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INSTREAM FLOW DETERMINATION USING A MULTIPLE INPUT FUZZY-BASED RULE SYSTEM: A CASE STUDY

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ABSTRACT

The attempts made to manage water to meet human requirements should also consider the needs of freshwater species and ecosystems. There are many tools available to assess instream flow needs, one of which is the use of habitat preference models. In this study, a fuzzy approach was used for modelling habitat preferences for two life stages of Atlantic salmon (*Salmo salar*). Experienced fish biologists and technicians contributed to the development of fuzzy sets and fuzzy preference rules for spawning and parr habitat. Fuzzy sets were defined for water depth, velocity and substrate composition. Fuzzy preference rules for the two life stages were then defined as sets of IF–THEN rules relating the physical attributes to habitat suitability. The fuzzy suitability indices are then used to obtain weighted usable area (WUA) at different discharges and to estimate the ecologic flow required to preserve habitat. Different methods are applied to combine the membership function and rules defined by the experts. A sensitivity analysis of rules of the combined system indicated that a limited number of rules are determinant and results are highly dependent on the consequences of these rules. A modification in the consequence of these rules can significantly alter WUA estimations. It is therefore recommended to combine the knowledge of many experts in the elicitation process and to quantify the uncertainty associated with the combination of expert knowledge. Copyright © 2008 John Wiley & Sons, Ltd.

KEY WORDS: fuzzy set; model; habitat preference; Atlantic salmon

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INTRODUCTION

Following the increase in water demand of the mid-20th century, biologists and hydrologists recognized the need for 'instream flows' to protect fish and aquatic habitat (Stewart *et al.*, 2005). Instream flow refers to water that is retained in a river after human actions such as impoundment or diversion for out-of-stream use by industry, agriculture, etc. Instream flows are valuable for maintaining fish and wildlife habitat. This has led to the provision of instream flows specifically for environmental purposes, also sometimes called environmental flows. These are designed to enhance or maintain the habitat for riparian or aquatic life.

Construction of dams to impound water, diversion of water for irrigation, and municipal and industrial uses may deplete natural stream flows to the point where instream flow needs are no longer met. Regulatory agencies as well as managers of hydroelectric facilities are faced with making difficult decisions on how to allocate water among multiple uses. To make the water allocation decisions, regulatory agencies need to know how flow alterations will affect fish and aquatic habitats. The need to sustain the ecological values of rivers is now widely recognized and implemented in different policies and legislations around the world (e.g. Quebec's policy on instream flow for the protection of fish habitat, Faune et Parcs Québec, 1999; King *et al.*, 1999). Generally speaking, these legislations insist on maintaining sufficient flow in a river to allow different species (mostly fish) to successfully complete their different life stages (Leclerc *et al.*, 2003).

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Habitat requirements can be defined as environmental features necessary for the survival and persistence of individuals or populations (Armstrong *et al*., 2003; Rosenfeld, 2003). Physical habitat structure is of paramount importance in determining both the abundance and species composition of stream fishes, thus most habitat studies deal only with physical variables. The physical habitat characteristics mostly considered in this context include water depth, water velocity and flow, cover and substratum composition.

The classic approach of quantifying habitat consists of estimating local habitat indices based on available knowledge regarding optimum range of abiotic conditions for the targeted species life stages (Leclerc *et al*., 2003). The habitat suitability index (HSI), the most commonly used index of habitat, is an analytical tool used to represent preferences of different species for a combination of instream variables (e.g. velocity, depth, substrate, cover) (Heggenes, 1990; Vadas and Orth, 2001). In general, the indices are in the range of 0–1 for each variable. Several suitability indices must be combined to define a composite suitability index (Vadas and Orth, 2001).

Different methods have been used to combine the different suitability indices obtained for each physical factor. The indices are generally combined either by multiplication or additive functions. In many applications, the suitability indices for individual habitat variables are multiplied to obtain a composite HSI (Vadas and Orth, 2001). This method is based on the assumption that fish selects each particular variable independently of other variables (Bovee, 1986), as multiplication of individual indices is analogous to multiplying assumed independent probabilities of different variables. The key point is that a product equation yields zero suitability for any given unsuitable habitat variable:

$$\mathrm{HSI} = \mathrm{SI}_1 \times \mathrm{SI}_2 \times \ldots \times \mathrm{SI}_n \tag{1}$$

Several alternative methods are available for calculating a composite HSI. The arithmetic-mean HSI is based on the assumption that habitat variables are compensatory and good habitat conditions on one variable (e.g. velocity) can compensate for poor conditions on other variables (e.g. depth). Another approach, the lowest SI assumes that the most limiting factor determines the upper limit of habitat suitability and the fact that high SI values cannot compensate for low SI values in other variables (Korman *et al*., 1994). The geometric mean HSI is the nth root of the product of n individual indices (e.g. the fourth root of the product of four indices). This approach also implies some compensation (Korman *et al*., 1994), yet like the product equation, it yields zero suitability for any zero-valued HSI (Brown *et al*., 2000). Several assumptions are implicitly used in studies using composite indices: (1) all variables are equally important to the growth and survival of the aquatic organisms (this assumption is often compensated for by using weighted means), (2) all environmental variables are independent and there is no interaction between them. Recently, more efficient methods have been proposed to estimate habitat suitability indices such as the logistic regression, discriminant analysis and artificial neural networks (see Ahmadi-Nedushan *et al*. (2006) for a detailed review).

Jorde *et al*. (2001) reported that the problems still remaining with most current methods are: (1) Habitat requirements, which in fact cannot be precisely specified, are defined by precise numbers, (2) input variables are not always independent from each other although this is a required assumption in many methods (e.g. multiple linear regression), (3) high resolution field data are needed.

Fuzzy rule-based systems offer a methodological approach to resolving the above problems. There have been few applications of fuzzy logic in habitat studies. One important feature of fuzzy approaches is that they offer a methodology to consider uncertainties that often exist in ecological modelling and in habitat studies. Sources of uncertainty of ecological data include the presence of random variables, incomplete or inaccurate measurements and the use of approximate estimations instead of direct measurements (Salski, 2003).

Compared to conventional methods, a fuzzy rule-based approach presents the following advantages: (1) it allows for the numerical processing of qualitative knowledge of experts about fish habitat, (2) it can consider multivariate effects of variables without the assumption of independence of the input parameters, (3) new parameters can be added easily, thereby allowing for the inclusion of numerous combinations of physical parameters into habitat simulation tools and (4) it is relatively easy to implement (Jorde *et al*., 2001; Kerle *et al*., 2002). These aspects present significant advantages in habitat modelling as qualitative knowledge is often readily available from experienced fish biologists and can therefore be used and transferred into preference data sets.

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The main application areas of the fuzzy set theory in ecological research are data analysis, knowledge-based modelling and decision making (Salski, 2003; Adriaenssens *et al*., 2004). Several applications of fuzzy approaches are reported for assessment and classification of habitat (Kampichler *et al*., 2000; Svoray *et al*., 2004; Legleiter and Goodchild, 2005). A few of these applications are specifically related to stream habitat quality assessment (Jorde *et al*., 2001; Kerle *et al*., 2002; Schneider and Jorde, 2003).

A promising example of fuzzy modelling in habitat studies and river restoration is an ecohydraulic habitat suitability model similar to PHABSIM, which was developed using fuzzy logic as an alternative to traditional habitat suitability curves (Schneider and Jorde, 2003). The simulation model, Computer Aided Simulation Model for Instream Flow Requirements (CASIMIR), may be executed as a sub-model inside existing 1D, 2D or 3D hydrodynamic models. Schneider and Jorde (2003) used CASIMIR for fish habitat evaluation of several rivers in Switzerland and compared the fuzzy rule-based and preference functions. It was concluded that observed fish densities show a higher correlation with fuzzy-based simulations than for those based on preference functions.

In the aforementioned applications, expert knowledge was used to define the fuzzy systems. However, combination and aggregation of expert opinions and in particular using more than one expert opinion have not been fully analysed and discussed. The objective of the present study is to use fuzzy systems with multiple expert inputs to evaluate the habitat suitability and to compare these inputs by estimating weighted usable area (WUA) as a function of the instream ecologic flow.

STUDY AREA

The Romaine River is located in Northeastern Quebec and flows north to south for a total length of 496 km to empty in the St. Lawrence River (Figure 1). Its drainage area covers 14 350 km^2 and its mean annual flow is 340 $m^3 s^{-1}$. The Romaine River is home to a small Atlantic salmon (*Salmo salar*) population located in the lower reaches of the river, from the mouth to approximately 51 km upstream. Habitat studies were conducted on the river between 2001 and 2004 for spawning and rearing habitats.

Field investigations included the quantification of redd density between 1999 and 2004 and habitat characteristics (velocity, depth, substrate) at the five most important spawning sites located respectively 34.5, 46.2, 49.0, 51.4 and 51,6 km upstream of the mouth of the river. Parr density measurements were conducted in 2001 using six different fishing gears in known rearing habitats within the lower reaches of the river. Depth, velocity and substrate were measured in the field at four study reaches with spawning sites and four reaches for parr rearing.

METHODS

Fuzzy logic approach

Fuzzy logic was first developed by Zadeh (1965) in the mid-1960s for representing uncertain and imprecise knowledge. Since Zadeh (1965) published the fuzzy set theory, the fuzzy logic approach has been widely used in many fields of application, such as pattern recognition, data analysis, system control, etc. At present, fuzzy systems are being used in a wide range of industrial and scientific applications with the main application areas being fuzzy control, data analysis and knowledge-based systems (Ross, 2004). The fuzzy logic approach provides an approximate but effective means of describing the behaviour of systems that are too complex, ill-defined or not easily analysed mathematically.

The fuzzy set theory is as an extension of classic set theory, and is built around the central concept of membership functions. Conventional characteristic mappings of a classical set can only take two values (i.e. 1 or 0) and a value either belongs or does not belong to the set. In contrast, a fuzzy set is described by its membership function, indicating the membership degree. The values of the membership function are real numbers in the interval [0,1], where 0 means that the object is not a member of the set and 1 means that it belongs entirely.

A fuzzy system consists of three parts: (1) fuzzy input and output variables and their fuzzy membership functions; (2) fuzzy rules; (3) fuzzy inference methods (Kasabov, 1998). In the fuzzy approach, first, habitat suitability and inputs are subdivided in different classes (e.g. low-medium-high or poor-average-good, etc.). In this

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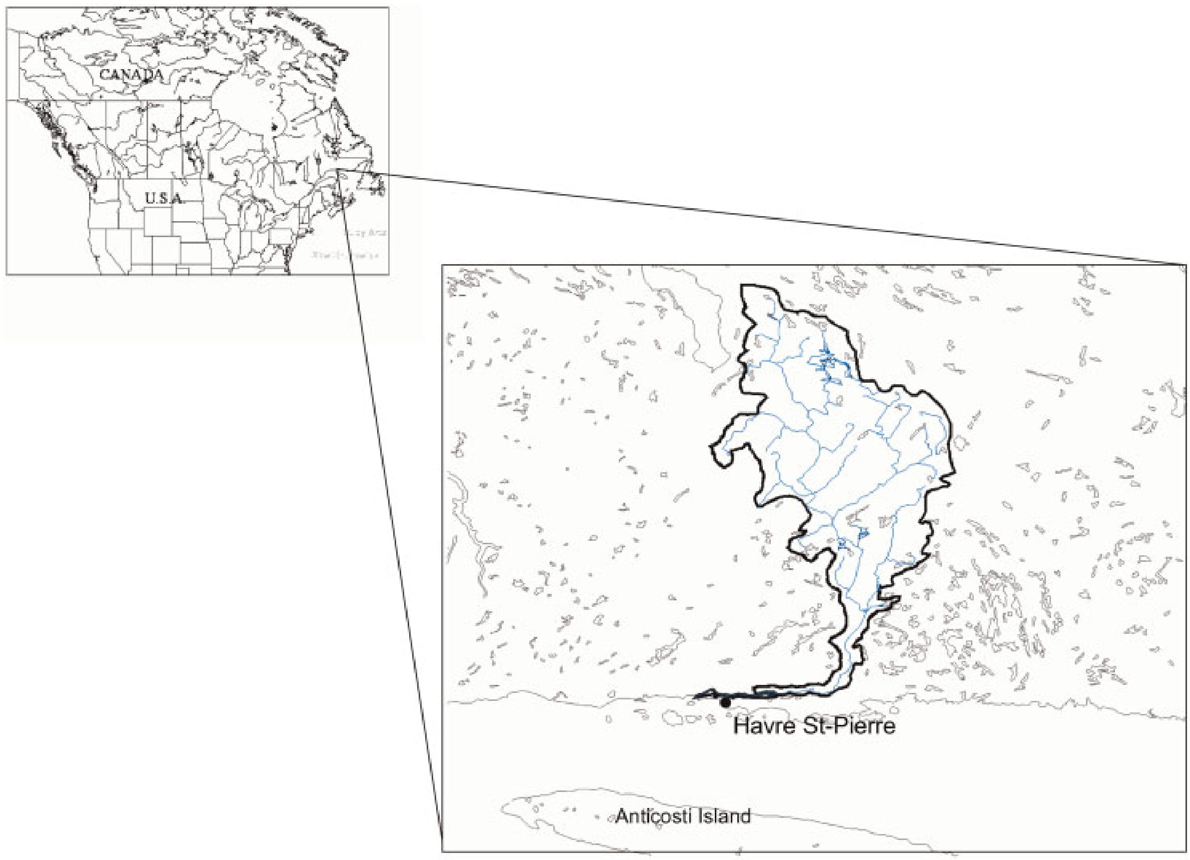

Figure 1. Location or Romaine River with drainage basin. This figure is available in colour online at www.interscience.wiley.com/journal/rra

study, depth, velocity and substrate diameters are used as input parameters. In each case, three categories were defined.

Simple trapezoidal and triangular functions are often used for defining the fuzzy sets for each input variable. A trapezoidal function is defined by four boundary values, for example a_1, a_2, a_3 and a_4 on Figure 2. Triangular functions are a special case of trapezoidal function where $a_2 = a_3$.

In the present study, each expert was asked to use trapezoidal membership function by defining the values of a_1, a_2, a_3 and a_4 for each of the three categories for three input variables. The output, that is HSI, was defined using a unique fuzzy set with three categories.

Figure 3 shows an example of the fuzzy sets used for the input variables and output variable which are each defined by three linguistic variables 'low', 'medium' and 'high' and their respective fuzzy sets, corresponding to a combination of simple linear functions. The range covered by the membership functions is determined by both the range of the physical attributes observed in the river and the niche of physical attributes used by the species under consideration.

As stated before, an element can partially belong to a fuzzy set and has a membership degree ranging from zero to one. For example in Figure 3, a velocity of 1.75 ms^{-1} partially belongs to two categories: medium velocities with a membership degree of 0.5 and high velocities with an equal degree of membership.

Once the fuzzy sets are defined for each physical attribute and for the HSI, experts must link this information by defining rules of association. In fuzzy rule-based systems, knowledge is represented by IF–THEN rules. Fuzzy rules consist of two parts: an antecedent part stating conditions on input variables; and a consequent part describing the corresponding category of the output variable resulting from the combination of different sets of input variables.

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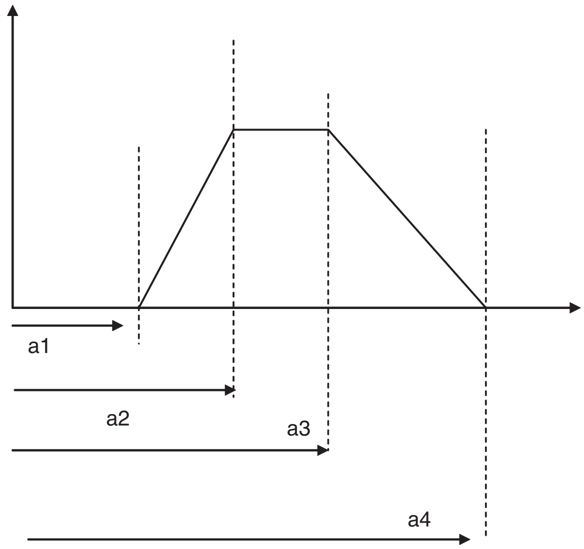

Figure 2. Trapezoidal membership function, a general form for all linear membership functions

Herein lies one of the main advantages of a fuzzy approach: the rules can be expressed verbally in a manner that is compatible with human cognition (e.g. if the water depth is medium, the flow velocity is medium, substrate is small, then HSI is medium). The rule base must cover the entire variable space, meaning that, for any possible combination of habitat characteristics, a rule must be provided. The number of rules is dependent on the number of input variables and the number of linguistic variables used to define each input variable. As three physical attributes are included in the model and each variable is defined by three fuzzy sets, 27 rules were needed to cover all the possibilities.

The fuzzy toolbox in Matlab (MathWorks, 2006) was used to implement fuzzy sets and rules defined by experts and to calculate the fuzzy HSI for each set of input variables, the following calculations are performed. First, crisp

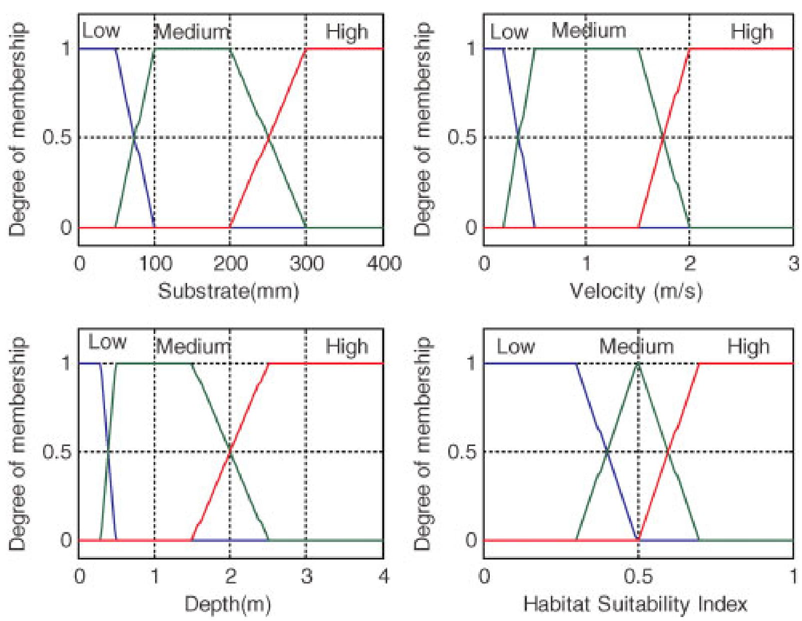

Figure 3. An example of fuzzy sets defined for spawning habitat for input variable (substrate diameter, depth, velocity) and output variable (habitat suitability index). This figure is available in colour online at www.interscience.wiley.com/journal/rra

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input numbers were obtained for the study sites. The membership values for each of these parameters were calculated using the membership functions. Then, the degree of fulfilment of each fuzzy rule is analysed. The fuzzy sets of the output variable (HSI) are weighted with these degrees of fulfilments and combined into a final fuzzy set. In a last step called defuzzification, the final fuzzy set is transformed back into a standardized crisp number to provide an HSI value between 0 and 1 representing unsuitable and the most suitable habitat, respectively. This last step is known as defuzzification. Defuzzification is employed because in many practical applications a crisp output is required. Different methods are available for defuzzification: (1) The Max Criterion Method produces the point at which the possibility distribution of the fuzzy output reaches a maximum value, (2) The Mean of Maximum Method generates an output which represents the mean value of all local inferred fuzzy outputs whose membership functions reach the maximum, (3) The Center of Gravity Method generates the centre of gravity of the possibility distribution (area under the combined fuzzy set) of the inferred fuzzy output. This is the method most commonly applied and used previously by Schneider and Jorde (2003). It was also selected for this study.

Hydraulic modelling

The hydraulic component of this study was performed using the HEC-RAS model (USACE, 2002). It was used to simulate water depths and velocities for different flow values. The HEC-RAS model uses geometric and flow data to calculate steady, gradually varied flow water surface profiles (steady-flow module) from energy loss computations. A quasi 2D approximation was obtained by dividing each transect in subsections and distributing the flow along the subsections using simple linear interpolation techniques and respecting the conservation of energy. The model was calibrated and validated using different subsamples of the velocity and depth measurements taken during field investigations. Details are provided in Hydro-Québec (2005).

Flow, depth and velocity estimated at each modelled transect were used along with substrate diameter as physical attributes or input variables. Mean substrate diameter was obtained by visually assessing the percentage of substrate associated with four grain size categories: silt, sand, small gravel, coarse gravel, cobble, rock, boulder and source rock. These percentages were then used to calculate a weighted mean.

The simulations were done for flows varying between 50 and 1200 $m^3 s^{-1}$ with the increment of 50 (24 in total). Each cross section was divided into a number of longitudinal subsections defining a grid for every study reach. Habitat suitability is evaluated for the targeted life stage (i.e. spawning or parr rearing) in each cell and fuzzy suitability indices were calculated and deffuzified.

Elicitation of expert knowledge

Six experts participated in the interviews, and all results were kept confidential. The experts included four experienced biologists and two experienced field technicians. Fuzzy elicitations were performed by detailed interviewing of one expert at a time. The specialists were first asked to define trapezoidal or triangular membership functions for each category of physical attributes. The interview was then followed by asking the experts to define the most likely consequence of habitat suitability for different combinations of input variables (i.e. substrate diameter, velocity and depth). This involved indicating low, medium or high category for 27 combinations.

Six different fuzzy models were thus developed for spawning and parr habitat. Defuzzified output of these fuzzy systems provides an index for each cell in the studied reaches. The defuzzified HSI was used as a weight for each cell and summing the product of this weight by the cell area provided a WUA every reach (one for each specialist) as shown in Equation (2):

$$\mathrm{WUA} = \sum_{i=1}^{n} A_i \, \mathrm{HSI}_i \tag{2}$$

where A represents the cell area and n is the total number of cells.

The value of WUA actually depends on the size (width) of the river and can have any numerical value. Maximum theoretical value of WUA is equal to the inundated area if habitat quality is optimal (HSI = 1) everywhere along the river.

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RESULTS

Comparison and combination of the rules

Two different approaches were used for combining the expert opinions. In the first approach, six different fuzzy systems were developed based on each expert definition for both spawning and parr rearing habitat. WUA-stage curve were established. Then, a 'standardized' WUA curve was calculated by dividing each WUA by the maximum value for each reach. The average of standardized WUA for all reaches associated with a given habitat type provided the normalized WUA for the river for each expert. Figures 4 and 5 present the normalized WUA of different experts for spawning and parr rearing habitat, respectively.

In both cases, initial increases in flow are associated with gains in habitat, up to a certain flow threshold, beyond which flow increase does not provide any substantial habitat increase. For spawning habitat (Figure 4), the normalized WUA curve of four specialists (1, 2, 3, 4) increases up to a certain point (between 250 to 400 $m^3 s^{-1}$) and decreases afterwards. Standardized spawning WUA for experts 5 and 6 does not decrease but flattens at higher flows (Figure 4).

For parr rearing habitat, the normalized WUA curves of four specialists experts (2, 3, 4 and 6) increase asymptotically for most of the flow range, but only marginal increases in WUA are obtained for discharge higher than 300 $m^3 s^{-1}$ (Figure 5). The fuzzy sets and rules provided by the other two specialists (1 and 5) yielded WUA decreases at higher flows.

Once these curves are obtained, it is important to select a method of combination of the information into a unique standardized WUA curve. Two combination approaches were tested: The simplest one consists of averaging the standardized WUA for each expert. In the second approach, a 'consensus-based' approach was used, whereby for each rule, the consequence for which most of the experts were in agreement was selected. The resulting consensus rules for spawning and parr habitat are presented in Table I.

Table II is a compilation of the number of rules with different number of experts in agreement. It can be seen that the experts were fairly consistent in devising rules. For instance, at least four experts defined the same consequences for 18 of 27 rules describing spawning habitat and 17 rules characterizing parr rearing habitat. At least four experts

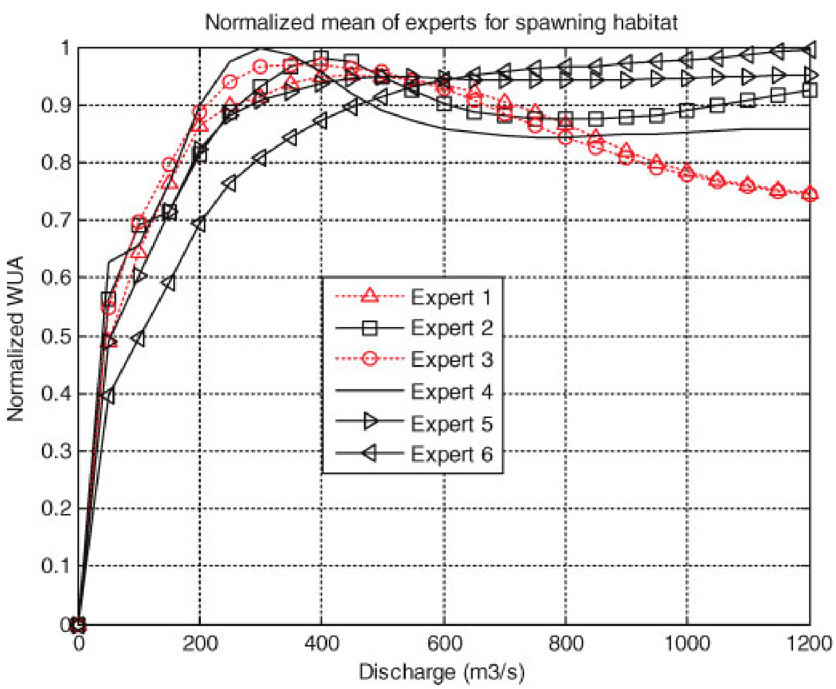

Figure 4. Normalized WUA curves, obtained by calculating the mean for four reaches for each expert for spawning habitat. This figure is available in colour online at www.interscience.wiley.com/journal/rra

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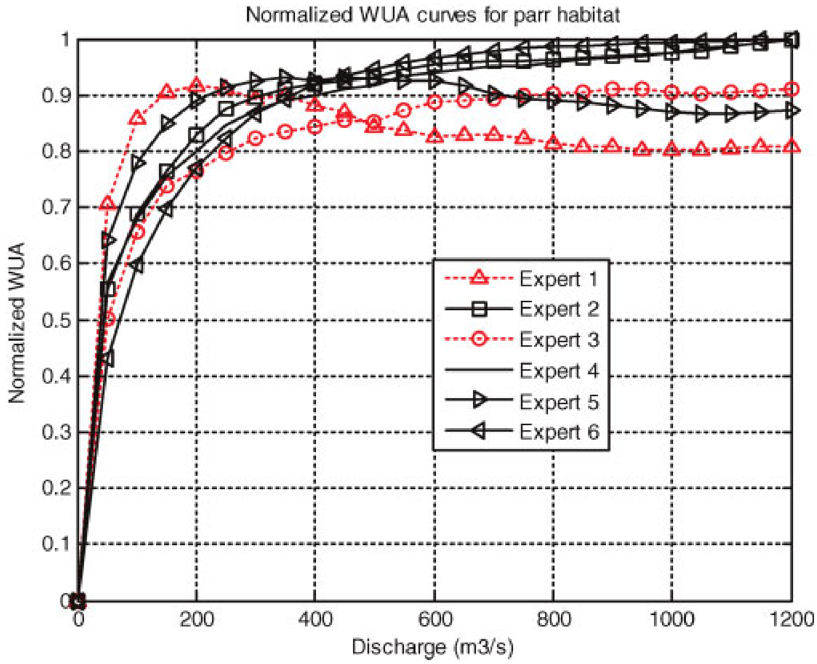

Figure 5. Normalized WUA curves, obtained by calculating the mean for four reaches for each expert for parr habitat. This figure is available in colour online at www.interscience.wiley.com/journal/rra

were in agreement on the same consequence for 24 of 27 rules for spawning habitat and 22 rules for parr rearing habitat.

All specialists provided separate input fuzzy sets. A combination rule had to be developed to define a consensus fuzzy set. Two approaches were used, that is calculating the mean and median of the values a_1, a_2, a_3 and a_4 of the trapezoidal functions defined by each specialist. Using the average gives equal weights to each expert's opinion while using the median implies that less weight is given to extreme values. The membership functions for spawning and parr habitat are presented in Figures 6 and 7, respectively. The results showed that the final normalized WUA curve obtained by using the mean and median are in fact very close for both spawning and parr habitat (Figures 8 and 9). These consensus-based WUA curves are compared with a simplistic approach consisting of calculating the mean of the curves shown in Figures 4 and 5. It should be noted that the mean of the standardized curves do not reach a maximum WUA value of 1, whereas the consensus-based curves reach the maximum value because the standardization is performed during the last step of the modelling exercise.

Sensitivity analysis

As shown in tables 1 and 2, there were some cases where disagreement between specialists led to an even split on the selection of a consequence associated with a given rule. A sensitivity analysis was therefore performed for parr rearing habitat to investigate of the variability of WUA estimation associated with rule definition. The combined experts system obtained by using the consensus among the experts (using the median) was used for this purpose. The numbers of applied rules for every cell were calculated. Summation of applications for all cells gives the number of applications of each rule in each reach and summation of applications for all reaches provides the number of applications of each rule for the river.

For parr rearing habitat, the three least applied rules were rules 16, 7, 25 which were applied less than 5% of the time. The six most common rules for parr rearing habitat in this case study were rules 15, 24, 6, 2, 5 and 27. It is interesting to compare the expert's agreement for these rules. Table III presents the consequence specified by experts for these rules.

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Table I. Consensus rules for spawning and parr habitat (L = low, M = medium, H = high)

Rules	Substrate	Velocity	Depth	Consensus rules	
				Spawning	Parr
1	L	L	L	L	L
2	L	L	M	L	L
3	L	L	H	L	L
4	L	M	L	L	L
5	L	M	M	M	M
6	L	M	H	L	L
7	L	H	L	L	L
8	L	H	M	L	L
9	L	H	H	L	L
10	M	L	L	L	L
11	M	L	M	M	M
12	M	L	H	M	L
13	M	M	L	H	H
14	M	M	M	H	H
15	M	M	H	M	H
16	M	H	L	M	L
17	M	H	M	M	M
18	M	H	H	L	M
19	H	L	L	L	L
20	H	L	M	L	M
21	H	L	H	L	L
22	H	M	L	L or M*	L
23	H	M	M	M	M
24	H	M	H	L	L
25	H	H	L	L	L
26	H	H	M	L	L
27	H	H	H	L	L

*Specialists were evenly split on the consequence.

Table II. Agreement of experts for rules defining spawning and parr habitat

Number of experts agreed on the consequence	Spawning habitat	Parr habitat
6	13	9
5	5	8
4	6	5
3	3	5

The most frequently applied rule in our case study was rule 15 which considers combination of medium substrate diameter, medium velocity and high depth (see Table I). The sensitivity of the WUA to this rule was investigated by considering all possible consequences (i.e. the HSI category, given the inputs) of this rule and calculating corresponding WUA for three possible consequences of 'low', 'medium' and 'high'. For this rule, three experts have selected the high category, two experts opted for medium category and one expert specified the low category (Table III).

Figure 10 shows the WUA-stage curve for different alternatives of rule 15. It can be seen that WUA changes significantly for these three cases. Sensitivity of WUA to other rules was also performed. Evidently, the calculated HSI and WUA were more sensitive to the most frequently applied rules (i.e. 15) and effect of other rules on WUA are smaller than this extreme case.

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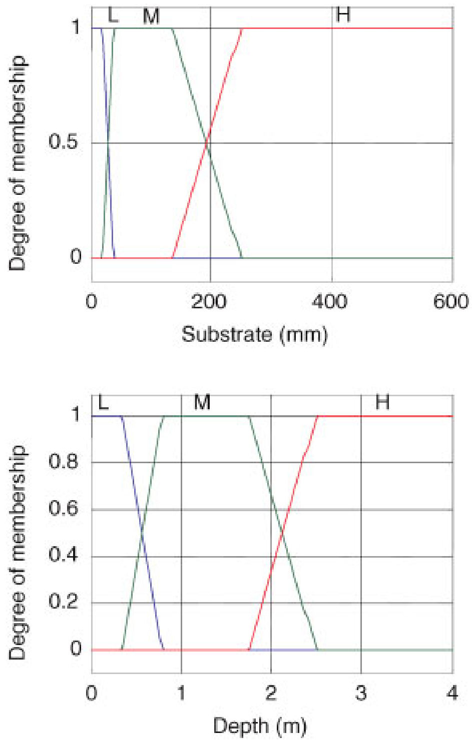

Figure 6. spawning habitat membership functions for inputs and outputs obtained by combination of experts (median). This figure is available in colour online at www.interscience.wiley.com/journal/rra

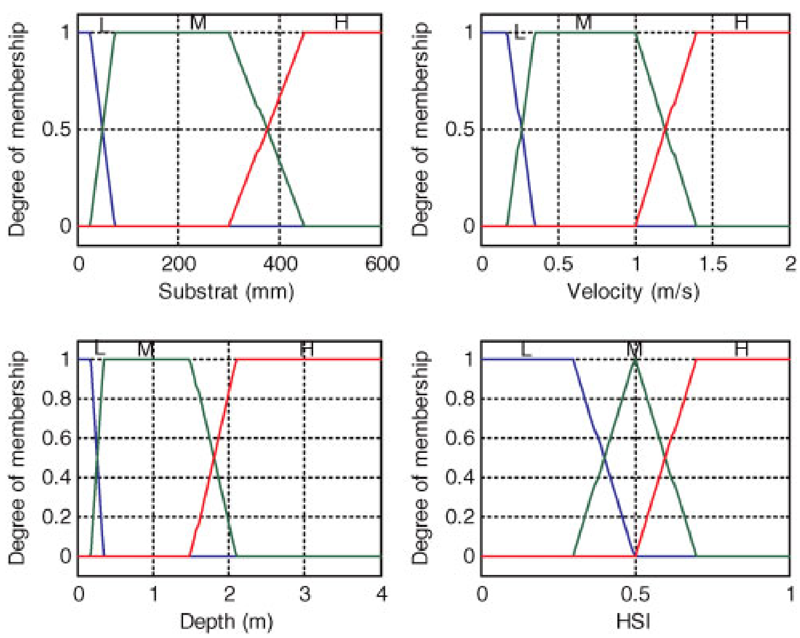

Figure 7. Parr habitat membership functions for inputs and outputs obtained by combination of experts (median). This figure is available in colour online at www.interscience.wiley.com/journal/rra

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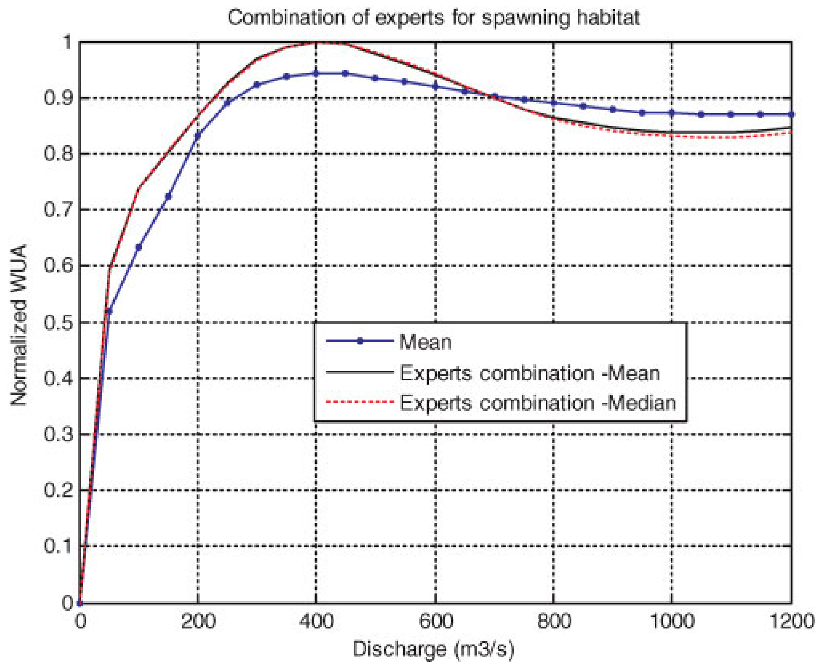

Figure 8. Normalized WUA curves for consensus system (mean and median), and mean obtained by calculating the mean for six experts for spawning habitat. This figure is available in colour online at www.interscience.wiley.com/journal/rra

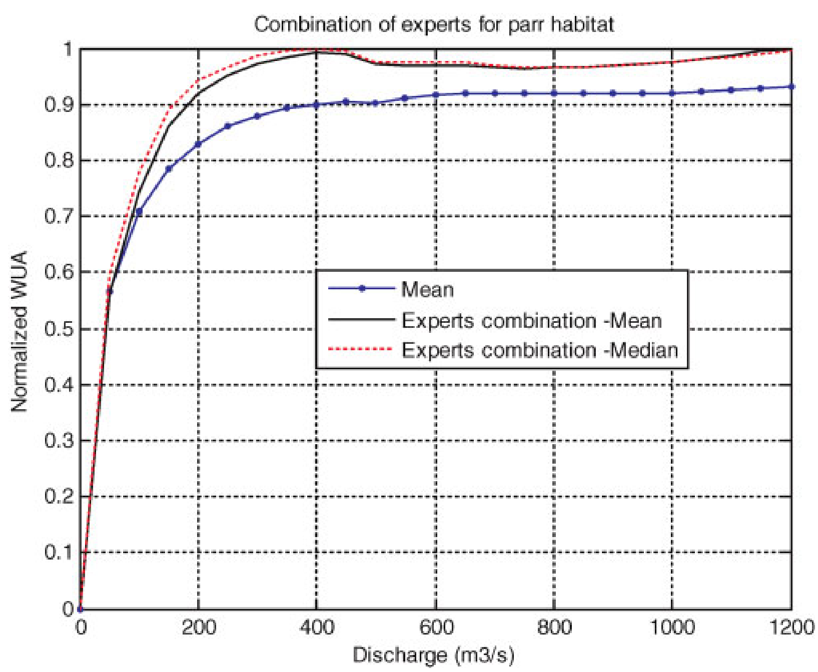

Figure 9. Normalized WUA curves for consensus system (mean and median), and mean obtained by calculating the mean for six experts for parr habitat. This figure is available in colour online at www.interscience.wiley.com/journal/rra

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Table III. Comparison of expert's agreement for the most applied rules

Rule number	Physical attributes			Number of experts chosen different categories of habitat suitability		
	Substrate	Velocity	Depth	Low	Medium	High
15	Medium	Medium	High	1	2	3
24	High	Medium	High	6	0	0
6	Low	Medium	High	5	1	0
2	Low	Low	Medium	5	1	0
5	Low	Medium	Medium	2	4	0
27	High	High	High	6	0	0

DISCUSSION AND CONCLUSION

In general, an HSI aims to assess the suitability of given site(s) for a certain species under the influences of several physical attributes. Data on species–environment relationship are relatively scarce, but qualitative expert knowledge is readily available. This makes the fuzzy approach a powerful tool in habitat studies.

To our knowledge, this study is the first to present a fuzzy framework for multi-specialist elicitation in the context of Atlantic salmon habitat modelling. Even if the number of experts participating in the exercise was limited to six,

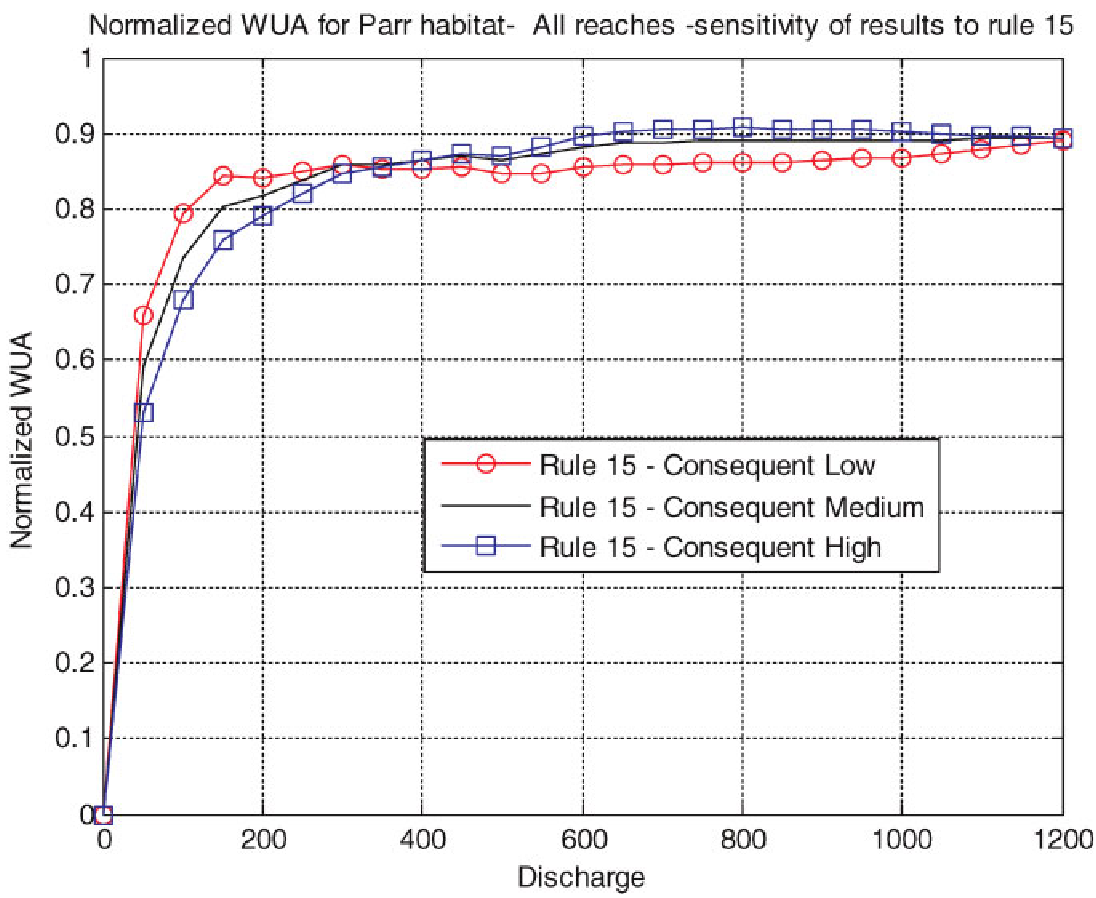

Figure 10. Weighted usable area (WUA) for different discharges in all reaches for different versions of rule 15 (* indicates the consensus rule). This figure is available in colour online at www.interscience.wiley.com/journal/rra

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this first attempt provides a basis for modelling uncertainty associated with the biological component of habitat models. Most recent studies dealing with uncertainty in habitat models emphasize the need for model validation (e.g. Fielding and Bell, 1997; Guisan and Zimmermann, 2000; Pearce and Ferrier, 2000). In most cases, resampling and cross-validation techniques are suggested to provide some sort of model validation/evaluation. Pearce and Ferrier (2000) proposed a methodology for assessing the frequency of incorrect estimations of the presence/absence in a logistic regression model. These methods are useful to assess model performance 'after the fact'. Alternatively, the present study proposes a methodology that allows modelling the inherent uncertainty of HSI curves. Representation of uncertainty is given in two stages: first, some of the uncertainty is represented by the membership functions that define a soft threshold, that is some physical attribute vales are shared between two categories. Second, once the model is established by a number of specialists, uncertainty associated with the elicitation process can be quantified by assessing the variability of WUA-stage curves from different specialists.

In many applications, there is a limited amount of field data, which are not necessarily representative of behaviour of fish species in all possible habitat conditions encountered on the river. Fuzzy logic allows using readily available expertise of specialists in the modelling process to estimate the habitat suitability and ecologic instream flow. Expert knowledge could be used as an important resource to improve the reliability of habitat modelling. It can be argued that this knowledge encompasses information from multiple sites and thus, the development of regional HSI could be envisaged. This could be especially useful to model sites where little systematic field investigations have been conducted or where significant flow changes are planned, for which future habitat use prediction can hardly be based solely on actual conditions and recent observations.

In the present study, only three physical attributes are used to develop the fuzzy HSI. Other factors influencing habitat preference such as water temperature, presence of cover, habitat connectivity were not examined but could be included in a more complex fuzzy model.

A sensitivity analysis of the rules indicated that the results can be highly dependent of their definition and sometimes changing even the consequence of only one rule greatly affects the results. It is therefore recommended to use more than one expert and discuss the discrepancies in the rules with experts in a group meeting. From our experience, it was also helpful to perform a sensitivity analysis of fuzzy rules and indicate the results to expert biologists. Experts can see the implications of their rules and can revise the most sensitive rules if necessary. For setting the fuzzy sets, it is easier to ask the experts to define the range of values of the input variable that they consider too low, adequate and too high for a suitable habitat.

Future research should aim at further studies on expert combination methods and calibrating/validating the models with detailed field data where available. Schneider and Jorde (2003) proposed calibration options for the CASIMIR model that include redefining fuzzy sets boundaries to better fit field data and modifying the defuzzification technique. Adriaenssens *et al*. (2004) suggested that fuzzy rule-based model calibration is easier when the fuzzy sets are defined using data-driven techniques such as artificial neural networks. Using such techniques, the fuzzy models can be initially developed using only expert knowledge and be further updated with available data. Once the initial model is constructed, updates can easily be performed by augmenting the knowledge with data collection or adding new experts to the pool. The rules and membership functions can be regularly undated and validated.

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