Interactions between chemical and biological parameters

It is needless to emphasize the importance of water in our life. Without water, there is no life on our planet. We need water for different purposes. We need water for drinking, for industries, for irrigation, for swimming and fishing, etc.

Water for different purposes has its own requirements fo composition and purity. Each body of water needs to be analysed on a regular basis to confirm to suitability. The types of analysis could vary from simple field testing for a single analyte to laboratory based multi-component instrumental analysis. The measurement of water quality is a very exacting and time consuming process, and a large number of quantitative analytical methods are used for this purpose. Water is a good solvent, and this property turns in the most efficient fluid for the transport of dissolved nutrients and is crucial for the transport of nutrients such as P, through biosphere. This property can be considered a disadvantage, it can be easily polluted, staying with in this state for a long time (Nicoara M., 2008). General properties of natural waters are primarily determined by liquid substances, solid and gaseous present in water the form of dissolved or suspended material. In order to characterise any water body, studies on the major components, hydrology, physico-chemical and biological characteristics, should be carried out. The physical and chemical properties of a freshwater body are characteristic of the climatic, geochemical, geomorphological and pollution conditions (largely) prevailing in the drainage basin and the underlying aquifer. Chemical water pollution can occur accidentally, but most often due to uncontrolled removal of various waste or liquid waste, solid or gaseous. Sources of water pollution are many, but most commonly, they are the household waste, industrial and agricultural buildings.

Water Framework Directive defines good chemical status of surface waters as the chemical status achieved by a body of water from which the pollutant concentrations do not exceed the environmental quality standards established in Annex IX and under Article 16 (7), and under other Community legislation that establish such standards. Environmental Quality Standards (EQS) are defined as concentrations of pollutants that should not be exceeded in order to protect human health and the environment. Water bodies that do not comply with all the environmental quality standard values indicate that not fulfill the objective of good chemical status. In assessing the chemical status, priority substances are relevant. In this respect, the European Commission approved the Directive. 2008/105/EC on environmental quality standards in the field of water policy and amending the Water Framework Directive (Annex II of Directive 2008/105/EC replaced Annex X of the Water Framework Directive) which shows values for environmental quality standard priority substances and other pollutants (33 substances and groups of substances, synthetic and non-synthetic, synthetic + 8 other pollutants).

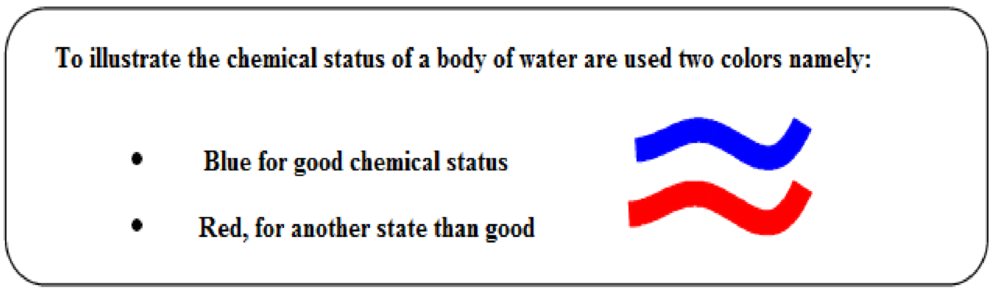


Fig. 1. The color code from the Water Framework Directive for the water chemical status

Also, a thorough knowledge of the hydrological properties of the water body must be acquired before an effective water quality monitoring system is established. Each of the inland waterbody is characterised by unique hydrological features. For example, rivers are characterised by uni-directional current with relatively high average velocity (0.1 – 1.0 m/S). In general, thorough and continuous vertical mixing is achieved in rivers due to the prevailing currents and turbulence.

Monitoring and assessment strategies are very important mainly in the North-Western Shelf of the Black Sea where the unique ecosystem is burdened by excessive loads of nutrients and hazardous substances from the coastal countries and the rivers that enter it – the most important of which is the Danube. The status of the Danube River, Delta and Romania’s coastal waters depends considerably on pollutant inputs from upstream countries (particularly for N and P loads). Diffuse agricultural sources, especially chemical fertilizer use in upstream countries and the improper working of wastewater treatment plants in Central and Eastern Europe is a major input. Many Romanian inland rivers, particularly those from mountain areas, remain undisturbed by major anthropogenic pressure (57% of water bodies) and are of high ecological value. However, economic development between 1960 and 1989 resulted in a significant worsening of the water quality of the Danube and inland rivers. Since this time, water quality has been improving (due to a reduction in economic activities and also new regulations based e.g. on the "polluter - pays" principle) but remains inferior to 1950s levels. The status of Romanian coastal waters depends considerably on Danube water quality. With regard to all sources (the Danube and other seashore based sources) the vast majority of pollutants are brought by the Danube: 99.5% of nutrients; 99%+ of N and 91.8% P-PO4. The dominant N-S flow of marine currents favours pollutant dispersion from the Danube in Romanian coastal waters. This has led to an increase in nutrient concentrations in marine sediments (levels decreasing N-S) (ICPDR).

Current monitoring activities include a river monitoring system for dangerous substances; heavy metals monitoring for all water categories and micro-pollutants monitoring. These have been implemented using Trans-boundary National Monitoring Network (TNMN) data. 582 industrial units (2001 data) have been inventoried as discharging dangerous substances into water resources /sewage systems. Starting in 2005, the Water Users Inventory (discharges of dangerous priority substances) and the Water Users Register (priority substances) are being updated. Currently monitoring purposes has enriched being pursued, in particular, the development quality of the aquatic environment and how the environment is affected by the release of contaminants resulting from human activities. This type of monitoring is often known as monitoring the impact of human activities on the environment (Mohamed, 2012), the study of interactions between biotopes, namely the relationship between environmental variables and their influence on aquatic communities is of paramount importance in the evaluation of water quality (Topa, 2011; Căldăraru, 2013).

An effective monitoring based on chemical parameters, on the Danube, must be based on a strict methodology of sampling and determination. The sample collected should be small in volume, enough to accurately represent the whole water body. The water sample tends to modify itself to the new environment. It is necessary to ensure that no significant changes occur in the sample and preserve its integrity till analysed (by retaining the same concentration of all the components as in the water body). The essential objectives of water quality assessment are to:

- define the status and trends in water quality of a given water body.

- analyse the causes for the observed conditions and trends.
- identify the area specific problems of water quality and provide assessments in the form of management to evaluate alternatives that help in decision-making.

Chemical parameters analysed to assess the water quality are:

- pH, Electrical Conductivity (E.C), Total Solids (TS), Total Dissolved Solids (TDS), Total Suspended Solids (TSS), Total Hardness, Calcium Hardness, Magnesium Hardness, Nitrates, Phosphates, Sulphates, Chlorides, Dissolved Oxygen (D.O), Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Fluorides, Free Carbon-di-oxide, Potassium and Sodium
- **Heavy metals:** Lead, Copper, Nickel, Iron, Chromium, Cadmium and Zinc

Water Quality Index

In respect to these aforementioned chemical parameters, a important tool to assess water quality is Water Quality Index. Water concept indexing by a numerical value that expresses quality based on physical measurements and chemical has been developed since 1965 in the United States. This has been studied extensively since the early 1970s in an effort to compare the quality of water bodies in all areas of the country. It is useful to compare the quality of the water in the water system over time.

Differences in the manner of calculation of WQI European and U.S. and Canada consist of the statistical method and manner of interpretation applied parameter values and their weights. WQI provides complex scientific information and synthesizes into a single number if the water falls in the class of suitable quality for use in human activities. This indicator is recognized as one of the 25 indicators that appreciate the quality of the environment, so-called environmental quality indicators (Environmental Performance Index - EPI). In the literature several methods are known for determining the WQI (Lumb, 2011).
To determine the water quality index using the following empirical equation:

$$WQI = \frac{\sum W_i q_i}{\sum W_i}$$

Europe has developed a concept based on the normalization of water quality parameters (concentrations) and then combining them into a model that contains all the parameters studied, each having a certain weight in the final calculation relationship (Milanovic , 2011).

Our research and tests reveal that some parameters have a greater influence on the values of the WQI index, namely heavy metals.

Parameters affecting the ecosystem of rivers

The first step for choosing an appropriate bio-index and obtaining its possible mathematical relationship with physicochemical characteristics of river water is identifying the parameters with considerable effects on the ecosystem of the river being studied. Studying the mathematical relationship between variations of biotic indices with these physicochemical characteristics is the second step. In this step, the proper biotic index which shows strongest statistical relation with the physicochemical parameters can be selected (Boulton, 1999). Some of the most influencing physicochemical characteristics of the river water bodies on the ecosystems can be listed as follows:

•River discharge is the most important hydrologic characteristic of rivers. It has direct and indirect impacts on the ecosystem health. While river discharge directly satisfies the needs of species in rivers, indirectly change the physical and chemical quality of water.

•Water velocity is among the major characteristics affecting river ecosystems. It has significant effects on morphology of river beds and movement of sediments which both have impacts on various species Floods and all types of hydrologic alterations can significantly change the ecosystem health one way or another.

•In addition to the hydrological conditions of the river, water quality parameters also play a major role in ecosystem health. Any change in water quality can lead to variations in compositions of plants and animal species. The most important water quality parameters in terms of impact on aquatic ecosystems include temperature, salinity, acidity, Total Dissolved Solids (TDS), pH, DO and BOD_5. Many physical processes and chemical and biological transformations are sensitive to temperature variations. Salinity increase in freshwater ecosystems generally decreases biodiversity and may reduce the available food resources (EPA; Nzecc & Armacanz, 2000). Generally lower acidity leads to reduced biodiversity and species composition of various invertebrate communities. Increased turbidity reduces light penetration depth and thus limits the growth of aquatic species. Since oxygen is needed for aerobic respiration of aquatic species, low DO concentration is harmful to plants and aquatic organisms (Yazdian, 2014).

Relationship between chemical characteristics of water and biotic indices

The criteria for understanding the quality of aquatic environment is rich, but there is a gap between these studies and those related to water resources planning and management. Most of the previous studies in the field of water resources planning and management have focused on socio-economic aspects of water allocation to different users while some also have considered physicochemical water quality constraints (Jager, 2008).

Bio-indices have not been used in these studies mostly because of the lack of knowledge of water resources modelers about these indices and also limited interval of limnological measurements. Previous studies some of which are also cited later in the section, show that the limnological information are only available in very short periods of time (mostly one or two years) in very limited rivers specially in the under developed countries while water resources planning and management studies require long records of data (usually longer than 30 years). To close this gap, one approach which is the focus of this study is to find a mathematical relationship between an ecological index which can reflect the overall environmental condition of a river in the study area and the physicochemical properties of water. Since there are widespread databases about physicochemical characteristics of water bodies in many basins around the world, finding this relationship can help in determining the quality of aquatic environments wherever no record on the quantity or diversity of species is available.

Several studies have shown consistency between variations of biotic indices and fluctuations in physicochemical characteristics of water: Czerniawska and Kusza (2005), studied correlation between bio-indices and diversity indices at the family level of benthic macro-invertebrates with physicochemical variables of Nysa Klodzka River in southern Poland, using Spearman's correlation coefficient. Yap et al. (2006) studied variations of a benthic species called

Oligochateas and physicochemical parameters of water in a river in Malaysia from March 1998 to February 1999, and showed that there has been a negative correlation between density and distribution of this benthic macro-invertebrate and DO and PH, and a positive correlation with electrical conductivity, BOD, NO3, NH3, TSS, COD, Cc and Zn. Azrina et al. (2006) studied the correlation between richness and diversity index of benthic macro-invertebrates communities with physicochemical parameters of water of Langat River, Malaysia for four consecutive months (March–June 1999), and showed that they are mainly affected by TSS and EC of the river water. They showed that the richness index has a strong negative correlation with TSS, width of the river and temperature while Simpson diversity index is strongly correlated with TSS and electrical conductivity of water (Yazdian, 2014).

One of our research initiatives is to determine the influence of environmental variables (chemical parameters) in the aquatic environment, respectively the Danube river, by analyzing the impact of these parameters on aquatic organisms. To quantify the influence of chemicals on biological indices taking into account the time required for reaction is justified analyzing the correlations between biological indices and WQI. The purpose of these correlations is to assess the time required for biological systems respond to changes in the physico-chemical properties and to determine which are the most important biotical indices suitable to be used in the monitoring and assessment of Lower Danube water quality.

For correlation of biological indices with quality index WQI have been used different regression models using as dependent variable biological indices and the independent variable WQI index.

Therefore, we tested the influence of WQI on 13 biotic indices in corresponding seasons. Based on our previous studies from 2011 and 2012 it had been statistically proved the influence of WQI on quality biotic indices and the results and test are presented below:

Corresponding seasons:
Data file: WQI_BIO corect.csv

Simple Regression - BMWP spring 2011 vs. WQI spring 2011
Dependent variable: BMWP spring 2011
Independent variable: WQI spring 2011
Squared-Y model: Y = sqrt(a + b*X)

Coefficients

	Least Squares	*Standard*	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
Intercept	-4762.74	733.46	-6.49353	0.0074
Slope	121.391	15.1289	8.02381	0.0040

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	2.36929E+06	1	2.36929E+06	64.38	0.0040
Residual	110403	3	36800.8		
Total (Corr.)	2.47969E+06	4			

Correlation Coefficient = 0.977485
R-squared = 95.5477 percent
R-squared (adjusted for d.f.) = 94.0636 percent
Standard Error of Est. = 191.835
Mean absolute error = 128.479
Durbin-Watson statistic = 1.28165 (P= 0.1653)
Lag 1 residual autocorrelation = -0.0685006

The StatAdvisor
The output shows the results of fitting a squared-Y model to describe the relationship between BMWP spring 2011 and WQI spring 2011. The equation of the fitted model is

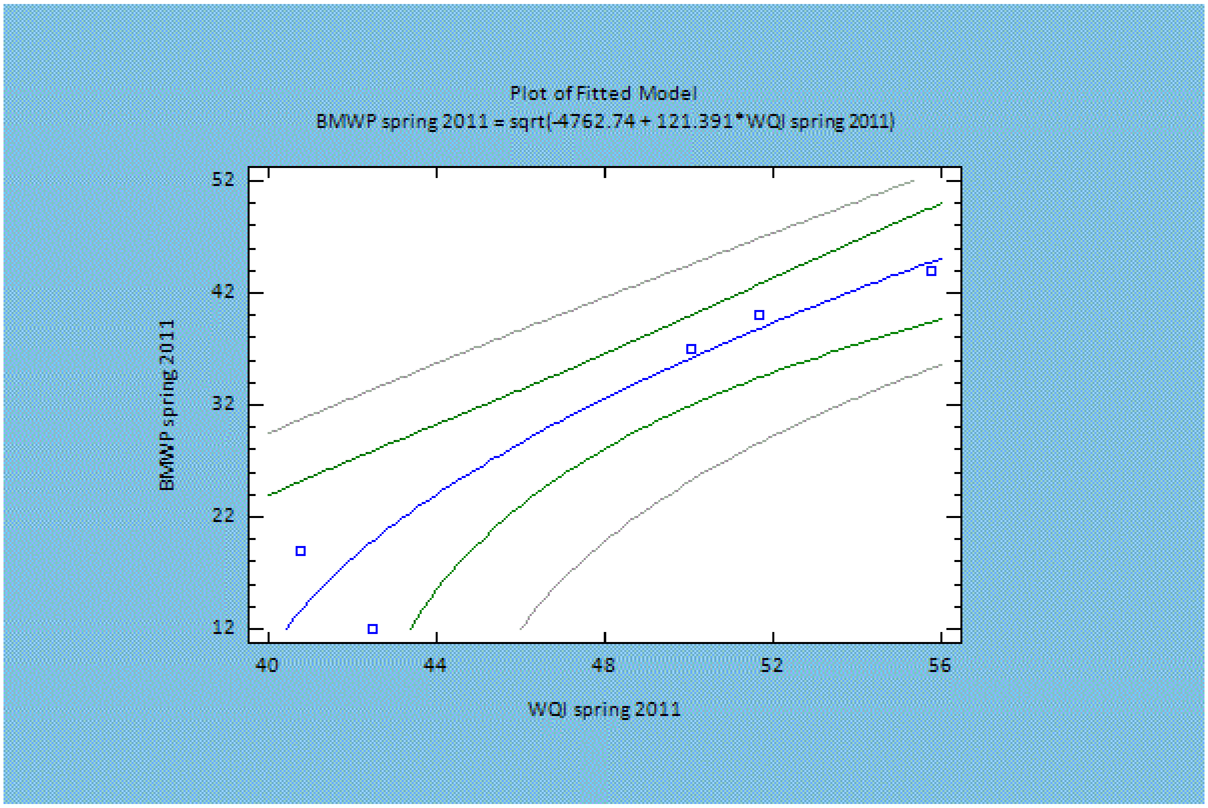
BMWP spring 2011 = sqrt(-4762.74 + 121.391*WQI spring 2011)

Since the P-value in the ANOVA table is less than 0.05, there is a statistically significant relationship between BMWP spring 2011 and WQI spring 2011 at the 95% confidence level.

The R-Squared statistic indicates that the model as fitted explains 95.5477% of the variability in BMWP spring 2011 after transforming to a reciprocal scale to linearize the model. The correlation coefficient equals 0.977485, indicating a relatively strong relationship between the variables. The standard error of the estimate shows the standard deviation of the residuals to be 191.835.

The mean absolute error (MAE) of 128.479 is the average value of the residuals. The Durbin-Watson (DW) statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in your data file. Since the P-value is greater than 0.05, there is no indication of serial autocorrelation in the residuals at the 95% confidence level.

Plot of Fitted Model



The StatAdvisor

The output shows the results of fitting a squared-Y model to describe the relationship between BMWP spring 2011 and WQI spring 2011. The equation of the fitted model, shown as a solid line, is

BMWP spring 2011 = sqrt(-4762.74 + 121.391*WQI spring 2011)

The inner bounds show 95% confidence limits for the mean BMWP spring 2011 of many observations at given values of WQI spring 2011. The outer bounds show 95% prediction limits for new observations.

Comparison of Alternative Models

Model	*Correlation*	*R-Squared*
Squared-Y model: Y = sqrt(a + b*X)	0.9775	95.55%
Squared-Y square root-X: Y = sqrt(a + b*sqrt(X))	0.9774	95.54%
Squared-Y logarithmic-X model: Y = sqrt(a + b*ln(X))	0.9769	95.44%
Double-squared: Y = sqrt(a + b*X^2)	0.9761	95.29%
Squared-Y reciprocal-X model: Y = sqrt(a + b/X)	-0.9747	95.00%

Logarithmic-X model: Y = a + b*ln(X)	0.9513	90.49%
Square root-X model: Y = a + b*sqrt(X)	0.9510	90.43%
Reciprocal-X model: Y = a + b/X	-0.9505	90.34%
Linear model: Y = a + b*X	0.9502	90.28%
Squared-X model: Y = a + b*X^2	0.9470	89.68%
Square root-Y logarithmic-X model: Y = (a + b*ln(X))^2	0.9302	86.53%
Square root-Y reciprocal-X model: Y = (a + b/X)^2	-0.9297	86.44%
Double square root model: Y = (a + b*sqrt(X))^2	0.9297	86.43%
Square root-Y model: Y = (a + b*X)^2	0.9287	86.24%
Square root-Y squared-X model: Y = (a + b*X^2)^2	0.9250	85.55%
Multiplicative model: Y = a*X^b	0.9030	81.54%
S-curve model: Y = exp(a + b/X)	-0.9026	81.47%
Logarithmic-Y square root-X model: Y = exp(a + b*sqrt(X))	0.9024	81.44%
Exponential model: Y = exp(a + b*X)	0.9013	81.23%
Logarithmic-Y squared-X: Y = exp(a + b*X^2)	0.8974	80.53%
Reciprocal-Y logarithmic-X model: Y = 1/(a + b*ln(X))	-0.8318	69.18%
Reciprocal-Y square root-X: Y = 1/(a + b*sqrt(X))	-0.8315	69.13%
Double reciprocal model: Y = 1/(a + b/X)	0.8307	69.01%
Reciprocal-Y model: Y = 1/(a + b*X)	-0.8306	68.99%
Reciprocal-Y squared-X: Y = 1/(a + b*X^2)	-0.8271	68.41%
Logistic model: Y = exp(a + b*X)/(1 + exp(a + b*X))	<="" td="">	
Log probit model: Y = normal(a + b*ln(X))	<="" td="">	

The StatAdvisor
This table shows the results of fitting several curvilinear models to the data. Of the models fitted, the squared-Y model yields the highest R-Squared value with 95.5477%. This is the currently selected model.

Simple Regression - BMWP summer 2011 vs. WQI summer 2011
Dependent variable: BMWP summer 2011
Independent variable: WQI summer 2011
Double-squared: Y = sqrt(a + b*X^2)

Coefficients

	Least Squares	*Standard*	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
Intercept	-1004.03	290.707	-3.45374	0.0408
Slope	0.650379	0.100083	6.49841	0.0074

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*

Model	1.27077E+06	1	1.27077E+06	42.23	0.0074
Residual	90275.9	3	30092		
Total (Corr.)	1.36104E+06	4			

Correlation Coefficient = 0.966267
R-squared = 93.3671 percent
R-squared (adjusted for d.f.) = 91.1562 percent
Standard Error of Est. = 173.47
Mean absolute error = 126.709
Durbin-Watson statistic = 2.25142 (P= 0.5112)
Lag 1 residual autocorrelation = -0.457009

The StatAdvisor
The output shows the results of fitting a double squared model to describe the relationship between BMWP summer 2011 and WQI summer 2011. The equation of the fitted model is

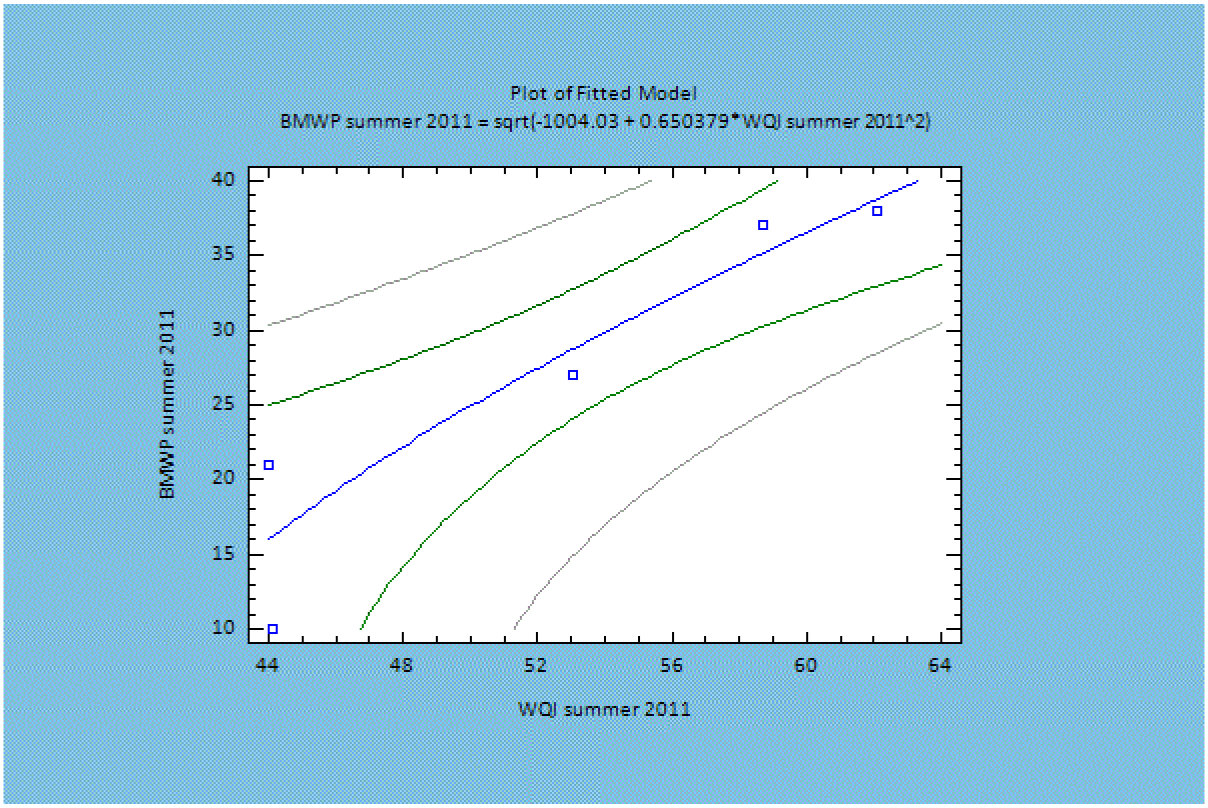
BMWP summer 2011 = sqrt(-1004.03 + 0.650379*WQI summer 2011^2)

Since the P-value in the ANOVA table is less than 0.05, there is a statistically significant relationship between BMWP summer 2011 and WQI summer 2011 at the 95% confidence level.

The R-Squared statistic indicates that the model as fitted explains 93.3671% of the variability in BMWP summer 2011. The correlation coefficient equals 0.966267, indicating a relatively strong relationship between the variables. The standard error of the estimate shows the standard deviation of the residuals to be 173.47.

The mean absolute error (MAE) of 126.709 is the average value of the residuals. The Durbin-Watson (DW) statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in your data file. Since the P-value is greater than 0.05, there is no indication of serial autocorrelation in the residuals at the 95% confidence level.

Plot of Fitted Model



<u>The StatAdvisor</u>
The output shows the results of fitting a double squared model to describe the relationship between BMWP summer 2011 and WQI summer 2011. The equation of the fitted model, shown as a solid line, is

BMWP summer 2011 = sqrt(-1004.03 + 0.650379*WQI summer 2011^2)

The inner bounds show 95% confidence limits for the mean BMWP summer 2011 of many observations at given values of WQI summer 2011. The outer bounds show 95% prediction limits for new observations.

Comparison of Alternative Models

Model	*Correlation*	*R-Squared*
Double-squared: Y = sqrt(a + b*X^2)	0.9663	93.37%
Squared-Y model: Y = sqrt(a + b*X)	0.9646	93.05%
Squared-Y square root-X: Y = sqrt(a + b*sqrt(X))	0.9631	92.77%
Squared-Y logarithmic-X model: Y = sqrt(a + b*ln(X))	0.9612	92.40%
Squared-Y reciprocal-X model: Y = sqrt(a + b/X)	-0.9563	91.45%
Square root-X model: Y = a + b*sqrt(X)	0.9360	87.61%
Logarithmic-X model: Y = a + b*ln(X)	0.9360	87.60%
Linear model: Y = a + b*X	0.9356	87.53%

Reciprocal-X model: Y = a + b/X	-0.9348	87.38%
Squared-X model: Y = a + b*X^2	0.9334	87.12%
Square root-Y reciprocal-X model: Y = (a + b/X)^2	-0.9085	82.54%
Square root-Y logarithmic-X model: Y = (a + b*ln(X))^2	0.9078	82.42%
Double square root model: Y = (a + b*sqrt(X))^2	0.9069	82.25%
Square root-Y model: Y = (a + b*X)^2	0.9055	82.00%
Square root-Y squared-X model: Y = (a + b*X^2)^2	0.9015	81.27%
S-curve model: Y = exp(a + b/X)	-0.8720	76.04%
Multiplicative model: Y = a*X^b	0.8696	75.62%
Logarithmic-Y square root-X model: Y = exp(a + b*sqrt(X))	0.8678	75.30%
Exponential model: Y = exp(a + b*X)	0.8655	74.91%
Logarithmic-Y squared-X: Y = exp(a + b*X^2)	0.8598	73.92%
Double reciprocal model: Y = 1/(a + b/X)	0.7824	61.22%
Reciprocal-Y logarithmic-X model: Y = 1/(a + b*ln(X))	-0.7773	60.42%
Reciprocal-Y square root-X: Y = 1/(a + b*sqrt(X))	-0.7742	59.94%
Reciprocal-Y model: Y = 1/(a + b*X)	-0.7707	59.39%
Reciprocal-Y squared-X: Y = 1/(a + b*X^2)	-0.7625	58.14%
Logistic model: Y = exp(a + b*X)/(1 + exp(a + b*X))	<="" td="">	
Log probit model: Y = normal(a + b*ln(X))	<="" td="">	

The StatAdvisor
This table shows the results of fitting several curvilinear models to the data. Of the models fitted, the double squared model yields the highest R-Squared value with 93.3671%. This is the currently selected model.

Simple Regression - BMWP autumn 2011 vs. WQI autumn 2011
Dependent variable: BMWP autumn 2011
Independent variable: WQI autumn 2011
Squared-Y reciprocal-X model: Y = sqrt(a + b/X)

Coefficients

	Least Squares	*Standard*	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
Intercept	4915.45	1322.75	3.71608	0.0339
Slope	-201123	71407.1	-2.81657	0.0669

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	1.28195E+06	1	1.28195E+06	7.93	0.0669
Residual	484788	3	161596		
Total (Corr.)	1.76674E+06	4			

Correlation Coefficient = -0.851823
R-squared = 72.5603 percent
R-squared (adjusted for d.f.) = 63.4137 percent
Standard Error of Est. = 401.99
Mean absolute error = 258.711
Durbin-Watson statistic = 1.30488 (P= 0.1758)
Lag 1 residual autocorrelation = -0.104446

The StatAdvisor
The output shows the results of fitting a squared-Y reciprocal-X model to describe the relationship between BMWP autumn 2011 and WQI autumn 2011. The equation of the fitted model is

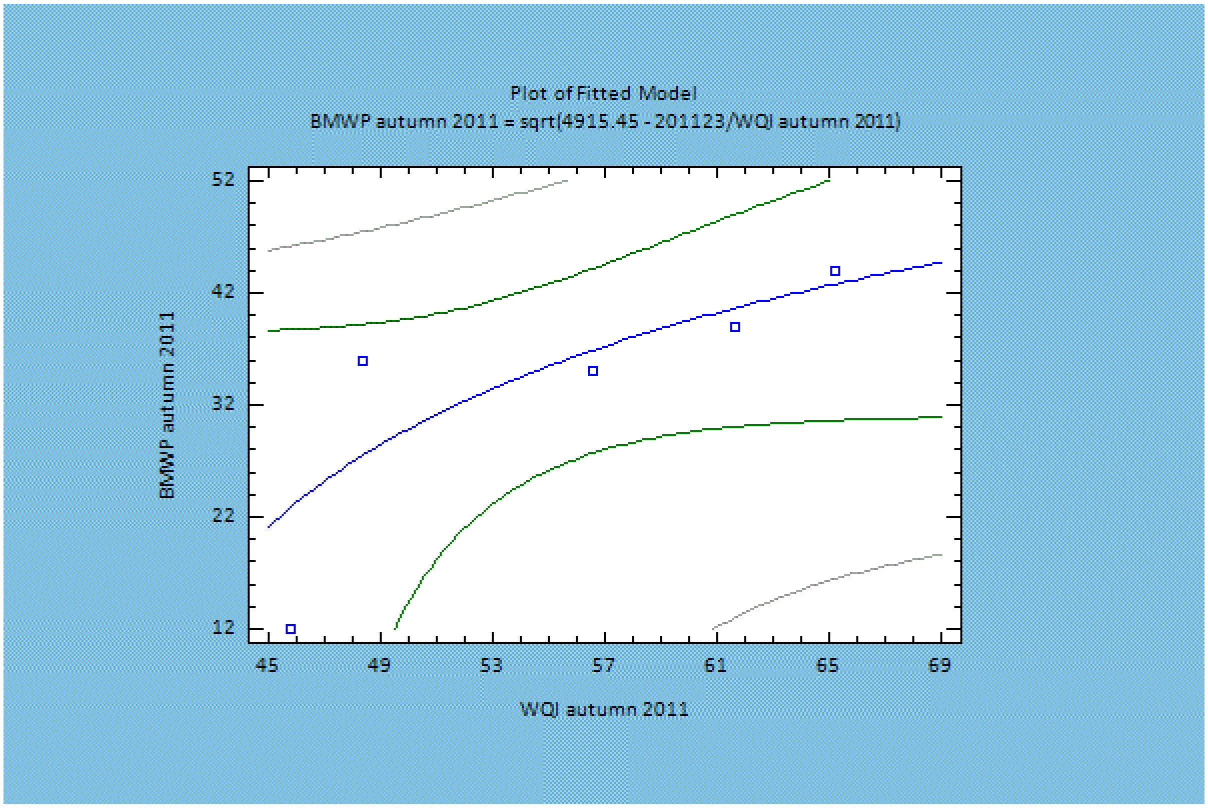
BMWP autumn 2011 = sqrt(4915.45 - 201123/WQI autumn 2011)

Since the P-value in the ANOVA table is greater or equal to 0.05, there is not a statistically significant relationship between BMWP autumn 2011 and WQI autumn 2011 at the 95% or higher confidence level.

The R-Squared statistic indicates that the model as fitted explains 72.5603% of the variability in BMWP autumn 2011. The correlation coefficient equals -0.851823, indicating a moderately strong relationship between the variables. The standard error of the estimate shows the standard deviation of the residuals to be 401.99.

The mean absolute error (MAE) of 258.711 is the average value of the residuals. The Durbin-Watson (DW) statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in your data file. Since the P-value is greater than 0.05, there is no indication of serial autocorrelation in the residuals at the 95% confidence level.

Plot of Fitted Model



The StatAdvisor
The output shows the results of fitting a squared-Y reciprocal-X model to describe the relationship between BMWP autumn 2011 and WQI autumn 2011. The equation of the fitted model, shown as a solid line, is

BMWP autumn 2011 = sqrt(4915.45 - 201123/WQI autumn 2011)

The inner bounds show 95% confidence limits for the mean BMWP autumn 2011 of many observations at given values of WQI autumn 2011. The outer bounds show 95% prediction limits for new observations.

Comparison of Alternative Models

Model	*Correlation*	*R-Squared*
Squared-Y reciprocal-X model: Y = sqrt(a + b/X)	-0.8518	72.56%
Squared-Y logarithmic-X model: Y = sqrt(a + b*ln(X))	0.8474	71.81%
Squared-Y square root-X: Y = sqrt(a + b*sqrt(X))	0.8451	71.42%
Squared-Y model: Y = sqrt(a + b*X)	0.8427	71.02%
Double-squared: Y = sqrt(a + b*X^2)	0.8376	70.16%
Reciprocal-X model: Y = a + b/X	-0.8152	66.46%
Logarithmic-X model: Y = a + b*ln(X)	0.8053	64.85%
Square root-X model: Y = a + b*sqrt(X)	0.8002	64.03%

Linear model: Y = a + b*X	0.7950	63.20%
Square root-Y reciprocal-X model: Y = (a + b/X)^2	-0.7936	62.97%
Squared-X model: Y = a + b*X^2	0.7843	61.52%
Square root-Y logarithmic-X model: Y = (a + b*ln(X))^2	0.7812	61.02%
Double square root model: Y = (a + b*sqrt(X))^2	0.7749	60.04%
S-curve model: Y = exp(a + b/X)	-0.7722	59.62%
Square root-Y model: Y = (a + b*X)^2	0.7685	59.05%
Multiplicative model: Y = a*X^b	0.7577	57.42%
Square root-Y squared-X model: Y = (a + b*X^2)^2	0.7554	57.07%
Logarithmic-Y square root-X model: Y = exp(a + b*sqrt(X))	0.7504	56.31%
Exponential model: Y = exp(a + b*X)	0.7430	55.20%
Double reciprocal model: Y = 1/(a + b/X)	0.7362	54.20%
Logarithmic-Y squared-X: Y = exp(a + b*X^2)	0.7279	52.99%
Reciprocal-Y logarithmic-X model: Y = 1/(a + b*ln(X))	-0.7188	51.67%
Reciprocal-Y square root-X: Y = 1/(a + b*sqrt(X))	-0.7100	50.41%
Reciprocal-Y model: Y = 1/(a + b*X)	-0.7011	49.16%
Reciprocal-Y squared-X: Y = 1/(a + b*X^2)	-0.6832	46.67%
Logistic model: Y = exp(a + b*X)/(1 + exp(a + b*X))	<="" td="">	
Log probit model: Y = normal(a + b*ln(X))	<="" td="">	

The StatAdvisor
This table shows the results of fitting several curvilinear models to the data. Of the models fitted, the squared-Y reciprocal-X model yields the highest R-Squared value with 72.5603%. This is the currently selected model.

Simple Regression - Margalef autumn 2011 vs. WQI autumn 2011
Dependent variable: Margalef autumn 2011
Independent variable: WQI autumn 2011
Square root-Y reciprocal-X model: Y = (a + b/X)^2

Coefficients

	Least Squares	*Standard*	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
Intercept	2.61763	0.392182	6.67453	0.0069
Slope	-66.471	21.1714	-3.13966	0.0517

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.140027	1	0.140027	9.86	0.0517
Residual	0.0426157	3	0.0142052		
Total (Corr.)	0.182643	4			

Correlation Coefficient = -0.875598
R-squared = 76.6673 percent
R-squared (adjusted for d.f.) = 68.8897 percent
Standard Error of Est. = 0.119186
Mean absolute error = 0.0839355
Durbin-Watson statistic = 1.41929 (P= 0.2103)
Lag 1 residual autocorrelation = 0.0700378

The StatAdvisor

The output shows the results of fitting a square root-Y reciprocal-X model to describe the relationship between Margalef autumn 2011 and WQI autumn 2011. The equation of the fitted model is

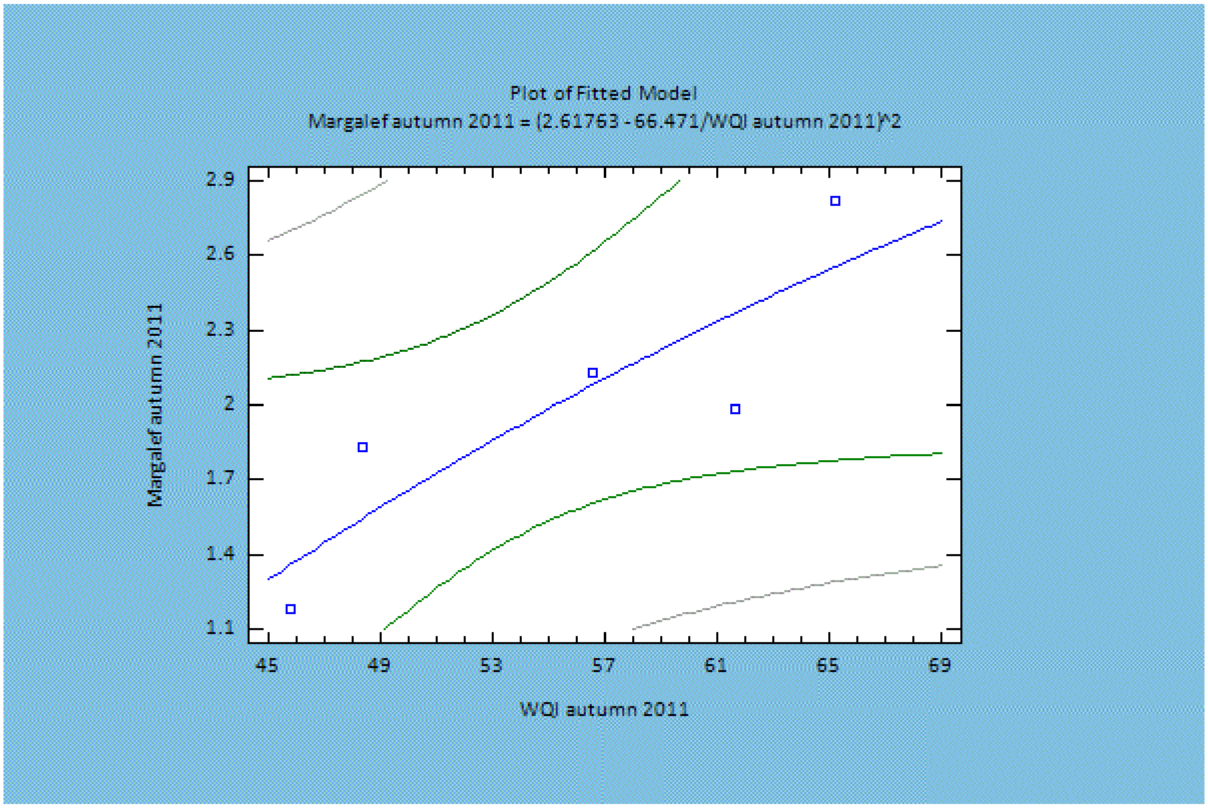
Margalef autumn 2011 = (2.61763 - 66.471/WQI autumn 2011)^2

Since the P-value in the ANOVA table is greater or equal to 0.05, there is not a statistically significant relationship between Margalef autumn 2011 and WQI autumn 2011 at the 95% or higher confidence level.

The R-Squared statistic indicates that the model as fitted explains 76.6673% of the variability in Margalef autumn 2011. The correlation coefficient equals -0.875598, indicating a moderately strong relationship between the variables. The standard error of the estimate shows the standard deviation of the residuals to be 0.119186.

The mean absolute error (MAE) of 0.0839355 is the average value of the residuals. The Durbin-Watson (DW) statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in your data file. Since the P-value is greater than 0.05, there is no indication of serial autocorrelation in the residuals at the 95% confidence level.

Plot of Fitted Model



The StatAdvisor

The output shows the results of fitting a square root-Y reciprocal-X model to describe the relationship between Margalef autumn 2011 and WQI autumn 2011. The equation of the fitted model, shown as a solid line, is

Margalef autumn 2011 = (2.61763 - 66.471/WQI autumn 2011)^2

The inner bounds show 95% confidence limits for the mean Margalef autumn 2011 of many observations at given values of WQI autumn 2011. The outer bounds show 95% prediction limits for new observations.

Comparison of Alternative Models

Model	*Correlation*	*R-Squared*
Square root-Y reciprocal-X model: Y = (a + b/X)^2	-0.8756	76.67%
S-curve model: Y = exp(a + b/X)	-0.8740	76.39%
Square root-Y logarithmic-X model: Y = (a + b*ln(X))^2	0.8738	76.35%
Squared-X model: Y = a + b*X^2	0.8732	76.25%
Linear model: Y = a + b*X	0.8729	76.19%
Double square root model: Y = (a + b*sqrt(X))^2	0.8727	76.17%
Square root-X model: Y = a + b*sqrt(X)	0.8725	76.13%
Logarithmic-X model: Y = a + b*ln(X)	0.8721	76.06%

Square root-Y model: Y = (a + b*X)^2	0.8716	75.97%
Reciprocal-X model: Y = a + b/X	-0.8710	75.87%
Multiplicative model: Y = a*X^b	0.8694	75.58%
Square root-Y squared-X model: Y = (a + b*X^2)^2	0.8690	75.52%
Logarithmic-Y square root-X model: Y = exp(a + b*sqrt(X))	0.8669	75.15%
Double-squared: Y = sqrt(a + b*X^2)	0.8645	74.74%
Exponential model: Y = exp(a + b*X)	0.8643	74.71%
Logarithmic-Y squared-X: Y = exp(a + b*X^2)	0.8589	73.77%
Squared-Y model: Y = sqrt(a + b*X)	0.8584	73.69%
Squared-Y square root-X: Y = sqrt(a + b*sqrt(X))	0.8553	73.15%
Double reciprocal model: Y = 1/(a + b/X)	0.8549	73.09%
Squared-Y logarithmic-X model: Y = sqrt(a + b*ln(X))	0.8520	72.59%
Squared-Y reciprocal-X model: Y = sqrt(a + b/X)	-0.8454	71.47%
Reciprocal-Y logarithmic-X model: Y = 1/(a + b*ln(X))	-0.8453	71.45%
Reciprocal-Y square root-X: Y = 1/(a + b*sqrt(X))	-0.8403	70.61%
Reciprocal-Y model: Y = 1/(a + b*X)	-0.8352	69.76%
Reciprocal-Y squared-X: Y = 1/(a + b*X^2)	-0.8247	68.01%
Logistic model: Y = exp(a + b*X)/(1 + exp(a + b*X))	<="" td="">	
Log probit model: Y = normal(a + b*ln(X))	<="" td="">	

The StatAdvisor
This table shows the results of fitting several curvilinear models to the data. Of the models fitted, the square root-Y reciprocal-X model yields the highest R-Squared value with 76.6673%. This is the currently selected model.

Simple Regression - Margalef spring 2012 vs. WQI spring 2012

Dependent variable: Margalef spring 2012
Independent variable: WQI spring 2012
Double reciprocal model: Y = 1/(a + b/X)

Coefficients

	Least Squares	*Standard*	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
Intercept	-1.12456	0.440117	-2.55514	0.0836
Slope	89.2275	20.8	4.28979	0.0233

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.321541	1	0.321541	18.40	0.0233
Residual	0.0524186	3	0.0174729		
Total (Corr.)	0.373959	4			

Correlation Coefficient = 0.927269
R-squared = 85.9828 percent
R-squared (adjusted for d.f.) = 81.3104 percent
Standard Error of Est. = 0.132185
Mean absolute error = 0.0844249
Durbin-Watson statistic = 2.80763 (P= 0.7967)
Lag 1 residual autocorrelation = -0.439997

The StatAdvisor
The output shows the results of fitting a double reciprocal model to describe the relationship between Margalef spring 2012 and WQI spring 2012. The equation of the fitted model is

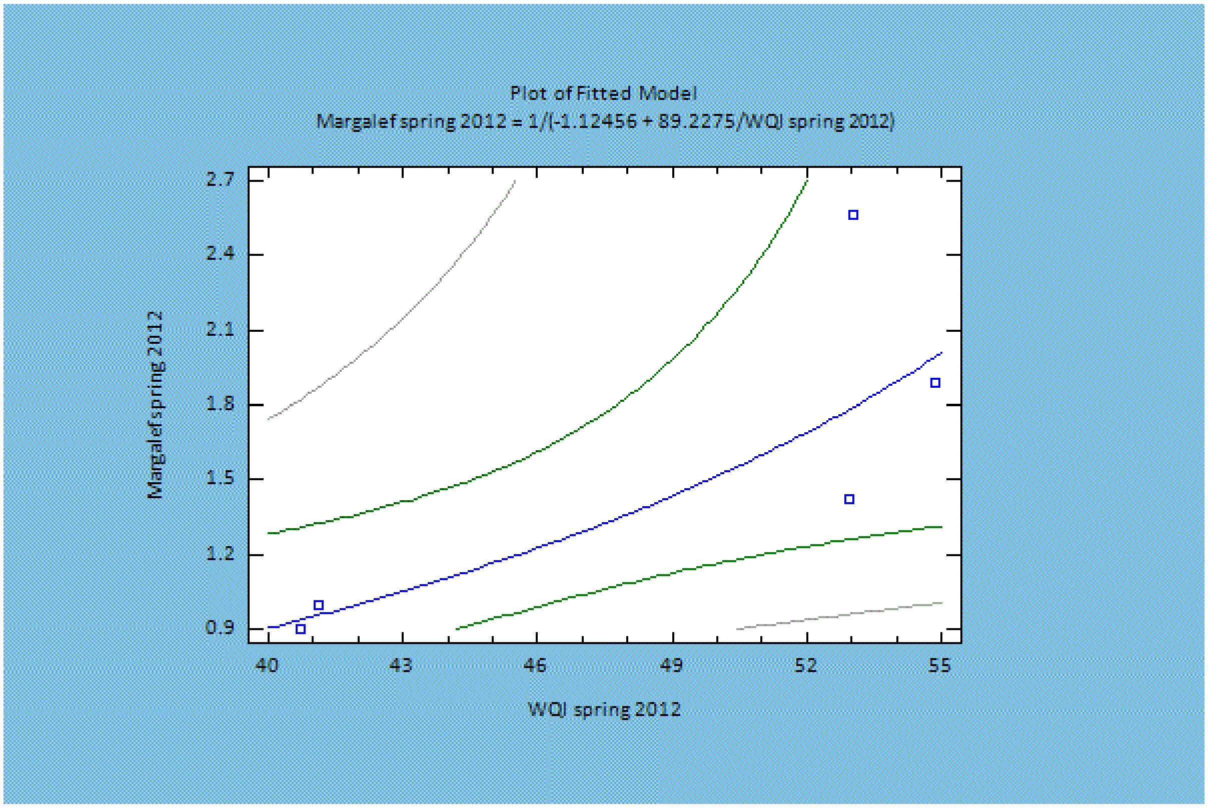
Margalef spring 2012 = 1/(-1.12456 + 89.2275/WQI spring 2012)

Since the P-value in the ANOVA table is less than 0.05, there is a statistically significant relationship between Margalef spring 2012 and WQI spring 2012 at the 95% confidence level.

The R-Squared statistic indicates that the model as fitted explains 85.9828% of the variability in Margalef spring 2012. The correlation coefficient equals 0.927269, indicating a relatively strong relationship between the variables. The standard error of the estimate shows the standard deviation of the residuals to be 0.132185.

The mean absolute error (MAE) of 0.0844249 is the average value of the residuals. The Durbin-Watson (DW) statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in your data file. Since the P-value is greater than 0.05, there is no indication of serial autocorrelation in the residuals at the 95% confidence level.

Plot of Fitted Model



The StatAdvisor
The output shows the results of fitting a double reciprocal model to describe the relationship between Margalef spring 2012 and WQI spring 2012. The equation of the fitted model, shown as a solid line, is

Margalef spring 2012 = 1/(-1.12456 + 89.2275/WQI spring 2012)

The inner bounds show 95% confidence limits for the mean Margalef spring 2012 of many observations at given values of WQI spring 2012. The outer bounds show 95% prediction limits for new observations.

Comparison of Alternative Models

Model	*Correlation*	*R-Squared*
Double reciprocal model: Y = 1/(a + b/X)	0.9273	85.98%
Reciprocal-Y logarithmic-X model: Y = 1/(a + b*ln(X))	-0.9264	85.81%
Reciprocal-Y square root-X: Y = 1/(a + b*sqrt(X))	-0.9258	85.72%
Reciprocal-Y model: Y = 1/(a + b*X)	-0.9252	85.61%
Reciprocal-Y squared-X: Y = 1/(a + b*X^2)	-0.9238	85.35%
S-curve model: Y = exp(a + b/X)	-0.8756	76.67%
Multiplicative model: Y = a*X^b	0.8745	76.48%
Logarithmic-Y square root-X model: Y = exp(a + b*sqrt(X))	0.8739	76.37%

Exponential model: Y = exp(a + b*X)	0.8732	76.24%
Logarithmic-Y squared-X: Y = exp(a + b*X^2)	0.8716	75.96%
Square root-Y reciprocal-X model: Y = (a + b/X)^2	-0.8410	70.72%
Square root-Y logarithmic-X model: Y = (a + b*ln(X))^2	0.8397	70.51%
Double square root model: Y = (a + b*sqrt(X))^2	0.8390	70.39%
Square root-Y model: Y = (a + b*X)^2	0.8382	70.25%
Square root-Y squared-X model: Y = (a + b*X^2)^2	0.8363	69.94%
Reciprocal-X model: Y = a + b/X	-0.8018	64.29%
Logarithmic-X model: Y = a + b*ln(X)	0.8003	64.05%
Square root-X model: Y = a + b*sqrt(X)	0.7995	63.92%
Linear model: Y = a + b*X	0.7985	63.77%
Squared-X model: Y = a + b*X^2	0.7964	63.43%
Squared-Y reciprocal-X model: Y = sqrt(a + b/X)	-0.7172	51.44%
Squared-Y logarithmic-X model: Y = sqrt(a + b*ln(X))	0.7151	51.14%
Squared-Y square root-X: Y = sqrt(a + b*sqrt(X))	0.7139	50.97%
Squared-Y model: Y = sqrt(a + b*X)	0.7127	50.79%
Double-squared: Y = sqrt(a + b*X^2)	0.7099	50.39%
Logistic model: Y = exp(a + b*X)/(1 + exp(a + b*X))	<="" td="">	
Log probit model: Y = normal(a + b*ln(X))	<="" td="">	

The StatAdvisor
This table shows the results of fitting several curvilinear models to the data. Of the models fitted, the double reciprocal model yields the highest R-Squared value with 85.9828%. This is the currently selected model.

Simple Regression - DSWI spring 2012 vs. WQI spring 2012
Dependent variable: DSWI spring 2012
Independent variable: WQI spring 2012
Reciprocal-Y squared-X: Y = 1/(a + b*X^2)

Coefficients

	Least Squares	*Standard*	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
Intercept	0.987238	0.102025	9.67643	0.0023
Slope	-0.000174157	4.13467E-05	-4.2121	0.0244

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.053301	1	0.053301	17.74	0.0244
Residual	0.00901277	3	0.00300426		
Total (Corr.)	0.0623138	4			

Correlation Coefficient = -0.924859
R-squared = 85.5365 percent
R-squared (adjusted for d.f.) = 80.7153 percent
Standard Error of Est. = 0.0548111
Mean absolute error = 0.030519
Durbin-Watson statistic = 2.80029 (P= 0.8010)
Lag 1 residual autocorrelation = -0.407444

The StatAdvisor
The output shows the results of fitting a reciprocal-Y squared-X model to describe the relationship between DSWI spring 2012 and WQI spring 2012. The equation of the fitted model is

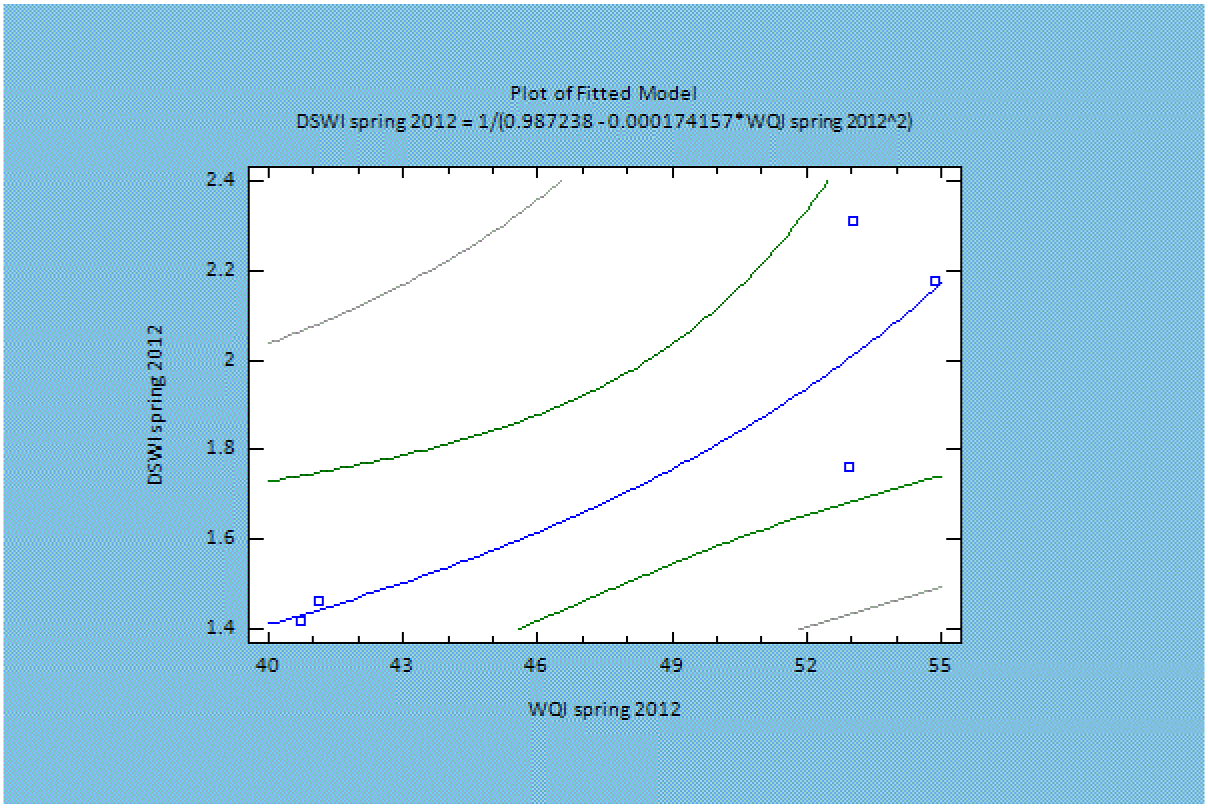
DSWI spring 2012 = 1/(0.987238 - 0.000174157*WQI spring 2012^2)

Since the P-value in the ANOVA table is less than 0.05, there is a statistically significant relationship between DSWI spring 2012 and WQI spring 2012 at the 95% confidence level.

The R-Squared statistic indicates that the model as fitted explains 85.5365% of the variability in DSWI spring 2012. The correlation coefficient equals -0.924859, indicating a relatively strong relationship between the variables. The standard error of the estimate shows the standard deviation of the residuals to be 0.0548111.

The mean absolute error (MAE) of 0.030519 is the average value of the residuals. The Durbin-Watson (DW) statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in your data file. Since the P-value is greater than 0.05, there is no indication of serial autocorrelation in the residuals at the 95% confidence level.

Plot of Fitted Model



<u>The StatAdvisor</u>
The output shows the results of fitting a reciprocal-Y squared-X model to describe the relationship between DSWI spring 2012 and WQI spring 2012. The equation of the fitted model, shown as a solid line, is

DSWI spring 2012 = 1/(0.987238 - 0.000174157*WQI spring 2012^2)

The inner bounds show 95% confidence limits for the mean DSWI spring 2012 of many observations at given values of WQI spring 2012. The outer bounds show 95% prediction limits for new observations.

Comparison of Alternative Models

Model	*Correlation*	*R-Squared*
Reciprocal-Y squared-X: Y = 1/(a + b*X^2)	-0.9249	85.54%
Reciprocal-Y model: Y = 1/(a + b*X)	-0.9244	85.45%
Reciprocal-Y square root-X: Y = 1/(a + b*sqrt(X))	-0.9241	85.39%
Reciprocal-Y logarithmic-X model: Y = 1/(a + b*ln(X))	-0.9238	85.33%
Double reciprocal model: Y = 1/(a + b/X)	0.9231	85.20%
Logarithmic-Y squared-X: Y = exp(a + b*X^2)	0.9040	81.72%
Exponential model: Y = exp(a + b*X)	0.9033	81.60%
Logarithmic-Y square root-X model: Y = exp(a + b*sqrt(X))	0.9030	81.54%

Multiplicative model: Y = a*X^b	0.9026	81.46%
S-curve model: Y = exp(a + b/X)	-0.9017	81.31%
Square root-Y squared-X model: Y = (a + b*X^2)^2	0.8924	79.64%
Square root-Y model: Y = (a + b*X)^2	0.8917	79.51%
Double square root model: Y = (a + b*sqrt(X))^2	0.8913	79.44%
Square root-Y logarithmic-X model: Y = (a + b*ln(X))^2	0.8909	79.36%
Square root-Y reciprocal-X model: Y = (a + b/X)^2	-0.8899	79.20%
Squared-X model: Y = a + b*X^2	0.8802	77.48%
Linear model: Y = a + b*X	0.8794	77.34%
Square root-X model: Y = a + b*sqrt(X)	0.8790	77.26%
Logarithmic-X model: Y = a + b*ln(X)	0.8785	77.18%
Reciprocal-X model: Y = a + b/X	-0.8776	77.01%
Double-squared: Y = sqrt(a + b*X^2)	0.8543	72.99%
Squared-Y model: Y = sqrt(a + b*X)	0.8535	72.84%
Squared-Y square root-X: Y = sqrt(a + b*sqrt(X))	0.8530	72.76%
Squared-Y logarithmic-X model: Y = sqrt(a + b*ln(X))	0.8525	72.68%
Squared-Y reciprocal-X model: Y = sqrt(a + b/X)	-0.8515	72.51%
Logistic model: Y = exp(a + b*X)/(1 + exp(a + b*X))	<="" td="">	
Log probit model: Y = normal(a + b*ln(X))	<="" td="">	

The StatAdvisor
This table shows the results of fitting several curvilinear models to the data. Of the models fitted, the reciprocal-Y squared-X model yields the highest R-Squared value with 85.5365%. This is the currently selected model.

Simple Regression - Oligochaeta [%] spring 2012 vs. WQI spring 2012
Dependent variable: Oligochaeta [%] spring 2012
Independent variable: WQI spring 2012
Double-squared: Y = sqrt(a + b*X^2)

Coefficients

	Least Squares	*Standard*	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
Intercept	3780.22	979.11	3.86087	0.0307
Slope	-1.1592	0.396795	-2.9214	0.0614

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	2.3614E+06	1	2.3614E+06	8.53	0.0614
Residual	830058	3	276686		
Total (Corr.)	3.19146E+06	4			

Correlation Coefficient = -0.860182
R-squared = 73.9912 percent
R-squared (adjusted for d.f.) = 65.3217 percent
Standard Error of Est. = 526.01
Mean absolute error = 291.78
Durbin-Watson statistic = 2.66934 (P= 0.7515)
Lag 1 residual autocorrelation = -0.335515

The StatAdvisor
The output shows the results of fitting a double squared model to describe the relationship between Oligochaeta [%] spring 2012 and WQI spring 2012. The equation of the fitted model is

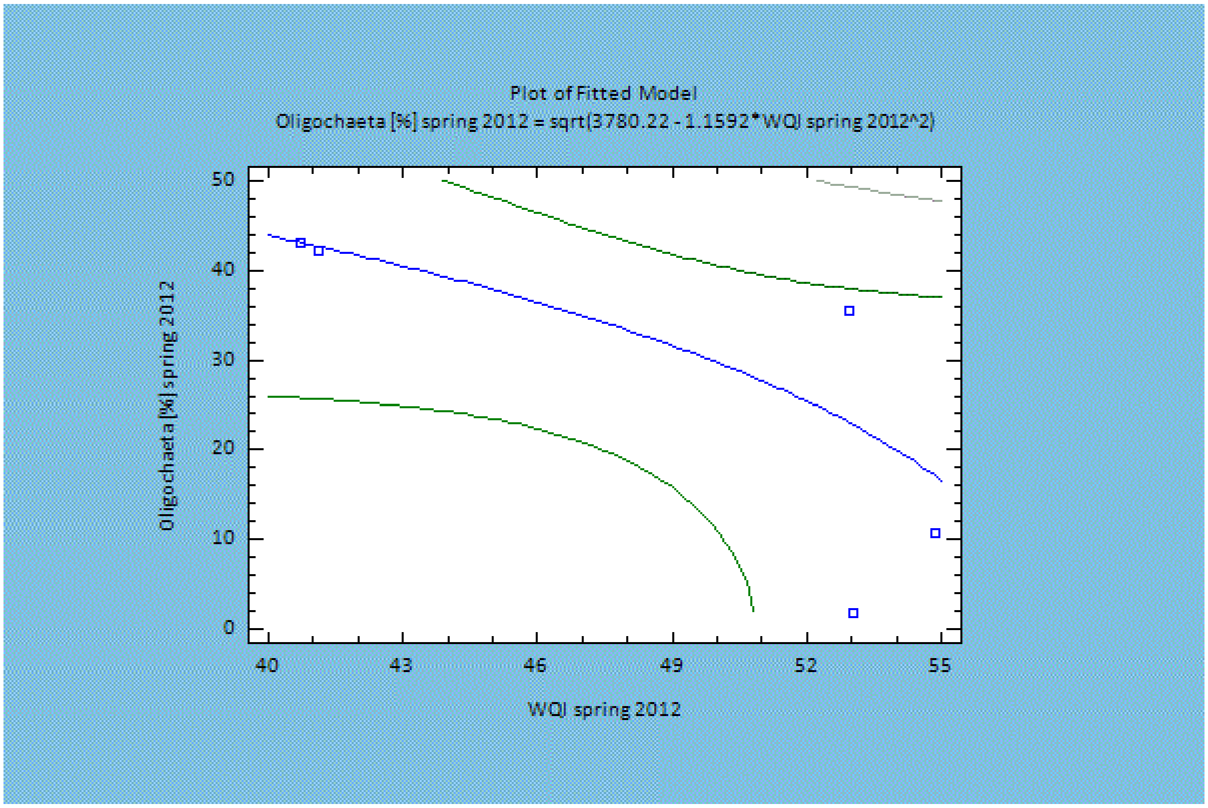
Oligochaeta [%] spring 2012 = sqrt(3780.22 - 1.1592*WQI spring 2012^2)

Since the P-value in the ANOVA table is greater or equal to 0.05, there is not a statistically significant relationship between Oligochaeta [%] spring 2012 and WQI spring 2012 at the 95% or higher confidence level.

The R-Squared statistic indicates that the model as fitted explains 73.9912% of the variability in Oligochaeta [%] spring 2012. The correlation coefficient equals -0.860182, indicating a moderately strong relationship between the variables. The standard error of the estimate shows the standard deviation of the residuals to be 526.01.

The mean absolute error (MAE) of 291.78 is the average value of the residuals. The Durbin-Watson (DW) statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in your data file. Since the P-value is greater than 0.05, there is no indication of serial autocorrelation in the residuals at the 95% confidence level.

Plot of Fitted Model



The StatAdvisor

The output shows the results of fitting a double squared model to describe the relationship between Oligochaeta [%] spring 2012 and WQI spring 2012. The equation of the fitted model, shown as a solid line, is

Oligochaeta [%] spring 2012 = sqrt(3780.22 - 1.1592*WQI spring 2012^2)

The inner bounds show 95% confidence limits for the mean Oligochaeta [%] spring 2012 of many observations at given values of WQI spring 2012. The outer bounds show 95% prediction limits for new observations.

Comparison of Alternative Models

Model	*Correlation*	*R-Squared*
Double-squared: Y = sqrt(a + b*X^2)	-0.8602	73.99%
Squared-Y model: Y = sqrt(a + b*X)	-0.8579	73.60%
Squared-Y square root-X: Y = sqrt(a + b*sqrt(X))	-0.8567	73.40%
Squared-Y logarithmic-X model: Y = sqrt(a + b*ln(X))	-0.8556	73.20%
Squared-Y reciprocal-X model: Y = sqrt(a + b/X)	0.8534	72.82%
Squared-X model: Y = a + b*X^2	-0.7816	61.09%
Linear model: Y = a + b*X	-0.7801	60.86%
Square root-X model: Y = a + b*sqrt(X)	-0.7793	60.74%

Logarithmic-X model: Y = a + b*ln(X)	-0.7786	60.62%
Reciprocal-X model: Y = a + b/X	0.7770	60.37%
Square root-Y squared-X model: Y = (a + b*X^2)^2	-0.7138	50.95%
Square root-Y model: Y = (a + b*X)^2	-0.7137	50.94%
Double square root model: Y = (a + b*sqrt(X))^2	-0.7136	50.92%
Square root-Y logarithmic-X model: Y = (a + b*ln(X))^2	-0.7135	50.91%
Square root-Y reciprocal-X model: Y = (a + b/X)^2	0.7131	50.86%
S-curve model: Y = exp(a + b/X)	0.6219	38.67%
Multiplicative model: Y = a*X^b	-0.6204	38.49%
Logarithmic-Y square root-X model: Y = exp(a + b*sqrt(X))	-0.6195	38.38%
Exponential model: Y = exp(a + b*X)	-0.6186	38.27%
Logarithmic-Y squared-X: Y = exp(a + b*X^2)	-0.6165	38.01%
Double reciprocal model: Y = 1/(a + b/X)	-0.4473	20.01%
Reciprocal-Y logarithmic-X model: Y = 1/(a + b*ln(X))	0.4427	19.60%
Reciprocal-Y square root-X: Y = 1/(a + b*sqrt(X))	0.4402	19.38%
Reciprocal-Y model: Y = 1/(a + b*X)	0.4376	19.15%
Reciprocal-Y squared-X: Y = 1/(a + b*X^2)	0.4319	18.65%
Logistic model: Y = exp(a + b*X)/(1 + exp(a + b*X))	<="" td="">	
Log probit model: Y = normal(a + b*ln(X))	<="" td="">	

The StatAdvisor
This table shows the results of fitting several curvilinear models to the data. Of the models fitted, the double squared model yields the highest R-Squared value with 73.9912%. This is the currently selected model.

Conclusions

From the results can be observed that in the corresponding seasons was registered a big influence of WQI index on certain biological indicators such as: BMWP (Biological Monitoring Working Party), ASPT (Average Score per Taxon), DSI (Simpson index), Margalef index (Margalef) and the abundance of Oligochaetes (Oligo. no.). Thus, is verified the hypothesis that macroinvertebrates communities are influenced by water chemistry. These correlations express that there is the possibility of immediate reactions from benthic communities to influence environmental parameters due to the existence of sensitive species that may disappear after a wave of major accidental pollution. Even if WQI not exceeded in all seasons monitored, any anthropogenic impact leads to changes in the benthic communities which are sensitive, statistical correlations pointing out that the abundance,

diversity, sensitivity and number of species in the community are closely related to water chemistry, even if the ecosystem has not been subjected to high anthropogenic pressure. Also, our study show that different types of bio-indices have statistically significant relationships with chemical characteristics of water expressed in WQI index.

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