

# Modelling the factors that influence fish guilds composition using a back-propagation network: Assessment of metrics for indices of biotic integrity

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## Abstract

Fish assemblages are reckoned as indicators of aquatic ecosystem health, which has become a key feature in water quality management. Under this context, guilds of fish are useful for both understanding aquatic community ecology and for giving sound advice to decision makers by means of metrics for indices of biotic integrity. Artificial neural networks have proved useful in modelling fish in rivers and lakes. Hence, this paper presents a back-propagation network (BPN) for modelling fish guilds composition, and to examine the contribution of five environmental descriptors in explaining this composition in the Garonne basin, south west France. We employed presence–absence data and five variables: altitude, distance from the river source, surface of catchment area, annual mean water temperature, and annual mean water flow. We found that BPN performed better for predicting species richness of guilds than multiple regression models. The standardised determination coefficient of observed values against estimated values was used to characterise model performance; it varied between 0.55 and 0.82. Some models showed high variability which was presumably due to spatial heterogeneity, temporal variability or sampling uncertainty. Surface of catchment area and annual mean water flow were the most important environmental descriptors of guilds composition. Both variables imply human influence (i.e. land-use and flow regulation) on certain species which are of interest to environmental managers. Thus, predicting guilds composition with a BPN from landscape variables may be a first step to assess metrics for water quality indices in the Garonne basin.

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## 1. Introduction

Artificial neural networks (ANNs) have demonstrated their utility in areas that are important to environmental decision-making, like: pattern re-

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cognition, learning, classification, generalization, abstraction, non-linearity, and interpretation of incomplete or noisy data (Lek et al., 1996b; Lein, 1997; Lek et al., 2000). In the case of freshwater environmental management, a greater worldwide concern is being given to aquatic ecosystem health as a key feature of water quality. This health can be reflected in organisms such as fish, which are considered as indices of aquatic quality (Karr et al., 1986; Angermeier and Winston, 1999; Oberdorff et al., 2001b). Angermeier and Schlosser (1995) point out that, although a long-term goal for fish ecologists should be the understanding of communities and populations dynamics, the study of fish assemblages is a good short-term tool for decision makers. Thus, in order to gain an insight into fish assemblage structure, we use ANNs for estimating groups of guilds which we reckon as a practical approach for modelling fish communities, and for giving advice to environmental decision-makers, like in the construction of metrics for indices of biotic integrity (IBI) (Karr et al., 1986).

Abundances or presence of fish fauna have been estimated by ANNs in lotic systems (Baran et al., 1996; Lek et al., 1996a; Mastrorillo et al., 1997, 1998; Guégan et al., 1998; Brosse et al., 2001) and in lentic systems (Brosse et al., 1999a,b,c; Laë et al., 1999). Hence, in this paper we present an application of a back-propagation network (BPN; a supervised ANN) for modelling riverine fish assemblages in south west France with two objectives: (a) to predict species richness of fish guilds; and (b) to test the contribution of environmental variables for explaining guilds structure. We chose two groups of guilds: (a) by their origin—in native, diadromous, and introduced species; and (b) by their trophic structure—in planktivore, benthivore, nectivore, and multivore species. The latter comprised species with more than one habit (e.g. benthivore and nectivore). We considered these guilds of interest to resource managers due to their implications in community ecology and for landscape planning (Jackson et al., 2001). For example, introduced species may lead to fauna homogenisation (Rahel, 2000) or may have socio-economic repercussions (Bartley and Subasinghe, 1996), leading to conservation concerns on native

species (Angermeier and Schlosser, 1995). Benthivore fish are considered as good indicators of water quality in Maryland rivers (Scott and Hall, 1997), as diadromous species are in estuaries and large rivers (McDowall and Taylor, 2000). Nectivore fish (i.e. piscivores) have also special interest to conservation (Schlosser, 1991) and for sport-fishing (Oberdorff and Hughes, 1992).

## 2. Methods

### 2.1. Data

The data were obtained from the fish database of the Aquatic Environment Team, School of Agronomy at Toulouse (ENSAT), France. The main sampling techniques were electro-fishing by wading in small rivers, and electro-seining and seining in larger rivers. According to Seegert (2000), these methods allow an efficient assessment of species richness. We chose a subset from this database with 154 sampling sites for which collection of species richness was the objective of the sampling, and were spread over the whole Garonne basin (Fig. 1). For these sampling sites, we estimated altitude (m-ALT), distance from the river source (km-DIST), and surface of catchment area (km<sup>2</sup>-SURF) with cartographic maps (scale = 1:25 000). Besides, we coupled these data with the 1990–1996 annual mean water temperature (°C-TEMP) and annual mean water flow (m<sup>3</sup>/s-FLOW) obtained from the Regional Water Agency database. Since variables had different units, they were standardised by autoscaling to have zero means and unit standard deviations. The recorded species were classified in the groups of guilds above mentioned according to the information of Keith and Allardi (2001).

### 2.2. Modelling technique

A former study in the Garonne basin (Mastrorillo et al., 1998) demonstrated that fish species richness can be predicted by means of a BPN using three explanatory variables: altitude, distance from the river source, and surface of catchment area. Our study went further by looking into guild

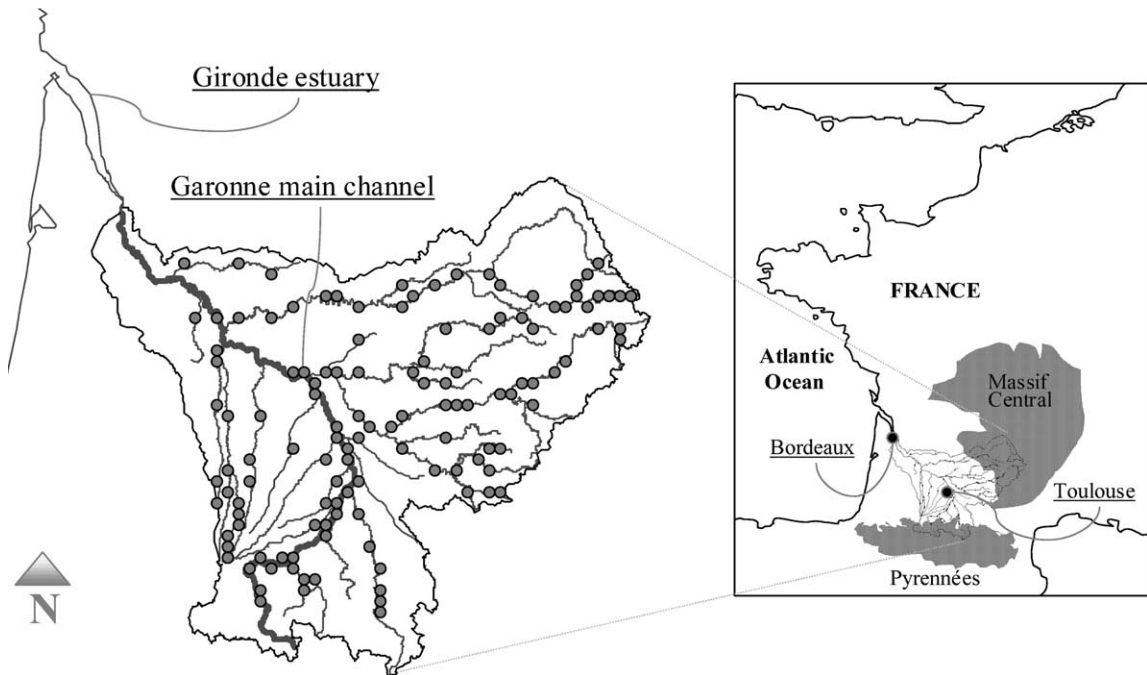


Fig. 1. Sampling sites in the Garonne basin, south west France. The main channel of the Garonne basin is indicated with bold line.

structure and adding two critical variables to fish communities: water temperature and water flow (Schlosser, 1990).

The construction of the BPN model was based on Lek et al. (1996b, 2000) and made in a MATLAB® platform. The BPN structure was made up of a three-layered feed-forward network (5:5:1) with information flowing from the input layer to the output layer. The input nodes comprised the environmental variables and the output node corresponded to the species richness of each guild. The information flow was represented by five changing weights, and an additional constant weight (value = 1) acting as the bias. A typical sigmoid function was used as the transfer function. Training was carried out by changing the weights according to the prediction errors. Each calculation of the weights is called an epoch or iteration. Epochs were repeated until the generalisation error reached the global minimum (i.e. early-stopping). This was done for avoiding overfitting of the BPN.

As the number of observations was not enough for splitting the data into training and testing sets, the BPN was tested instead with the leave-one-out

method (Kohavi, 1995). It consists of considering each observation (i.e. a sampling site) as a unique piece of information, repeating the estimation  $n - 1$  times. The leave-one-out method is an ANN testing technique frequently employed in ecology (Lek et al., 2000).

The contribution of explanatory variables was calculated by the partial derivatives method proposed by Dimopoulos et al. (1995). This sensitivity analysis modifies several inputs (i.e. the environmental variables) to look at the variation of the outputs (i.e. guild structure) by means of the Jacobian matrix of the activation function. Thus, the degree of influence of each variable with respect to the activation threshold can be examined.

The modelling was carried out for each of the seven guild data sets. To test the stability of the predictions, each model was repeated 10 times with an initial set of random weights (Kohavi, 1995).

Finally, in order to have an idea of the classical modelling technique, we applied multiple regression models to each guild. The performance of each model was verified with the standardised

determination coefficient of observed values against estimated values.

### 3. Results

We performed a predictive model of species richness and determined the contribution of environmental variables for each guild. Table 1 shows the standardised determination coefficients ( $r^2$ ) and the standard errors (SE) of the relations between observed and estimated values obtained for both the BPN and the linear regressions (LR). The BPN models showed higher predictability than the regressions. On the basis of high  $r^2$  and low SE, the best performance among BPN models was obtained for the nectivore, diadromous, and multivore guilds. In contrast, the poorest fit was for primary species.

An environmental descriptor was regarded as significant to the model when its contribution was higher than the mean uniform distribution (i.e. 20%) of the five variables (Brosse et al., 2001). Fig. 2 shows the importance of contribution in percentage for each descriptor after applying the partial derivatives method. With the exception of secondary species, SURF turned out to be by far the most important variable in explaining guilds composition. FLOW was frequently significant among

guilds, except for multivore and primary species. ALT and DIST were less constant but highly ranked in several cases: ALT for secondary species, and DIST for benthivore and primary species. In contrast, TEMP was not meaningful in any BPN model.

The partial derivatives method allowed to find the sensitivity of the BPN for each guild by plotting environmental descriptors against their partial derivatives. This is shown in Fig. 3 for SURF, which resulted the most important variable for most guilds. The values above the horizontal axis mean a positive relationship and the values below it represent a negative influence for the corresponding values of SURF. We can see that SURF has a positive effect on planktivore and introduced species. For other guilds, its influence was twofold: certain species seem favoured while others do not.

With respect to LR, the contribution of the variables was considered according to their regression coefficients (Beta) (Table 2). The order in decreasing importance of the variables was: DIST, SURF, TEMP, ALT and FLOW for the regressions. Contrary to the BPN models, TEMP was more relevant and FLOW was the lowest ranked.

## 4. Discussion

### 4.1. Prediction of guilds composition

The use of BPN models for predicting fish species richness in groups of guilds was better than regressions. This was probably due to the non-linearity of the relationships between variables (Lek et al., 1996b). Between 55 (for the guild of primary species) and 82% (guild of introduced species) of the variance was explained with the BPN models. This is comparable to the works of Schleiter et al. (1999), Mastroiillo et al. (1998).

However, the predictions showed high variability in several guilds for which the SE were rather high (Table 1). These high variations were more evident with the guilds of primary (SE = 1.81), benthivore (1.56), and introduced species (1.21). The same happened with the regression models, reflecting perhaps the fact that species included in

Table 1  
Standardised correlation coefficients ( $r^2$ ) and SE of the relations between observed and estimated values for each guild

Guilds	BPN		MR	
	$r^2$	SE	$r^2$	SE
<i>Trophic</i>				
Benthivore	0.74	1.56	0.64	1.84
Multivore	0.63	0.48	0.33	0.65
Nectivore	0.80	0.43	0.56	0.64
Planktivore	0.69	0.97	0.55	1.18
<i>Origin</i>				
Diadromous	0.80	0.58	0.67	0.74
Introduced	0.82	1.21	0.72	1.53
Native	0.55	1.81	0.36	2.17

The first two columns display the values obtained by the leave-one-out method of the BPN, and the left columns show the results for the multiple regressions (MR).

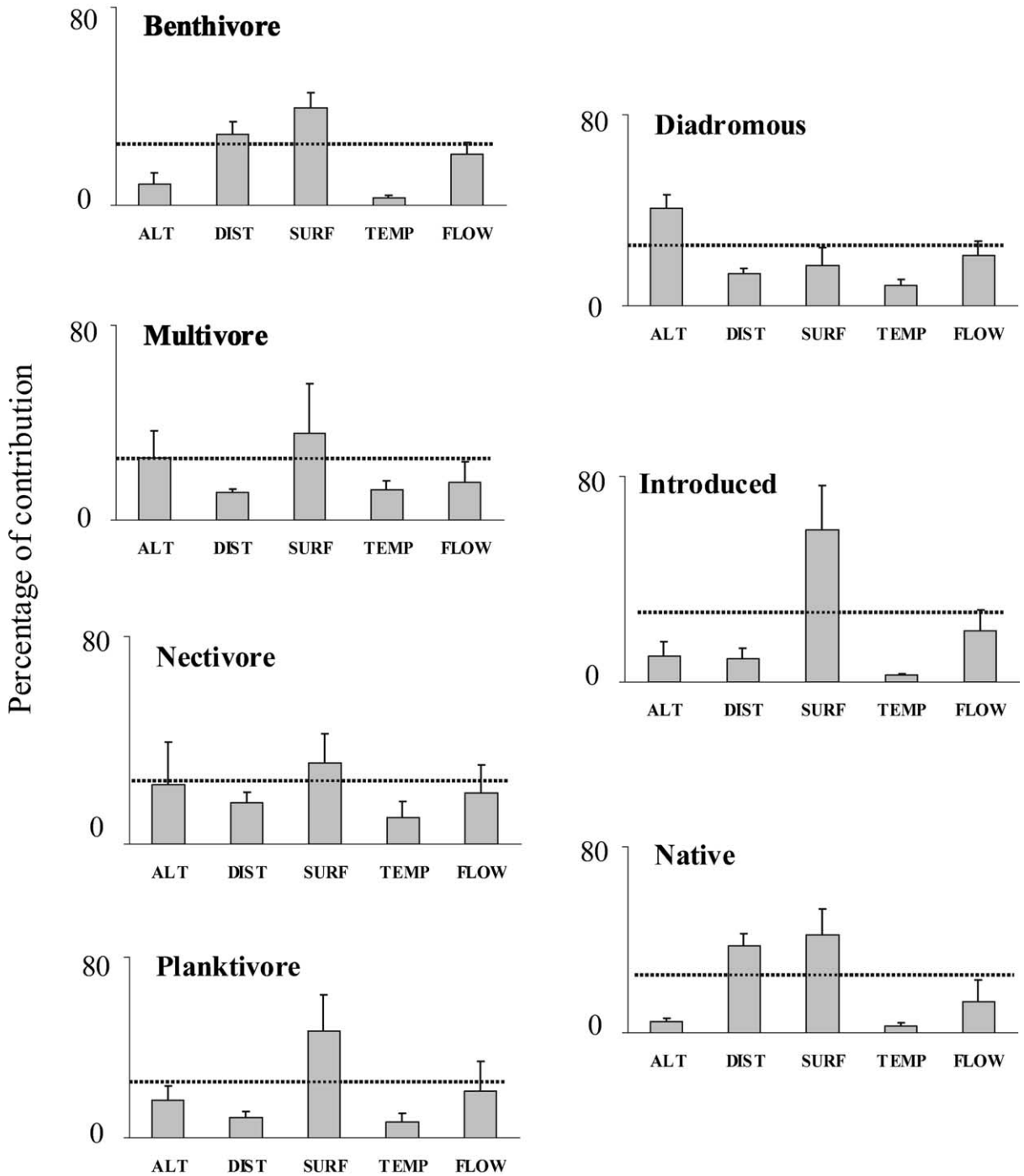


Fig. 2. Contribution of explanatory variables (percentage) for each guild. The dotted line represents the significance level (i.e. 20%). Graphs on the left correspond to trophic guilds and on the right to origin guilds. The environmental variables are: altitude (ALT), distance to source (DIST), surface of catchment area (SURF), mean annual water temperature (TEMP), and mean annual water flow (FLOW).

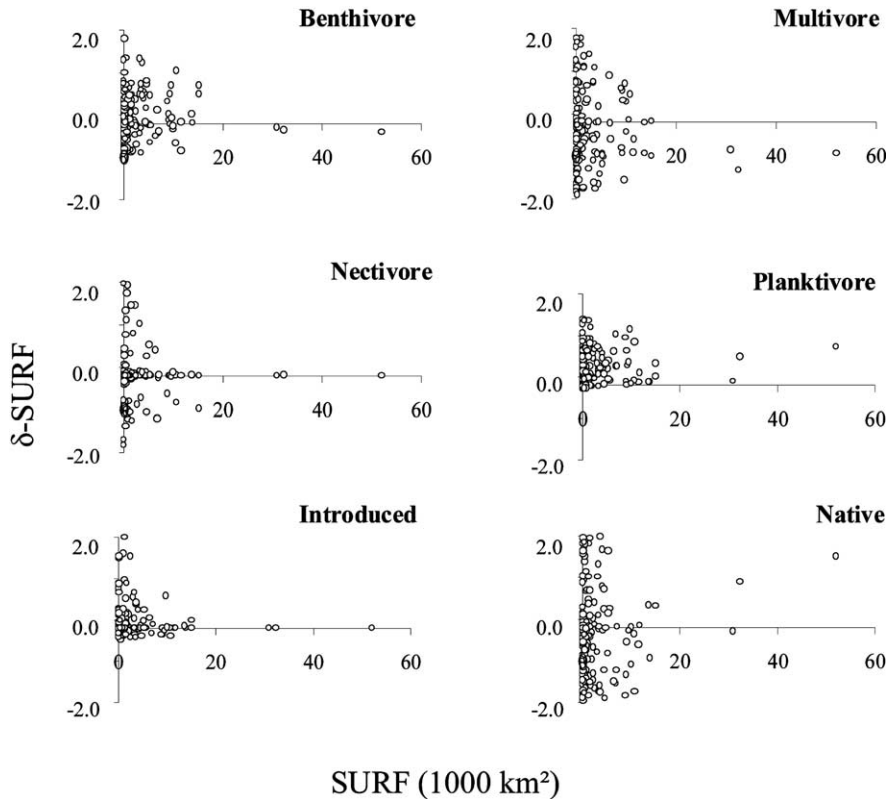


Fig. 3. Partial derivative values ( $\delta$ -SURF) for the model sensitivity to surface of catchment area (SURF). The first four graphs correspond to trophic guilds and the two below to origin guilds. The graph corresponding to diadromous species is not shown because SURF was not significant for this guild.

those guilds are more widely distributed, occupying a diverse range of habitats in the Garonne basin (Keith and Allardi, 2001). In contrast, the BPN models for secondary and nectivore species gave better fits (Table 1). These species have a more restricted distribution, dwelling in the larger stretches closer to estuaries or large pools. This fact may lead both BPN and regression models to lose certain power of generalisation when trying to predict species richness within heterogeneous habitats. Schlosser (1990), Paller (1994) demonstrated that there are relevant differences in fish assemblages between upstream and downstream reaches, suggesting the existence of different physiographic regions or source/sink areas within the basin (Angermeier and Winston, 1999; Smogor

and Angermeier, 2001). The natural variability of fish assemblages in rivers—not taken into account in the present study—could also affect the accuracy of the predictions (Oberdorff et al., 2001a). Another point relates to the nature of the data. Since surveys were carried out by different teams and consequently with unequal fishing effort, some bias may be present in the sampling data set. Nevertheless, the objective of these surveys was the collection of total species richness and, as recommended by Seegert (2000), it was carried out with different fishing gears for having a good estimation of species richness. A loss of accuracy may be another source of uncertainty in our results since we dealt with large spatial and temporal scales of analysis (Angermeier, 1995). However, as



Table 2  
Regression coefficients (Beta), SE and *P*-values (*P*) of the MR models for each guild

	Beta	SE	<i>P</i>	Beta	SE	<i>P</i>
	<i>Benthivore</i>			<i>Diadromous</i>		
ALT	−0.14	0.00	0.05	−0.12	0.00	0.07
DIST	0.34	0.00	0.00	−0.04	0.00	0.63
SURF	0.44	0.00	0.03	0.99	0.00	0.00
TEMP	0.26	0.12	0.00	0.00	0.05	0.97
FLOW	−0.25	0.01	0.22	−0.20	0.00	0.29
	<i>Multivore</i>			<i>Introduced</i>		
ALT	0.12	0.00	0.22	−0.10	0.00	0.10
DIST	0.54	0.00	0.00	0.32	0.00	0.00
SURF	−0.57	0.00	0.04	0.23	0.00	0.19
TEMP	0.16	0.04	0.14	0.32	0.10	0.00
FLOW	0.56	0.00	0.04	0.03	0.01	0.84
	<i>Nectivore</i>			<i>Native</i>		
ALT	−0.08	0.00	0.31	−0.13	0.00	0.18
DIST	0.40	0.00	0.00	0.45	0.00	0.00
SURF	0.50	0.00	0.02	−0.16	0.00	0.55
TEMP	0.01	0.04	0.88	0.21	0.14	0.05
FLOW	−0.14	0.00	0.54	0.01	0.01	0.96
	<i>Planktivore</i>					
ALT	−0.22	0.00	0.01			
DIST	0.16	0.00	0.10			
SURF	0.08	0.00	0.72			
TEMP	0.28	0.08	0.00			
FLOW	0.17	0.01	0.45			

Poff and Allan (1995) demonstrated, ecological hypothesis may be examined by using data collected in this way.

#### 4.2. Contribution of environmental variables

The significant variables which explained species composition of guilds with the BPN were coincident with the findings of Oberdorff et al. (1995). They found that surface of catchment area and mean annual river discharge were the most important factors influencing global fish species richness. However, a factor not included in our analysis—energy availability—may also play an important role on freshwater fish assemblages composition (Guégan et al., 1998). Our results were as well congruent with landscape theory, which relates components of the surrounding landscape with the functioning of lotic systems (Schlosser, 1991; Angermeier and Schlosser, 1995;

Schlosser, 1995). Although no single environmental descriptor has the explanatory power to account for fish community structure, Angermeier and Winston (1999) noted that surface of catchment or drainage area (i.e. SURF) could be broadly useful in explaining variation among aquatic communities. We found SURF as the most important descriptor in explaining fish guilds in the Garonne basin, except for secondary species. The latter could be explained on the basis that these fish migrate from the sea into freshwater and they remain in certain specific areas of large rivers. For them, ALT and FLOW were more relevant.

Taking into account values close to 20% (i.e. nectivore and introduced guilds), the second most influential variable was FLOW which was also consistently significant among guilds (Fig. 2). This variable involves natural drastic changes in headwater streams and more stable conditions in downstream areas (Schlosser, 1995). Nevertheless, water flow regulation does play a role in fish community structure (Bain and Finn, 1988; Oberdorff et al., 2001a). Physical barriers such as weirs, dams and flood-control structures are a crucial factor on fish communities. Schlosser (1990) indicates that indirect effects on fish assemblages like alteration of habitat, nutrients, energy and food, and direct effects such as reduction of larvae survival, are a consequence of flow regulation in rivers.

The third place of explanatory power, corresponding to ALT and DIST, was a standard outcome for explaining fish assemblage composition in rivers (Wootton, 1991). TEMP instead was not meaningful in any BPN model. Two conceivable explanations, not necessarily mutually exclusive, may be explored. First, Reyjol et al. (2001) related the highest temperature of the year to the presence of salmonid fish and the coldest to cyprinid species in the Garonne river. Thus, extreme values would be more relevant than mean annual temperature, as shown by Lyons (1996), who found that fish community composition in Wisconsin was strongly associated with summer temperature whereas altitude was not meaningful. This leads to the second explanation: ALT, SURF, and FLOW accounted for the effects of TEMP in the BPN models.

A different circumstance was present in the regression models as TEMP was among the most significant variables and FLOW the lowest ranked (Table 2). TEMP may have explained guilds species richness, masking the effects of ALT and FLOW. We reckon, though, that the poorer predictive power of regression models (Table 1) and their non-linear nature make them more unreliable in comparison with BPN models. It has to be noted that the role of descriptors may vary across landscapes or scales (Angermeier and Winston, 1999) and as shown here, among guilds as well.

#### 4.3. Environmental management issues

Following the landscape ecology concepts of Schlosser (1991), SURF, as an integrative variable, implies human influence on rivers due to agriculture, deforestation, and urban and industrial developments which take place in the Garonne basin. These economic activities result in significant alterations in fish assemblages affecting primary productivity and nutrient concentration, which have in turn a direct influence on trophic guilds. For example, planktivore species seem to be favoured by an increase of both drainage area and of organic matter (Fig. 3). But organic matter also means sedimentation, so that benthivore species which are adapted to it may present greater resistance (i.e. dots above the horizontal axis in Fig. 3) than the ones which feed from intolerant invertebrates or plants (dots below the horizontal axis). Something similar may explain the pattern of nectivore and multivore species which consume planktivore or tolerant benthic species and have a positive relationship with SURF, while for others it is a rather adverse condition. Sedimentation in rivers is strongly linked to agricultural practices. For example, Harding et al. (1999) point out that the degree of intensity in agriculture along a river catchment is closely related to the impacts on the lotic system, and Peterson (2000) shows that the changes in land use that influence the structure and dynamics of fish populations can also have economic consequences. The fact that FLOW was also a meaningful descriptor is of relevance to decision-makers because it implies a growing

concern in environmental management of rivers (Schlosser, 1990), including the preservation of aquatic diversity (Angermeier and Schlosser, 1995).

Modelling guilds thus, may prove relevant for IBI. Guilds are used for constructing metrics for IBI which vary in conformity with regional features. For example, Oberdorff and Hughes (1992) modified the IBI for the Seine-Normandie basin in Northern France. Thus, predicting guilds composition from landscape variables may be a first step to evaluate metrics for environmental quality indices in the Garonne basin. As IBI metrics are often subjectively assessed (Karr et al., 1986), BPN models may give a quantitative approximation for assessing IBI metrics. We have to note, nevertheless, that the use of ANNs are just a way to verify or assess IBI metrics, not to substitute the expertise of biologists in constructing an IBI (Karr et al., 1986).

A final word should be said about some of the drawbacks involved in modelling ANNs. First, there is a need for large databases to have better predictions. Second, an independent data set for validating the models is desirable. Both large databases and independent data sets are often difficult to find in ecological work. Thus, for small data sets like the one used for this paper, the leave-one-out method has to be carried out, a method which may present sometimes high variance (Kohavi, 1995). Third, as probabilistic approaches (Oberdorff et al., 2001b), ANNs are not able so far to assess the elements of fish assemblages which respond to human influences. Further research is thus needed for modelling both ecological and economic aspects in aquatic environmental management (Peterson, 2000), taking into account regional heterogeneity (Smogor and Angermeier, 2001).

## 5. Conclusion

We predicted guilds composition by means of a BPN, showing that the main descriptors of fish assemblages in the Garonne basin might imply human influence (i.e. land-use and flow regulation) in rivers. However, the heterogeneous habits and



spatial distribution of the species, along with temporal variability and data uncertainty, led presumably to a loss of prediction power for BPN. We found nevertheless, that ANNs were useful tool for gaining a first insight into fish assemblages in the Garonne basin—by means of guilds and the factors that determine their composition. Furthermore, we provided an objective way to assess or to evaluate IBI metrics, which may be of interest to decision makers under the EU Water Framework Directive. Further work thus, should be directed in understanding ecological and human processes within the studied region.

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