

# An Empirical Model for River Ecological Management with Uncertainty Evaluation

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Abstract River Basin District Authorities make use of water quality models in order to assess the environmental status of water bodies. The current Italian procedure aiming to classify the ecological status of a watercourse employs the quality assessment of four biological elements with the support of some chemical and physical elements. Since many measures of the Directive 2000/60/CE affect the chemical and physical elements of the river, the Tiber River Basin Authority

The original version of this article was revised: Due to an oversight, the author names were incorrectly captured in the original publication. The first and last names of the authors were inverted. The correct presentation of the author names is shown above.

Highlights • An empirical model able to simulate the ecological status of river water bodies is proposed here.

• 121 river sampling stations were analyzed in Adriatic side of central Italy and Ecological Quality Ratios were determined.

• The empirical model can shed new insights in the relationships among pressures, impacts and environmental responses, allowing mostly to estimate the uncertainty in the predictions.

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(TRBA) has designed an empirical model linking the anthropogenic pressures, the chemical and physical elements of impacts and river biological quality elements. The general model is named PARBLEU, which stands for Pressures/impacts/responses Assessment into River Basins Leading to Environmental Uses. In the present manuscript, only a sub-model of PARBLEU (ecological sub-model concerning the interactions of impacts on water and biota matrices) is discussed. The sub-model is able to simulate the ecological status of river water bodies by acting on the control of impacts, in particular relating to changes of nutrients and dissolved oxygen. The aim of the present study was threefold. First, to select an appropriate functional form for the model and choose which variables to be included (specification process but without validation). Second, to simulate the responses (and the associated uncertainty) on biological elements due to a hypothesized change of chemical and physical conditions. Third, to provide a user friendly tool, but sufficiently reliable, for the professionals, regional technical structures and Authorities.

Keywords Ecological quality ratio. Ecological status. Empirical model. Nutrients. PARBLEU. Uncertainty

# 1 Introduction

The European Water Framework Directive (WFD) requires Member States to draw up for each River Basin District (RBD) a River Basin Management Plan (RBMP) and a Programme of Measures (PoM), in which the context for coordinating the implementation of the WFD key objectives is provided.

PoM must meet the environmental objectives and achieve the interests of all the involved stakeholders. Therefore, it is essential to find a link among PoM, the impacts of human activities and the WFD environmental objectives. In response to the requirements of the WFD, the Tiber River Basin Authority (TRBA) developed a modeling-system. The heart of the modeling system is the module related to the definition of scenarios for water resource management and its name is PARBLEU (which stands for Pressures/impacts/responses Assessment into River Basins Leading to Environmental Uses). Generally speaking, models can be categorized into two broad categories: mechanistic, trying to represent in a simplified form the mechanisms governing the complex systems of water bodies, and empirical, trying to match the input and output signals of the system without attempting to describe the underlying processes (Cox [2003](#page-13-0)). With regard to the definition of scenarios for surface water bodies resources management, several models are available: SENEQUE (Billen and Garnier [1999](#page-13-0)) and SWAT (Arnold et al. [1998](#page-13-0)) are examples of mechanistic models, while GREEN (Grizzetti et al. [2005\)](#page-14-0) and MONERIS (Behrendt et al. [2002\)](#page-13-0) are examples of empirical models.

It has been shown that application of different models in the same river can provide results that may differ by more than 100% and sometimes project system responses that are contradictory (Rode et al. [2010](#page-14-0)). Thus, selecting a model becomes a complex task (Ji [2008\)](#page-14-0).

In particular, the mechanistic approach is based on the up scaling from field-scale to larger scale patterns by simply describing processes in a spatially distributed way (Ebel and Loague [2006](#page-14-0)). This approach has several weaknesses: mechanistic models are usually overparameterized and there are difficulties in calibrating them, especially in data-poor condition (Keupers and Willems [2015\)](#page-14-0). Indeed environmental processes are far too complex to be fully represented in even the most accurate mechanistic models (Reckhow [1999\)](#page-14-0) and the inability to describe all relevant processes contributes to increment the uncertainty in the model predictions.

In fact, the models should also include information about the uncertainties of their outcomes when they are used for decision support (Beven and Binley [1992](#page-13-0); Uusitalo et al. [2015](#page-15-0)). There are still difficulties to conduct a complete uncertainty analysis for process-based models (Tao [2008\)](#page-14-0).

Thus, also relying on principle of parsimony, in the selected case study, the data scarcity suggested adopting an empirical approach based on regression analysis. There were many studies that used the regression analysis to identify and quantify the sources/factors that influence the water quality (Sliva and Williams [2001](#page-14-0); Simeonov et al. [2003;](#page-14-0) Ahearn et al. [2005\)](#page-13-0).

One of the environmental objectives for surface water bodies is represented by the achievement of Good Ecological Status (GES) and, in case of heavily modified or artificial water body, Good Ecological Potential (GEP). In Italy, in order to assess the ecological status, four Biological Quality Elements (BQEs) were determined and the following indexes were attributed to each BQE: STAR\_ICMi (macro-invertebrates), IBMR (aquatic macrophytes), ICMi (benthic diatoms), and ISECI (ichtyofauna). The four indexes must be supported, according the Italian legislation, by other indexes (see Minister Decree of Environment n. 260 of 8 November 2010): a) LIMeco, that focuses on the trophic status of freshwaters considering different nutrients (ammonium nitrogen  $NH_4$ -N, nitrate nitrogen  $NO<sub>3</sub>-N$ , total phosphorus TP) and dissolved oxygen  $DO$ ; b) hydromorphological indexes and specific pollutants (not considered here). The final indexes values related to each BQE are expressed using a numerical scale between 0 and 1, the so-called Ecological Quality Ratio (EQR). The EQR represents the ratio between the value of the observed biological parameter for a considered surface water body and the same measured value in a corresponding reference water body macro-type in "good" condition. Starting from these premises, tools capable of evaluating the status of each BQE could become useful in order to simulate ecological quality in RBDs only if they allow the uncertainty evaluation. So, with regard to surface water bodies, PARBLEU is divided into two main sub models: the first linking pressures to impacts (described by the physic-chemical parameters, LIMeco, supporting the Ecological Status), the second linking LIMeco to EQRs (Environmental Objective). The sub-models work in sequence (the results of the first sub-model are utilized as an input in the second one) achieving convergence toward the optimal solution through an iterative process. Up to now, difficulties due to acquiring reliable information related to pressures led to develop only the second sub-model, described in the present manuscript.

Although the regression approach is widespread for developing models of water quality, no other study (to our knowledge) has used this approach for providing a methodology useful to evaluate scenarios in all four EQRs controlling the changes of physical-chemical elements. The advantage of using EQRs is the immediacy of the representation of the results without other conversions, but they need to be expressed as annual mean values. The aim of this study is hence: 1) to reconstruct a system of relationships that allows user to determine whether the ecological status of a considered water body is improving or worsening through the development of a simple and understandable operational tool for decision makers on the environmental-quality topic, and 2) to quantify the uncertainty associated with the individual EQR assessment.

# 2 Materials and Methods

#### 2.1 Study Area

This study focuses on 121 river sampling stations in Abruzzo region in Central Italy (Fig. [1](#page-3-0)). In the region two different paths of development can be distinguished: the inland area, with

<span id="page-3-0"></span>

Fig. 1 Abruzzo region river sampling stations used in the study

low population density, is essentially devoted to agriculture, while along the highly populated coast and lower courses of rivers, important civil settlements and tourism centers are located. In effect in the final stretch, the rivers reach the sea through the coastal plain, after providing water to irrigation and receiving treated urban wastewaters. Due to this situation, the territory of Abruzzo region is divided into two main hydroecoregions (in according to Italian legislation).

## 2.2 Data Collection

Data were collected by Abruzzo Regional Environmental Prevention and Protection Agency (ARTA), which is the institution responsible for environmental monitoring in the territory of Abruzzo region.

A total of 121 river sampling stations belonging to 111 river water bodies were identified. Data of BQEs expressed as EQRs and LIMeco, each one with its four components, associated to each station, were analyzed. Two representative samples of the above parameters distributed in the Abruzzo region were obtained by considering the values recorded during the years 2010 and 2011 during which monitoring activities were almost completed.

A first set was constituted by stations where all aforementioned elements except  $EQR_{STAR}$ <sup>−</sup> ICMi and ISECI were calculated (108 stations). Another set was constituted by stations where all aforementioned elements were calculated (88 stations). In this study, it was preferred to sacrifice the validation process in favor of a greater sample. Following the rule of Thumb, it has been selected a form for the fit such that there are at least 10 observations per regressor. It <span id="page-4-0"></span>is known that the rule of Thumb represents a benchmark and addresses the concern for overfitting of models.

The four components of LIMeco representing the impacts needed to be converted in annual mean values reported in the same year in which EQRs were calculated. Biological indexes are briefly reported with the corresponding biological element in the following.

The STAR Intercalibration Common Metric Index (STAR\_ICMi) for aquatic macroinvertebrates. The Macrophytes Biological Index for Rivers (IBMR) for macrophytes. Intercalibration Common Metric Index (ICMi) for diatom communities. Ecological Status of Fish Communities Index (ISECI) for ichtyofauna population.

#### 2.3 Statistical Analysis

A system of functional relationships representing the sub-model (concerning the interactions of impacts with biota matrix) was formulated and was simplified according to Fig. 2, due to complexity of river ecosystem and lack of data, assuming that:

- & dissolved nutrients are used by macrophytes and diatoms, affecting living conditions of macrobenthos and fishes;
- all organisms need oxygen to survive;
- many benthic species (diatoms and macrobenthos) and macrophytes are consumed by fishes;
- macrophytes provide invertebrates and fish with shelter from predators and act as spawning sites for attachment of eggs;
- macrobenthos transform organic detritus (from macrophytes, diatoms and fishes);
- macrophytes and diatoms live together in conditions of competition and/or cooperation.

During the specification procedure, a dummy variable has been introduced in order to take into account the hydroecoregions (HER - in order to differentiate the water bodies belonging to the inner part of Abruzzo region from those flowing through the coastal plain), i.e. the dependence of the water body ecological specifity from its location. The chemical pollution indexes were not considered as relevant monitoring data since the concentrations of the main substances reported in the WFD are much lower than the environmental quality standard.





<span id="page-5-0"></span>The simplified conceptual sub-model was transformed into a general system of regressions and then subject to the specification procedure. Each regression is expressed as in the following:

$$
EQR = \beta_0 + \beta_i * I_i + \beta_k *EQRs_k + \varepsilon
$$
 (1)

Where:

- & EQR is the ecological quality ratio chosen as dependent variable;
- $EQRs<sub>k</sub>$  are the remaining ecological quality ratios (considered regressors according to the bio-complexity of river ecosystem);
- $I_i$  are impacts constituted by components of LIMeco (considered regressors);
- $\cdot$   $\beta_0$  is the intercept coefficient (regression parameter);
- $\beta_i$  and  $\beta_k$  are coefficients associated to relevant regressors (regression parameters);
- $\epsilon$  is the error term.

#### 2.3.1 The Specification of the Sub-Model

The general system of regressions was transformed into the following regressions (according to the simplified conceptual sub-model):

$$
EQR_{ICMi} = \beta_0 + \beta_1 EQR_{IBMR} + \beta_2 (NH_4-N) + \beta_3 (NO_3-N) + \beta_4 TP + \beta_5 DO + \epsilon_1;
$$
 (2)

$$
EQR_{IBMR} = \beta_0' + \beta_1'EQR_{ICMi} + \beta_2'(NH_4-N) + \beta_3'(NO_3-N) + \beta_4'TP + \beta_5'DO + \epsilon_2;
$$
 (3)

$$
EQR_{STAR-ICMi} = \beta_0 + \beta_1 EQR_{ICMi} + \beta_2 (NH_4-N) + \beta_3 (NO_3-N) + \beta_4 TP + \beta_5 DO
$$
 (4)  
+  $\beta_6 EQR_{IBMR} + \beta_7 ISECI + \varepsilon_3;$ 

$$
ISECI = \beta_0'' + \beta_1''EQR_{ICMi} + \beta_2''(NH_4-N) + \beta_3''(NO_3-N) + \beta_4''TP + \beta_5''DO + \beta_6''EQR_{IBMR} + \beta_7''EQR_{STAR-ICMi} + \varepsilon_4.
$$
 (5)

where:

- $EOR_{ICMi}$  is the ICMi index expressed as ecological quality ratio;
- $\cdot$  EQR<sub>IBMR</sub> is the IBMR index expressed as ecological quality ratio;
- $\cdot$  EQR<sub>STAR ICMi</sub> is the STAR ICMi index expressed as ecological quality ratio;
- & ISECI is the index for fish fauna (ISECI calculation is based on 5 key indicators whose calculation is based on a comparison between the measured and expected values in the autochthonous conditions, so, the ISECI final numerical value is a normalized value between 0 and 1 and then can be assimilated to a EQR);
- $\beta_0, \beta_1, \ldots, \beta_5$  are the intercept and the regression coefficients, in the regression of EQRICMi;
- $\phi = \beta_0, \beta_1, \ldots, \beta_5$  are the intercept and regression coefficients in the regression of EQR<sub>IBMR</sub>;
- $\cdot$  β<sub>0</sub>, β<sub>1</sub>, ..., β<sub>7</sub> are the intercept and regression coefficients in the regression of EQR<sub>STAR</sub> ICMi;
- $\cdot$   $\beta_0^{\prime\prime}, \beta_1^{\prime\prime}, \ldots, \beta_7^{\prime\prime}$  are the intercept and regression coefficients in the regression of ISECI;
- $\varepsilon_1$ ,  $\varepsilon_2$ ,  $\varepsilon_3$  e  $\varepsilon_4$  are the errors associated with each regression;
- $(NH_4 N)$ ,  $(NO_3 N)$ , DO and TP are expressed as annual mean concentrations.

The final specification of the sub-model was conducted through two different approaches. The first approach was to assess the influence of each variable, one at a time, on each EQR, using scatterplots, correlation matrix and an analysis of simple regression for each pair of variables.

The second approach consisted in understanding how each EQR was simultaneously related to variables chosen as predictors through partial residual plots and comparison among multiple regressions for each equation. It is important to notice, for each variable in all regressions, that maximum two orders were tested. The final formulation of model was determined using a backward elimination procedure. During whole procedure, the same confidence interval has been chosen (95%).

#### 2.3.2 Sub-Model Parameter Estimation

Each parameter was estimated with ordinary least squares (OLS) method. The Shapiro-Wilk test (with significance level of 5%), histograms, and quantile-quantile plots (QQ plots) were used to test normality. The homoskedasticity of the error distribution was evaluated with plots of residuals versus fitted values and Breusch-Pagan tests (in particular, the studentized version proposed by Koenker [1981](#page-14-0) and significance level of 5%).

The absence of strong multicollinearity between the predictors was tested with Variance Inflation Factors (VIF). AVIF larger that 10 was considered indicative of a harmful collinearity problem in the explanatory variables (Kennedy [1992\)](#page-14-0). However, the presence of cross-relationships between the elements of the ecosystem (as is the reality) has reduced the importance of collinearity whose presence has not been considered a "stumbling" lack of the model. When these assumptions were violated, data were improved by deleting outliers or methods that are not very sensitive to violations of the OLS assumptions (robust standard error estimations) were used. Theoretically, the Generalized Least Squares method should have been used, but it would have required a much deeper understanding of the phenomena or some theoretical assumptions on error-composition process. All the results discussed in the following were obtained using the R Project for Statistical Computing version 2.11.1 ([http://www.r-project.org\)](http://www.r-project.org).

The estimated regressions were solved computer iteratively using a convergence method to estimate the values of each EQR through successive simulations with check on residuals. The results were reported with a point estimate of each EQR for each station together with the associated 95% confidence level.

# 3 Results

Table [1](#page-7-0) shows the statistically significant variables with the value of each coefficient and the pvalue associated, showing the functional form chosen for each variable.

For the first regression, the assumptions of homoskedasticity and normality were violated. So, Table [2](#page-8-0) displays the OLS regression estimates as well as the estimated standard



<span id="page-7-0"></span>Table 1 Regressions describing relations between each ecological quality ratios (EQR) and related independent variables (others EQRs and the four components of LIMeco), with final Table 1 Regressions describing relations between each ecological quality ratios (EQR) and related independent variables (others EQRs and the four components of LIMeco), with final

	ß	Standard error estimator			
		<b>OLS</b>		HC <sub>3</sub>	
		<b>SE</b>	p	<b>SE</b>	p
EQR <sub>IBMR</sub> $NH4-N$ D <sub>O</sub>	0.61 $-0.2$ 0.042	0.136 0.057 0.012	1.82e-05 $6.2e-04$ 6.7e-04	0.145 0.030 0.012	$2.3e-0.5$ $2.4e-11$ $4.7e-04$

<span id="page-8-0"></span>Table 2 Comparison of uncorrected OLS and HC3 Standard Errors and p-values for each regression coefficient  $β$  in the analysis of EQR<sub>ICMi</sub>

errors and p-values for each regression coefficient related to  $EQR_{ICMi}$  using both the uncorrected OLS estimator and Heteroskedasticity–Consistent Standard Error Estimator (HC3). For the second regression, a new variable called TN was created summing each  $NH_4$ -N value with the corresponding NO3-N value. For the third regression, it had been preferred to adopt a function of a linear kind in each term since the significant variables number was greater than that related to the other regressions and the introduction of higher-order terms would have made this regression more complex than data generation process. For all the regressions, it is noteworthy that by removing the intercept (that was statistically insignificant) the term constituted by DO became significant: this result is perfectly obvious. In addition, the variable TP and the HER dummy variable were statistically insignificant in each regression.

Data reported in Table [1](#page-7-0) allow testing the significance of the model. Each regression has a high adjusted  $R^2$  implying that the predictor variables explain high percentages of the total variation in each index. It has also a high F-statistic with the corresponding p-value that is lower than 0.05 indicating statistical significance. Only for the first regression, the heteroskedasticity-robust-F-statistic was calculated.

Table [1](#page-7-0) shows that the diagnostic tests for normality and homoskedasticity applied to the four regressions are satisfactory except for the regression related to  $EQR<sub>ICMi</sub>$ . The QQ plot of the EQR<sub>ICMi</sub> residuals shows deviations from normality (Figure3). For the corresponding regression, the Breusch Pagan test results indicate the presence of heteroskedasticity. Then, the robust standard errors were used in order to obtain more accurate significance tests and confidence intervals. For the regression associated to  $EQR<sub>IBMR</sub>$ , the QQ plot suggests a heavy right tail (Fig. [3\)](#page-9-0) but it does not give a strong indication of non-normality. In fact, the Shapiro-Wilk test is satisfactory. An outlier was identified in the corresponding QQ plot and it was removed from the data set. For the equations related to  $EQR<sub>ICMi</sub>$  and  $EQR<sub>STAR-ICMi</sub>$ , the values of the VIFs indicate that collinearity does not exist between the explanatory variables (Table [1](#page-7-0)). Conversely, the regressions related to  $EQR<sub>BMR</sub>$  and ISECI are affected by multicollinearity since polynomial regressions were used (Table [1\)](#page-7-0).

# 4 Discussion

For the following considerations, it is important to consider that the investigated regression model estimates the spatial variability of EQRs indices expressed as annual mean values; this circumstance implies that the impacts needed to be converted in annual mean values. However, PARBLEU sub-model aims at interpreting the procedure of ecological status classification: it

<span id="page-9-0"></span>

Fig. 3 QQ plots of residuals against t-distribution. The dashed lines are the borders for 95% confidence

links the EQRs to chemical-physical elements, which can be easily monitored through the implementation of measures to counteract the effects of pressures. Specifically, in Abruzzo region, the significant pressures consist of water withdrawals, pollution load from wastewater treatments plants and agricultural activities: these pressures lead to significant impacts on nutrients and DO.

#### 4.1 Assumptions Violation in the Regression of  $EQR<sub>ICMi</sub>$

The results show that the diagnostic tests for normality and homoskedasticity applied to the four regressions are satisfactory except for the first regression (Table [2\)](#page-8-0). Thus, as Table [2](#page-8-0) shows, the results for  $NH<sub>4</sub>-N$  variable are mostly influenced by any corrections for heteroskedasticity, having greater uncorrected than corrected standard errors.

This violation of assumptions could be related to the fact that diatoms present one of the shortest generation times of all biological indicators (Rott [1991\)](#page-14-0) and that they have a high environmental fitness reflecting rapidly environmental change and providing early warnings of both pollution increases and habitat restoration success (Stevenson et al. [2010](#page-14-0)). Therefore, the variability in their environmental status is commonly less evident as respect to the variability of LIMeco regressors expressed as annual mean values (Taylor et al. [2007\)](#page-14-0).

#### 4.2 The Interpretation of the Double-Headed Arrows

The regressions have shown the strong weight of the cross-relationships between diatoms and aquatic macrophytes (Fig. [2](#page-4-0)) in the evaluation of its indexes. The macrophytes contribute to the physical structure of the colonized aquatic habitats and their morphological complexity influences the primary productivity of microalgae (diatoms constitutes a predominant component of microalgae) in a habitat (Fernandes et al. [2016](#page-14-0)). On the other hand, diatoms are at the basis of the trophic food web and any alteration of their communities may have repercussions at higher trophic levels. This strong relationship could be due to the fact that the two indices give redundant information (Schneider et al. [2012\)](#page-14-0). The results of regressions displayed also the strong weight of the cross-relationship between macroinvertebrates and fishes. Macroinvertebrates constitute an important source of food for numerous fishes but they have a key role on decomposition of matter (Wallace and Webster [1996](#page-15-0)); indeed dead organic matter is one of the main sources of energy for benthic species in shallow-water habitats (Covich et al. [1999\)](#page-13-0).

The results also show the influence of macrophytes. Infact, macrophytes represent an important food resource for aquatic organisms, providing organic matter (Thomaz and Cunha [2010\)](#page-14-0). In addition, they offer a habitat to aquatic organisms; architectural features of this habitat can affect invertebrate species diversity, density and distribution (Carpenter and Lodge [1986\)](#page-13-0).

#### 4.3 The Effect of the  $NH_4$ -N and  $NO_3$ -N on the Biotic Indices

The IBMR index is a macrophytes-based method to assess the trophic status of rivers (Haury et al. [2006](#page-14-0)). The new variable (TN) was significant. The partial residual plot suggested a polynomial relationship for the TN independent variable. In this regression the IBMR values decrease to increasing TN concentrations (but at a decreasing rate), showing that status assessment based on macrophyte communities is worsening. In fact, elevated concentrations of nitrogen from human activities contribute to the widespread phenomenon of the eutrophication of aquatic ecosystems (Camargo and Alonso [2006](#page-13-0)).

The link between nutrients and macro-invertebrates is showed in many studies (Wang et al. [2007](#page-15-0); Miltner [2010](#page-14-0)). The result of regression related to STAR-ICMi displayed a negative response of STAR-ICMi index to increasing  $NO<sub>3</sub>-N$  and  $NH<sub>4</sub>-N$  concentrations. Indeed toxic effects due to high levels of inorganic nitrogenous compounds on the invertebrates are described by Camargo and Alonso ([2006](#page-13-0)).

#### 4.4 The Effect of the TP on the Biotic Indices

The TP variable was not significant for all elements: nitrogen would appear to be more affecting than phosphorus in this study area. This lack of significance was interpreted in different ways; Graham [\(2003\)](#page-14-0) demonstrates that even low levels of collinearity causes exclusion of significant predictor variables during model creation. Indeed,  $NH_4$ -N and  $NO_3$ -N are each correlated much with the TP variable.

But phosphorus also plays a unique and important role in the eutrophication of receiving waters (Correll [1998\)](#page-13-0), accumulating in the sediments of the watercourse; its cycle differs from that of oxygen and nitrogen, which have much faster cycles (Holtan et al. [1988\)](#page-14-0). In addition, ecological processes, such as those which occur in the substratum, and water velocity can also modify TP availability and thus plant nutrition (Thiebaut [2008](#page-14-0)). Therefore, data related to other parameters (especially related to sediment matrix) that were not available should also be taken into account.

# 4.5 The Effect of the DO on the Biotic Indexes

The variable oxygen was significant for all elements with a positive response of corresponding index to increasing DO. Moreover, the adverse effects due to the decline in dissolved oxygen concentrations are generally known (Killgore and Hoover [2001](#page-14-0); Camargo and Alonso [2006\)](#page-13-0).

The partial residual plot suggested a polynomial relationship of the DO variable in the regressions of  $EQR<sub>IBMR</sub>$  and ISECI. This means that the marginal effect of DO is not constant in these regressions, i.e. the effect of a change in oxygen is greater at low than high oxygen levels.

#### 4.6 The Effect of the HER Variable on the Biotic Indices

HER was not significant when introduced in all the regressions. This was interpreted with the fact that the EQRs already take into account the specificity of the sampling station. The preliminary analysis showed a strong correlation between NO3 and HER. This means that the highest NO3-N concentrations are recorded in the coastal area and in the lower courses of rivers after the nitrification.

## 4.7 The Utility of the Ecological Sub-Model

After the regression model was calibrated and the major assumptions of the regression were tested, different scenarios were simulated. Only a scenario is reported for brevity. Fig. 4 shows the effect on EQR<sub>IBMR</sub> index by implementing the following simultaneous hypotheses: 1) 10% DO increase; 2)  $10\%$  N-NH<sub>4</sub> decrease; 3)  $10\%$  N-NO<sub>3</sub> decrease.

In Fig. 4b, the simulated values were compared, as respect to the original situation (Fig. 4a), taking into account class limits for  $EQR<sub>IBMR</sub>$ . The gap in percentage difference between the observed and simulated values was calculated. The assessment of uncertainty was carried out for the stations in which the simulated value of  $EQR<sub>IBMR</sub>$  was included in class limits of good or high status; in fact, final objective of WFD is achieving 'good ecological status' for all water bodies.



Fig. 4 Comparison of observed (a) and simulated (b) values related to  $EQR<sub>IBMR</sub>$  taking into account class limits. Simulated values were obtained implementing the following simultaneous measures: 1) 10%DO increase; 2)  $10\%$  N-NH<sub>4</sub> decrease; 3)  $10\%$  N-NO<sub>3</sub> decrease

The confidence interval at a 95% level of each station was analyzed and used for the following assessment: if the lower limit of confidence interval belongs to good or high class then the status assessment based on macrophytes is satisfied (white points

in Fig. 5). If the lower limit of confidence interval belongs to moderate or poor or bad class then the status assessment based on macrophytes is not satisfied (black points in Fig. 5). This procedure was repeated for other EQRs, achieving similar results, not reported here for brevity.

The sub-model allows to classify the ecological status of a river water body in all those situations in which we simulate changes in the components of LIMeco through the implementation of suitable (or at least considered such as) measures of PoM. In scarcity of economic resources, the decision to invest (e.g.: to increase dissolved oxygen and to decrease the nutrients) should therefore take into account the uncertainty and not the average value of biotic indexes (this in mind: "one out all out"). Where the lower limit of the confidence interval (of an EQR) is placed away from the lower limit of good ecological status, the uncertainty of achieving the global target is too high and further restorative measures (here not taken into account) should be taken.

# 5 Conclusions

The main aim of the present study was to develop and demonstrate the use of an ecological quality model as a tool for the evaluation of different water management scenarios for a river basin district in Central Italy. Although mechanistic detailed water quality models (Chapra and Runkel [1998](#page-13-0); Danish Hydraulic Institute [2008;](#page-14-0) Tsakiris and Alexakis [2012\)](#page-14-0) have been used in many case studies, their applicability is limited in large scale river basins for the lack of data required and the difficulty in understanding and calculating uncertainty in model results (Reckhow [1999](#page-14-0)). The main advantage of using multiple and simultaneous regressions, such



Fig. 5 Analysis of confidence-interval. Black points: lower limit of confidence interval belonging to moderate or poor or bad class; white points: lower limit of confidence interval belonging to good or high class

<span id="page-13-0"></span>as in the proposed model, named PARBLEU (Pressures/impacts/responses Assessment into River Basins Leading to Environmental Uses), is the simple quantification of uncertainty.

In the present study, 121 river sampling stations were analyzed and the EQRs were determined, allowing assessing the ecological quality and the uncertainty in the model simulations pertaining to different scenarios.

Results show that its application allows shedding new insights in the relationships not only between impacts and ecological responses but also between pressures and impacts because the latter are also correlated.

However, regression analyses can be hindered by the complex nature of ecological data, in which targeted ecological responses are linked to many explanatory variables that are often correlated among each other (Graham [2003](#page-14-0)). They can obviously be affected also by endogeneity. In this study the endogeneity is due to bidirectional causality (Kendall [2015](#page-14-0)) among biological indexes. Notwithstanding, understanding complex human– environmental interactions, including the basis for land-use decision making, is one of the first challenges that underlie bio complexity research (Michener et al. [2001](#page-14-0)). The OLS estimator is biased and inconsistent: its comparison and those resulting from more advanced statistical methods (both used in predictive phase) with the future monitoring results may indicate in more conclusive form the actual limits of using the OLS method in empirical modeling of complex systems.

When a greater number of data will be available in space and time, feasible alternatives to a multiple regression system will be represented by artificial neural network (ANN) techniques (Xie et al. [2006](#page-15-0); Wu et al. [2010\)](#page-15-0), like for instance the ANFIS system (Adaptive-Networkbased Fuzzy Inference System).

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