period from 2017 to 2019, water temperature, dissolved oxygen, nitrates, total nitrogen, TN/TP ratio, chromium, and SiO_2 show a statistically significant positive correlation with the concentration of chlorophyll a. To some extent, these results confirm the previously created prognostic model.

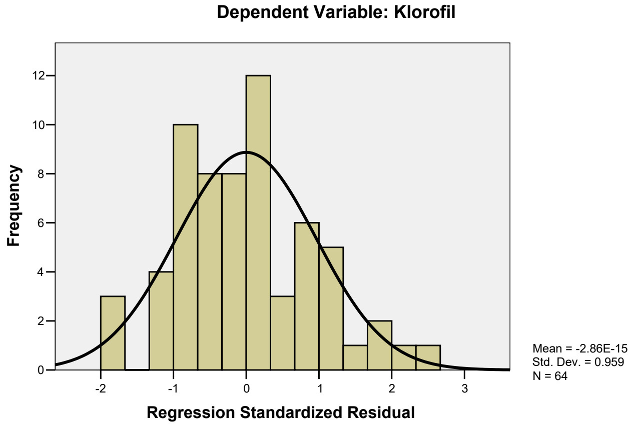

Figure 2. Multiple regression histogram, dependent variable chlorophyll a; independent variables: Temperature, Fe, SiO_2, pH, TN/TP of filtered samples; dependent variable: Chlorophyll a

Table 3. Pearson's correlation coefficient with the concentration of chlorophyll a

Parameter	Pearson's correlation coefficient
Temperature water (°C)	-0.79273
Temperature air (°C)	-0.57882
pH (pH unit)	-0.54017
Suspended matter (mg L^{-1})	0.286044
CND (µS cm^{-1})	0.297066
Dissolved oxygen (mg L^{-1})	**0.719949**
Oxygen saturation (%)	-0.35766
BOD (mg O_2 L^{-1})	0.17771
Permanganate index (mg O_2 L^{-1})	-0.14558
NH_4^+ (mg L^{-1})	0.293404
NO_3^- (mg L^{-1})	**0.829257**
Total N (mg L^{-1})	**0.868945**
Total P (mg L^{-1})	0.195754
TN/TP	**0.635985**
Cl^- (mg L^{-1})	-0.03122
SO_4^{2-} (mg L^{-1})	-0.20641
TOC (mg L^{-1})	-0.10359
Cu (µg L^{-1})	0.501051
Cr (µg L^{-1})	**0.822928**
Zn (µg L^{-1})	0.171639
SiO_2 (mg L^{-1})	**0.737193**

4. Conclusions

Analysing the quality of the water can be done for a variety of reasons. In this respect, they represent prospective data and information for prognostic models, ranging in importance from those of general importance to those that are extremely particular, such as warning, monitoring, or projecting the development of the situation. A water quality monitoring model that is gradually developed will allow for the determination of the factual condition, including basic to crucial supplementary data. It is necessary to continue to develop new and improve existing prognostic models in order to be able to predict the concentration of chlorophyll a. In this way, it is possible to prevent the eventual occurrence of eutrophication of the lake through a responsible approach to the sustainable management of the wider area of Blidinje Nature Park.

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