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A new definition of Minimum Sustainable Flow based on water quality modelling and fuzzy processing

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Abstract: Water resources in temperate and Mediterranean regions are increasingly scarce and water authorities need efficient criteria for the management of this precious commodity, guaranteeing an amount of water which ensures the preservation of aquatic life. This minimal discharge is referred to as the Minimum Sustainable Flow (MSF) and has been subject to many differing definitions in differing contexts. Gradually the purely hydraulic definition, very popular in the past, has given way to more comprehensive indicators taking into account the river ecosystem, and fish in particular, leading to very popular methods such as the IFIM (Instream Flow Incremental Methodology). The drawback of this approach is that it requires extensive field measurements and is very localized in space. This paper presents an extension of IFIM, extending its validity from the microhabitat to the macrohabitat and introducing several water quality parameters. From the methodological viewpoint, the new MSF definition is based on a Sugeno fuzzy inferential system, enhancing the system flexibility in producing environmental scenarios. As an example the method is applied to the middle-lower course of the Arno river, flowing in central Italy, showing that this method is better able to detect critical situations than the conventional IFIM approach.

Keywords: Minimum Sustainable Flow, water quality modelling, fuzzy reasoning, fuzzy inference, artificial intelligence.

1. INTRODUCTION

The growing concern about water shortage has fostered an increasing interest in the parameters defining the ecological status of natural water bodies, and rivers in particular, as tools in implementing water conservation strategies. The concept of Minimum Sustainable Flow (MSF), see e.g. [Stalnaker et al., 1995], once defined in purely hydraulic terms, in receiving renewed interest and several new definitions are being proposed to extend its ecological significance in addition to the original hydraulic meaning. The foremost effort to produce an all-encompassing habitat-oriented definition is the IFIM (In-stream Flow Incremental Methodology). It is a complex analytical and conceptual structure, conceived for the management of river flow regimes variations caused by human exploitation of the resource (Stalnaker *et al.*, 1995). Therefore, IFIM can provide answers to problems of river management in relation to the aquatic ecosystem [Bovee *et al.*, 1998]. However, its limitation, as a biological method, is its focus on the high-end of the food chain, i.e. fish, disregarding all the underlying water quality parameters and the aquatic food chain, which contribute to the welfare of the whole ecosystem. Further, the practical implementation of the IFIM procedure requires extensive field work and its results are very limited in space, being microhabitat-oriented. Conversely, the growing need for regulatory tools calls for simpler assessment tools, which can be used for scenario generation using synthetic water quality data.

In this paper, a new MSF definition is proposed, which takes into account some ecological parameters than were previously disregarded in the conventional MSF definition based on the IFIM approach. In this proposal, not only flow, velocity and depth are considered, but also water quality parameters such as temperature, pH, dissolved oxygen and unionized ammonia. All these parameters contribute to the computation of the Composite Suitability Index (CSI) from which the MSF is obtained. This new methodology results from the integration between an extension of the IFIM approach and a water quality model (QUAL2Kw) [Pellettier *et al.*, 2006] fed with hydraulic data computed with HEC-RAS 6 [HEC, 1991], a widely-used one-dimensional open channel flow computational scheme. Both packages are of public domain and can be freely downloaded from the internet. A fuzzy computational method based on Sugeno fuzzy inference [Babuska, 1998] is used to combine the individual suitability contributions and yield the extended MSF.

The paper is organized as follows: after describing the three steps of the computational method, this is applied to the computation of the MSF for the lower part of the Arno catchment, for which critical conditions often develop during the summer months. It is shown that the proposed method is more flexible and comprehensive in determining the critical MSF during the low-flow season.

2. A COMPUTATIONAL SCHEME FOR THE MINIMUM SUSTAINABLE FLOW

The proposed method is an extension of the well-known IFIM (In-stream Flow Incremental Methodology) approach [Stalnaker *et al.*, 1995; Bovee *et al*, 1998], which is supposed to be implemented in five sequential phases: problem identification, study planning, study implementation, alternatives analysis, and problem resolution. The main difference between this approach and IFIM is the spatial scale, which in our case is catchment-oriented as contrasted to the micro-habitat approach adopted by IFIM.

The MSF computation develops in three successive steps, as illustrated in Figure 1.

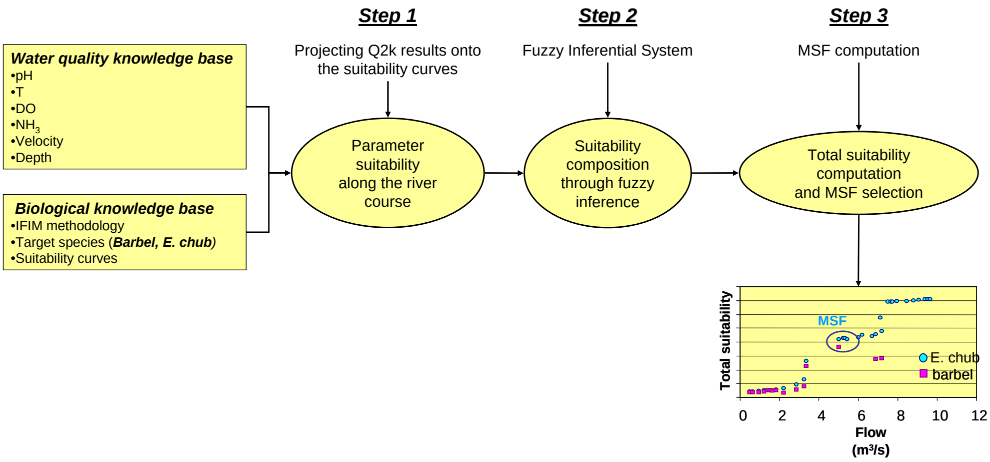

Figure 1. The three step in the procedure for the MSF computation.

The example figures shown in this section to illustrate the method refer to the Arno river case study and the two most typical fish species abundant in that environment: Barbel (*Barbus tyberinus*) and European Chub (*Leuciscus cephalus*), the most widespread autochthonous and reophyl species. The three steps of Figure 1 are now examined.

2.1. Step 1: Projecting the quality data onto the suitability curves.

The suitability curves for each parameter shown in Figure 2 were obtained from experimental observation regarding the fish habitat. Combining this information with the catchment quality obtained through simulation of the hydrodynamic (Hec-Ras) and quality (QUAL2Kw) models yields the river-wide suitability curve for each parameter, shown in

Figure 3. These curves are obtained separately from field studies and literature data and refer to the considered species (Barbel and European Chub). Each hydraulic or quality parameter contributes to the habitat suitability in a different manner, and for each of them the fish response has been normalized between 0 (totally unsuitable habitat) and 1 (perfectly comfortable habitat). The combination of individual suitability indexes will be described in the next step.

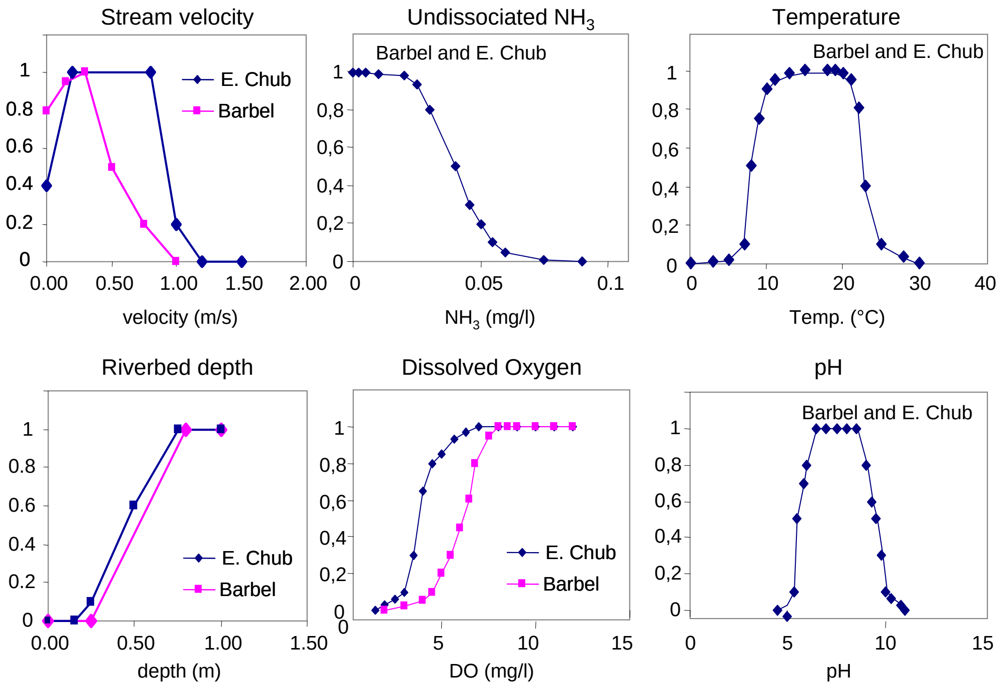

Figure 2. Normalized suitability curves for the river quality parameters considered in the study for European Chub and Barbel. Wherever a single line is shown both species exhibit the same suitability.

Feeding each diagram of Figure 2 with the quality data produced by QUAL2Kw the overall suitability for that parameter can be obtained for the whole river length, as shown by the examples of Figure 3.

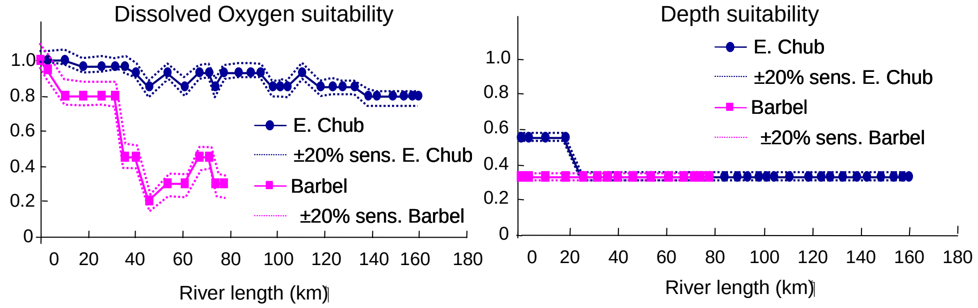

Figure 3. Example of single parameter suitability curves computed along the whole river length. The Barbel suitability data cover only the first 80 km because its habitat is limited to this upstream part. The dotted curves represent the ± 20% sensitivity with respect to the fuzzy membership functions: it can be seen that dissolved oxygen has a higher sensitivity than depth.

2.2. Step 2: The fuzzy inferential system.

Apart from the hydrologic data, which are processed separately, the Sugeno fuzzy inferential engine has four water quality suitability indexes as antecedents (dissolved oxygen, unionized ammonia, velocity and depth, all defined in the (0, 1) support) and four singleton consequents. Therefore the complete inferential set would be of 3×4×4 = 48 rules.

The knowledge base behind Table 1 was extracted by direct experimentation and prior biological experience, both direct and from the literature. By direct experimentation, however, this set was reduced to 31 practically useful rules, listed in Table 1, where H, M, L are Gaussian-shaped membership functions defined on the support of each antecedent variable qualifying suitability to DO, NH3, velocity U and depth H as High, Medium and Low respectively. The four consequent singletons are set at 1 (CSI_H), 0.8 (CSI_MH), 0.5 (CSI_ML) and 0.2 (CSI_L).

Table 1. Rules of the Sugeno fuzzy inferential system. The suffix ‘s’ after each antecedent parameter stands for ‘suitability’.

1. If (DOs is H) and (NH3s is M) and (Us is M) and (Hs is H) then (CSI is CSI_H)
2. If (DOs is H) and (NH3s is M) and (Us is H) and (Hs is M) then (CSI is CSI_MH)
3. If (DOs is M) and (NH3s is H) and (Us is M) and (Hs is H) then (CSI is CSI_MH)
4. If (DOs is H) and (NH3s is L) and (Us is H) and (Hs is L) then (CSI is CSI_ML)
5. If (DOs is L) and (NH3s is H) and (Us is H) and (Hs is L) then (CSI is CSI_ML)
6. If (DOs is L) and (NH3s is M) and (Us is L) and (Hs is M) then (CSI is CSI_L)
7. If (DOs is M) and (NH3s is L) and (Us is M) and (Hs is L) then (CSI is CSI_ML)
8. If (DOs is L) and (NH3s is M) and (Us is M) and (Hs is L) then (CSI is CSI_L)
9. If (DOs is H) and (NH3s is H) and (Us is M) and (Hs is M) then (CSI is CSI_MH)
10. If (DOs is H) and (NH3s is H) and (Us is L) and (Hs is L) then (CSI is CSI_ML)
11. If (DOs is M) and (NH3s is M) and (Us is H) and (Hs is H) then (CSI is CSI_H)
12. If (DOs is M) and (NH3s is M) and (Us is L) and (Hs is L) then (CSI is CSI_L)
13. If (DOs is L) and (NH3s is L) and (Us is M) and (Hs is M) then (CSI is CSI_ML)
14. If (DOs is H) and (NH3s is H) and (Us is H) and (Hs is L) then (CSI is CSI_MH)
15. If (DOs is M) and (NH3s is M) and (Us is M) and (Hs is H) then (CSI is CSI_MH)
16. If (DOs is M) and (NH3s is M) and (Us is M) and (Hs is L) then (CSI is CSI_ML)
17. If (DOs is H) and (NH3s is M) and (Us is M) and (Hs is M) then (CSI is CSI_MH)
18. If (DOs is H) and (NH3s is L) and (Us is L) and (Hs is L) then (CSI is CSI_L)
19. If (DOs is M) and (NH3s is H) and (Us is M) and (Hs is M) then (CSI is CSI_MH)
20. If (DOs is L) and (NH3s is H) and (Us is L) and (Hs is L) then (CSI is CSI_L)
21. If (DOs is M) and (NH3s is L) and (Us is L) and (Hs is L) then (CSI is CSI_ML)
22. If (DOs is M) and (NH3s is M) and (Us is H) and (Hs is M) then (CSI is CSI_H)
23. If (DOs is L) and (NH3s is L) and (Us is H) and (Hs is L) then (CSI is CSI_ML)
24. If (DOs is H) and (NH3s is M) and (Us is H) and (Hs is H) then (CSI is CSI_H)
25. If (DOs is H) and (NH3s is H) and (Us is M) and (Hs is H) then (CSI is CSI_MH)
26. If (DOs is L) and (NH3s is M) and (Us is L) and (Hs is L) then (CSI is CSI_L)
27. If (DOs is L) and (NH3s is L) and (Us is M) and (Hs is L) then (CSI is CSI_ML)
28. If (DOs is L) and (NH3s is M) and (Us is M) and (Hs is M) then (CSI is CSI_ML)
29. If (DOs is M) and (NH3s is M) and (Us is L) and (Hs is M) then (CSI is CSI_ML)
30. If (DOs is M) and (NH3s is M) and (Us is M) and (Hs is M) then (CSI is CSI_MH)
31. If (DOs is L) and (NH3s is L) and (Us is L) and (Hs is L) then (CSI is CSI_L)

The fuzzy inference engine and its preliminary part, generating the river quality parameters, is shown in Figure 4. The result of this procedure is the production of the **C**omposite **S**uitability **I**ndex (CSI)

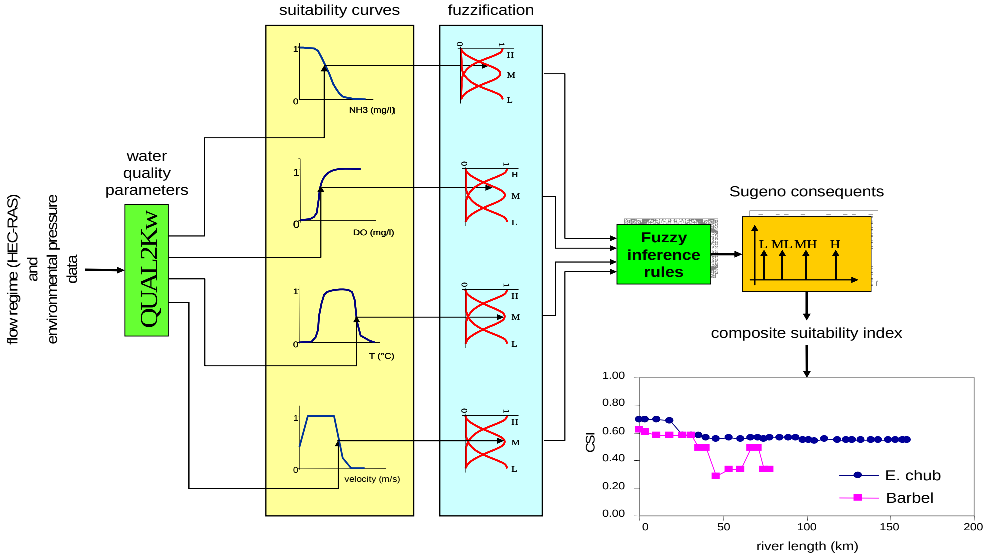

Figure 4. Computational scheme producing the Composite Suitability Index.

In the fuzzy rules of Table 1 the AND and THEN connectives are implemented with the 'minimum' operator. Then the *Composite Suitability Index* (CSI) is obtained by weighted average defuzzification

$$CSI = \frac{\sum_{i=1}^{31} \mu_i b_i}{\sum_{i=1}^{31} \mu_i}, \tag{1}$$

where μ_i is the degree of fulfilment of each rule in Table 1 and b_i is the corresponding singleton previously defined.

2.3. Step 3: Computation of the actual Minimum Sustainable Flow

The final goal of the study is to obtain the *weighted usable area* (WUA) as a function of flow, from which the minimum sustainable flow can be determined as the minimum discharge still providing a fish suitable habitat. However, the CSI defined by eq. (1) as the output of the computational scheme of Figure 4 is not yet in terms of WUA vs. flow, therefore we are not yet in a position to select the MSF on such a graph. It is in this final step that the present method differs considerably (apart from the fuzzy approach) from the conventional IFIM procedure. Contrary to the classical IFIM method, where the WAU is computed as the weighted sum of the products of the CSI by the pertinent cells, here the WUA is obtained as the product of the reach CSI multiplied by the average reach cross section, namely

$$WUA = CSI \times S_r, \tag{2}$$

where S_r is the average river section computed along the whole reach of interest. Thus there will be one WUA for each reach. In this way, the emphasis is shifted from the microhabitat, typical of IFIM, to a catchment-wide dimension.

In the WUA/flow diagram, the Minimum Sustainable Flow (MSF) is usually determined as the first break-point in the WUA-discharge diagram [Milhous et al., 1989]. To obtain such a diagram requires an iterated computation of the WUA for the whole range of expected flows. The break-point normally represents the point where a major change in the WUA/flow slope occurs. It represents the boundary between the monotonic part and the region where WUA increases can be obtained only at the expense of a major flow increase. Thus from a cost-benefit viewpoint the breakpoint flow represents the best compromise between environmental sustainability and the economic value of the water resource and as such it can be regarded as the Minimum Sustainable Flow. Figure 5 shows a typical WUA vs. flow diagram with the location of the breakpoint, which can be interpreted as the MSF. The figure refers to a typical section of the Arno river during the summer low-flow condition.

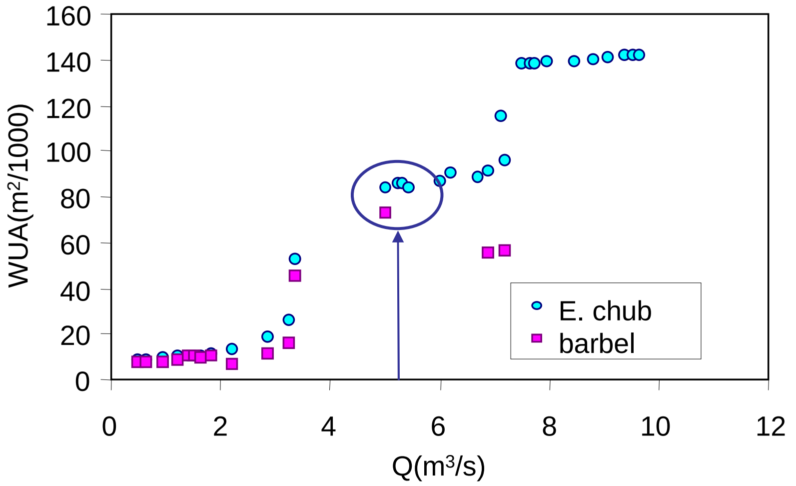

Figure 5. MSF computed for both target species at a typical section of the Arno river during low-flow conditions.

3. APPLICATION TO THE ARNO RIVER

The procedure outlined in Section 2 is now demonstrated with an application to the middle-lower course of the Arno river, flowing through Tuscany, central Italy, for an overall length of nearly 180 km. Figure 6 depicts the extent of the study together with reach boundaries and water exchanges.

3.1. Characteristics of the Arno catchment

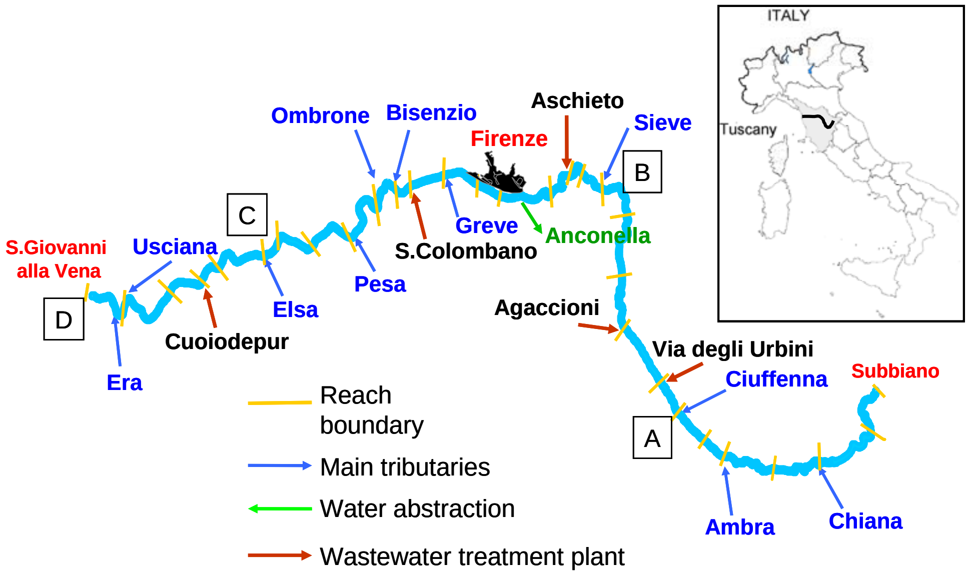

Figure 6. Reach boundaries and main features of the part of the Arno river considered in this study. The letters A, B, C, D refer to the MSF computations shown in Figure 7.The bars indicate the reach boundaries and the arrows show the water exchange points.

Running the procedure of Section 2 for a number of typical flow regimes, mostly in the low-to-middle range, the WUA/flow curves were obtained for each section. The most meaningful of them, corresponding to the reaches labeled as A, B, C, and D in Figure 6, are shown in Figure 7 where the typical low and medium flow are also indicated for comparison.

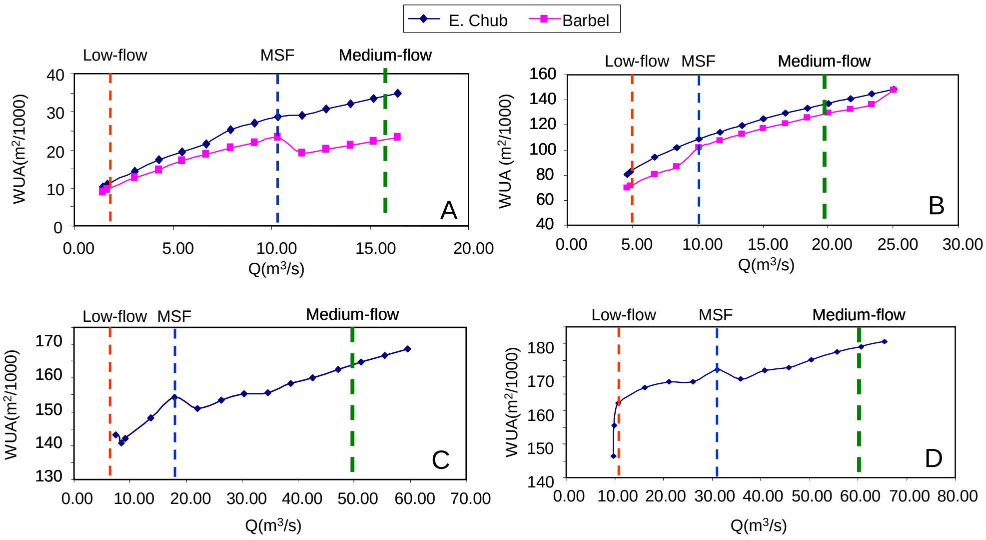

Figure 7. MSF values for four meaningful reaches labelled with the lettering in the map of Figure 6 resulting from the described algorithm. It can be seen that the low-flow condition is much lower than the recommended MSF. In reaches C and D only the European Chub is present, because in the downstream reaches Barbel is absent.

The results of Figure 7 show that during the low-flow condition the Arno river is in a highly critical condition. In fact, according to the method outlined in Section 2, the typical low-flow condition is considerably worse than the MSF, whereas in the medium-flow regimes the situation improves considerably.

4. CONCLUSION

The purpose of the study was twofold, one methodological and one applicative. From the methodological viewpoint, described in Section 2, a new definition of the Minimum Sustainable Flow (MSF) was proposed, based on water quality parameters and not only on an hydraulic basis. Further, the coupling with a water quality model (QUAL2Kw) allows the production of a large number of scenarios for management decision support. The aim of producing a new definition of MSF was to extend the IFIM concept from the microhabitat to the macrohabitat and introduce more water quality parameters in its definition. The Sugeno fuzzy inferential engine represents a neat way for combining the suitability index for each parameter to derive the composite index, from which the weighted usable area is eventually computed, enhancing the system flexibility and paving the way toward more comprehensive MSF definitions.

The applicative aspect, described in Section 3, was the MSF computation for the middle and lower Arno river course flowing through central Italy, showing its critical condition during the summer low flow, since in almost every reach the flow is well below the MSF.

5. ACKNOWLEDGEMENTS

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6. REFERENCES

Babuska R., *Fuzzy modeling for control.* Kluver Publ. Co., Amsterdam, 260 pp, 1998.

Bovee K.D., B.L. Lamb, J.M. Bartholow, C.B. Stalnaker, J. Taylor, and J. Henriksen, *Stream Habitat Analysis Using the Instream Flow Incremental Methodology.* Information and Technology Report USGS/BRD/ITR-1998-0004. Fort Collins, CO: U.S. Geological Survey-BRD. 130 pp, 1998.

Chapra, S. and G. Pelletier, *QUAL2K: A Modeling Framework for Simulation River and Stream Water Quality: Documentation and User Manual*. Civil and Environmental Engineering Dept., Tufts University, Medford, MA., 2003.

Milhous R.T., M.A. Updike and D.M. Schneider, *Physical habitat simulation system reference manual – version II.* U.S. Fish and Wildlife Service Biological Report 89 (16). Washington, D.C., 1989.

Pelletier G.J., S.C. Chapra, and H. Tao, QUAL2Kw e A framework for modeling water quality in streams and rivers using a genetic algorithm for calibration. Environmental Modelling & Software 21 (2006) 419 – 425, 2006.

Stalnaker, C., B.L. Lamb, J. Henriksen, K. Bovee, and J. Bartholow, *The instream flow incremental methodology: a primer for IFIM.* National Ecology Research Centre, Internal. Publication. U.S. Department of the Interior, National Biological Service, Fort Collins, Colorado: 43 pp, 1995.

Shepard R.B., *Quantifying Environmental Impact Assessments Using Fuzzy Logic.* Springer Science+ Businness Media, Inc., 2005.

Svobodova Z., R. Lloyd, J. Machova, and B. Vykusova, *Water Quality and fish health.* EIFEC Technical Paper, FAO, Rome, n.54, 1993.

U.S. Army Corps of Engineers, Hydrologic Engineering Center (HEC), *HEC-6, Scour and Deposition in Rivers and Reservoirs, User's Manual*, Davis, CA., 1991.