A comparison of Fuzzy, Bayesian and Weighted Average formulations of an in-stream habitat suitability model.

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Abstract: Three variations of a simple in-stream habitat suitability model were implemented and the effect on output for one organism at 22 sites on one short section of a river was examined. The model uses only two factors, depth and velocity, to calculate quality and a third factor, width to quantify utility. The implementations were based on 3 multi-criteria evaluation approaches: Weighted Average, Fuzzy Sets and Bayesian probability.   There was broad agreement between the formulations but important differences in detail. The model outputs indicate that uncertainty arising from model formulation is significant and can have a bearing on planning decisions.   There is a complex interaction between the formulations and the characteristics of the sites. Suitability models should be used thoughtfully and implemented in ways that: facilitate exploratory analysis; present ranges of possible outputs; present indicators of uncertainty; and facilitate back tracking to explain the outputs.

*Keywords***:** Uncertainty; Multi-criteria evaluation; Habitat suitability; Fuzzy; Bayes

1   INTRODUCTION

Environmental management decisions have to be taken in the context of uncertainty. Nowhere is this more the case than in relation to river habitat. Although gauging river flows is itself a challenging science, gauging river habitat is more difficult because: (1) it can vary continuously over spatial scales varying from a few m to the whole catchment (Lammert and Allen, 1999; Folt et al., 1998); and (2) the impacts of changes in drivers (e.g. river flow) are continuous in time and space. Although the relationship between habitat and use of habitat by organisms is a complex issue, there is still an academic focus upon determining the habitat template and the effects of interventions (e.g. flow regulation) on that template for rivers that are, effectively, 'ungauged' because of the difficulty of measuring ecological elements at scales that match the spatial and temporal variability in the drivers of those elements. Thus, habitat template modelling is an important element of river management (e.g. Leclerc, 2005).

This paper looks at one particular source of uncertainty in habitat modelling, model formulation. Three alternative implementations of a habitat suitability model: (1) Fuzzy sets; (2) Bayesian probability; and (3) Weighted Average approaches, are compared. The driving question is: could different model formulations lead to different decisions?

2   THEORY

2.1   Habitat suitability analysis

Habitat suitability analysis (HSA) is a methodology for informing environmental conservation and restoration decisions. The viability of species and organisms depends fundamentally on the availability of suitable habitat to support them. By analysing habitat in a model framework, in a way that recognises the interactions of factors that influence habitat, it is possible to establish a base-line, to estimate the predicted effects of management interventions and to monitor habitat change. Here, the focus is on instream river habitat, driven by two of the most common factors used to determine habitat suitability: flow depth and flow velocity (Lane et al., 2006).

This kind of analysis has a very long and established history. It is based upon the assumption that the ecologically-usable habitat in a river depends on several key parameters, notably flow velocity and depth, wetted perimeter, substrate, water temperature and pH (e.g. Elso and Giller, 2001, Maddock et al., 2001, Leclerc, 2005). Traditionally, emphasis has been placed upon hydraulic variables, notably velocity, depth and wetted perimeter because: (1) they are important controls upon organism metabolism, both directly and indirectly, controlling the balance between access to food and expenditure on swimming; and (2) the spatial and temporal changes in higher order parameters (such as pH and temperature) should track changes in velocity and depth to some extent. Width, depth and velocity are commonly incorporated into some form of habitat score such as PHABSIM (e.g. Milhous et al., 1984), which can be used to determine habitat suitability in situations where flow is uniform, or approximately uniform (Milhous et al., 1989). Concerns with the simple hydraulic basis of PHABSIM have resulted in a much wider research field concerned with developing hydraulic models of habitat, including development of more sophisticated one-dimensional hydraulic treatments as well as two-dimensional habitat modelling (e.g. Leclerc et al., 1995, 1996; Tiffan et al., 2002). The latter is important because the habitat that can be used by an organism varies continually in space (cross-stream and downstream) but may be prohibited by the data and computational demands when habitat assessment is needed at the scale of entire river basins. This is the subject of much debate in the habitat modelling literature (see Leclerc, 2005). However, there is an important additional issue that is the focus of this paper. It is now recognised that the choice of habitat suitability analysis is about more than the choice of appropriate hydraulic representation. Rather, it must capture the severe uncertainty associated with only poor or even no measured ecological data. Likewise, different suitability analyses use models with very different kinds of assumptions over how to handle this uncertainty as well as how to combine the different criteria (e.g. depth, velocity) to determine habitat.

2.2   Multi criteria evaluation

Habitat suitability analysis is a form of multi-criteria evaluation (MCE). MCE maps physical attributes such as depth to a value. Value is an abstraction; it cannot be measured directly but is inferred from measurements. Value can be expressed in two main ways: as a number such as an index or score (e.g. 80 out of 100), or as a class (e.g. "Good"). The transformation from attribute to value is by a **value function**. The second step is to combine multiple values into a single value using a **combination process**. Before the values can be combined they must be normalised to a single scale to avoid implicit weighting. If criteria are not equally important they should be explicitly weighted. There are two interpretations of value: quality and utility. Quality is calculated by the value and combination functions. Habitat utility depends on intrinsic quality and how much there is, so there is a third step - the **utility function**.

MCE is a huge field with a large literature and many formal models (see Jankowski 1995). Here three approaches are considered. The first approach is pragmatic. Attributes are scored independently, on a common scale of value, and then combined by taking the mean of each attribute score (e.g. Jiang and Eastman, 2000). In a two-step process the value functions map

attributes to scores and the combination function averages the scores. Because criteria can be weighted this method is known as weighted average (WA).

The next two approaches, Fuzzy and Bayes, address uncertainty by using soft classes. In conventional Boolean classes membership is binary and exclusive. Soft classes allow partial membership of classes and multiple memberships of alternative classes. Partial membership expresses how definite the classification is. An entity can simultaneously be classed as, say, both "good" and "medium" with different degrees of definiteness. For example, if there are three classes, poor, medium and good, an entity can be classified using a membership vector of the form $\{M_{(poor)}, M_{(medium)}, M_{(good)}\}$. A vector $\{0,100,0\}$ indicates certainty that the class is medium, $\{10,80,10\}$ indicates less certainty while $\{33,33,33\}$ says all classifications are equally likely. The value function maps attributes to class membership functions for each criterion. The next step is to combine criteria classes to a resultant classification using cross-memberships. With 2 criteria and 3 classes for each there are 9 class combinations. These can be mapped onto fewer resultant classes as illustrated in Table 1 of section 3 where good-good maps to excellent and both good-medium and medium-good map to very good.

Fuzzy and Bayes differ in the interpretation of membership and, consequently, the calculation of cross-membership. In Fuzzy, partial membership represents vagueness about the meaning of the classes while in Bayes partial membership represents the probability of membership (Fisher 2000). Fuzzy relates to conceptual uncertainty and Bayes relates to factual uncertainty. The Bayesian approach is grounded in probability theory and is consistent with statistical error modelling (Aspinall and Veitch 1993). It is the basis for Bayesian Belief Networks, which integrate quantitative and qualitative uncertainties in a single rigorous framework (Henriksen et al., 2006). The Fuzzy approach is based on Fuzzy set theory, which was developed to address the problem of vagueness (Fisher 2000, Legleiter and Goodchild 2005). Implementation of Fuzzy is less rigorous than Bayes (Fisher 2000) and here only one typical implementation is considered. The Bayesian class combination function is the joint probability. With reference to Table 1, the probability of habitat being excellent is the joint probability that depth is good and velocity is good. For Fuzzy it is a set operation to calculate the intersection of two classes. Typically, it is implemented as a fuzzy_and (see Box 1) operator (Fisher 2000). The Fuzzy and Bayes cross membership functions are shown in Box 1.

Box 1 Fuzzy and Bayes Cross membership functions

Given two membership vectors $\{X_1, X_2,…X_i\}$ and $\{Y_1,Y_2..Y_i\}$ for criteria X and Y,

there are i*j cross-memberships M_{ij}

Bayesian joint probability $\qquad M_{ij} = X_i * Y_j \qquad$ for all i,j

Fuzzy_and $\qquad\qquad\qquad M_{ij} = min(X_i,Y_j)$ for all i,j

3   THE IN-STREAM HABITAT MODEL

The in-stream habitat model (ISH) uses two criteria, flow depth and flow velocity, to evaluate habitat quality. Separate value functions were created for each criterion using presence/ absence data from the literature. Problems in this approach are discussed elsewhere (Lane et al., 2006). Each numerical value of depth or velocity maps to a quality value. In the original model (Lane et al., 2006) quality is expressed as fuzzy membership of 3 classes: good, medium and poor. Combining depth and velocity criteria gives 9 cross membership possibilities but these are mapped to 6 final classifications of habitat quality: nil, very poor, poor, good, very good and excellent. Table1 shows the correspondence between the cross memberships and the final habitat quality class. To calculate utility, quality is expressed as a score, from 0 for Nil up to 6 for Excellent, (Table 1) and multiplied by the width.

Table 1. Cross-classifications and associated scores

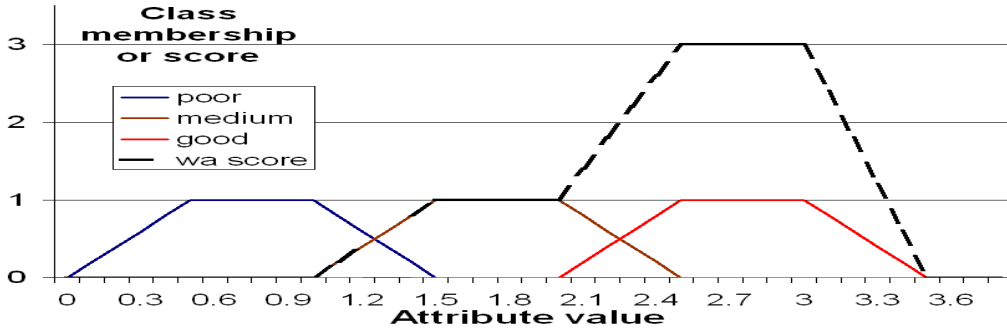| Depth	Velocity		
	Poor	Medium	Good
Poor	Nil-0	Very Poor-1	Poor-2
Medium	Very Poor-1	Good-3	Very Good-4
Good	Poor-2	Very Good-4	Excellent-6

The Bayes and Fuzzy methods use different combination functions and generate different cross membership values, as explained above. Utility is also calculated differently. For Bayes utility is based on expectation, where expectation is the sum of (probability * score) for each class. So for example, if excellent habitat scores 6 and the membership is 80%, and good habitat scores 4 and the membership is 20%, the overall score is (4.8 plus 0.8) which gives 5.6. Thus Bayes quality is a continuous function. Fuzzy uses the most likely outcome. The class with the highest membership is selected to give a single, Boolean, class. This means that the fuzzy model generates discrete quality scores {0,1,2,3,4,6}. The WA method maps attribute values map to a criterion score in the range 0 to 3. The combined quality score is thus between 0 and 6 giving the same range as the Fuzzy and Bayes methods.

Each site is a cross-section of a river channel and comprises a number of elements each with a modelled velocity, depth and width so there is a final step to generate a summary value for each site. Quality and utility are modelled per element. Quantity is expressed by scaling to width. Utility of a site is the sum of the utility of each element. Aggregation means that at the site level Fuzzy quality is not restricted to integers and can be any value from 0 to 6. With factors d(depth), v(velocity), classes M_{ij} and scores S_{ij}, quality per element, Q is :

|		
3.1.1	WA:	$Q = (Q_d + Q_v) /2$
3.1.2	Fuzzy:	$Q = S_{ij}$ where i,j are given by $M_{ij} = max(M_{ij})$ for all *i,j*
3.1.3	Bayes:	$Q = sum(M_{ij} * S_{ij})$ for all i,j

4   PROCEDURE AND RESULTS

The models were run for a single organism, adult brown trout, on 22 sites on a section of the River Don in Sheffield. The same habitat requirements were used in each run. Requirements were input as vectors specifying class, class boundaries and precision ({poor,min,max,P}) per class, criterion and species. The precision parameter P makes the classes soft. A value has 100% membership if it lies between (Min + P) and (Max - P), and 0% membership if it is outside (Min - P) to (Max + P). Intermediate membership values are interpolated by a linear function. High values of P represent large uncertainty. The Bayes and Fuzzy models used the same membership function. The WA value function was derived from the same input data, essentially by multiplying the membership by the relevant class quality score (3 for high, 1 for medium, 0 for poor) for each criterion (see Figure 1). P is not used in WA.

Figure 1. Relationship between Value (dashed) and Fuzzy membership (solid) functions

Before running with field data the models were run with depth and velocity values in the range 0 to 1.5. Figure 2 plots quality against depth and velocity and shows some differences between the models. The models produce different ranges of outputs: Fuzzy (0,1,2,4), Bayes (0-3.56) and WA (0-6). This is a consequence of the high uncertainty in the habitat requirements for brown trout. No depth or velocity results in un-ambiguously good classification but many values are unambiguously poor. Also, off-diagonal classifications (Table 1) are more likely than the diagonals. For example, very good results from a combination of good-medium or medium-good while only one possibility, good-good, leads to excellent. There is thus a bias towards lower scores in the Fuzzy and Bayes models but not in WA where there is no uncertainty treatment of the input. Another difference in the models is the trade-off between factors. As Table 1 shows, medium-medium is better than good-poor in the classification models whereas in WA (1+1) is less than (3+0). The integer values for Fuzzy are the result of hardening the fuzzy classes into a single Boolean class for output. The plots indicate uncertainty in the outputs; steep gradients indicate high sensitivity to the inputs.
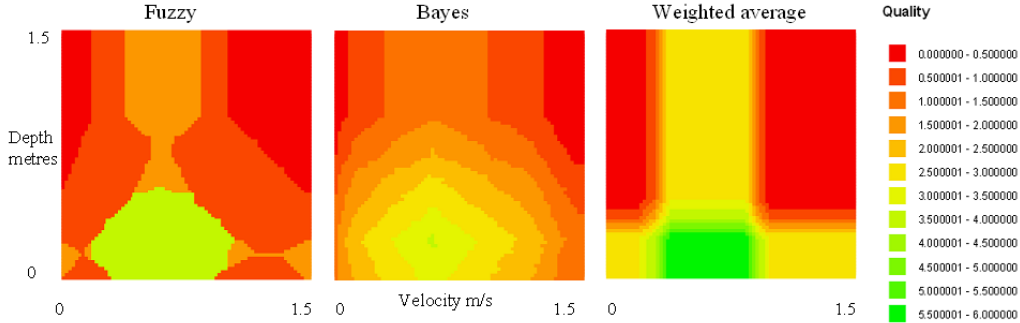
Figure 2. Quality as a function of depth and velocity

With the field data, there was enough general agreement between the models in terms of quality and utility to indicate that all three are consistent with each other. Flow velocities at most sites are too high for good habitat and most sites would be classed as poor by the velocity criterion. In contrast the depth is often good. Thus the expected upper bound for quality with the given sites is nearer 3 than the theoretical maximum of 6. Table 2 shows the minimum and maximum values for quality and utility produced by each model.

Table 2. Range of Quality and Utility values for each model.

Model	Average quality		Utility	
	min	max	min	Max
Fuzzy	0.99	2.09	7.4	32.7
Bayes	0.94	2.37	6.1	37.0
WA	1.19	3	7.8	32.1

The WA model has a similar range of values to Fuzzy and Bayes but has higher minimum and maximum values. This can be explained by the way that WA trades-off depth and velocity scores. A poor velocity (0) can still generate an aggregated score of 3 if the depth is good, whereas for Bayes and Fuzzy the best would be 2 (see Table1). For Bayes and Fuzzy the velocity has to be classed as Medium before the overall score can be 3 or more. With regard to utility, Fuzzy and WA are more similar to each other while Bayes has a larger range and more extreme values. The following section compares the results on a site-by-site basis.

Figure 3 shows quality per site for each model, sorted by Fuzzy quality. In general the differences between the models appear systematic; WA generates the highest scores, then Fuzzy with Bayes least. However, two sites, 2 and 13, have higher scores for Bayes, and in fact reverse the normal ordering of scores from WA-Fuzzy-Bayes to Bayes-Fuzzy-WA. These two sites are the highest ranked by the Bayes method but not by the other models. WA ranks 10 sites higher than site 13 and Fuzzy ranks 5 sites higher than site 2. Similarly, the models do not agree on the worst sites, which are: 7 and 12 (fuzzy), 4 and 14 (Bayes) and 2 and 12 (WA). Perhaps the most interesting result is that site 2 is ranked 2nd highest by Bayes and 2nd last by WA. The anomalous results for site 2 indicate uncertainty in the output. This is supported by looking at the membership vector used to generate the summary score. For site 2 it is {13, 27,19, 14,20,7} compared to the more typical site 1 {25, 36, 38, 0, 0, 0}.
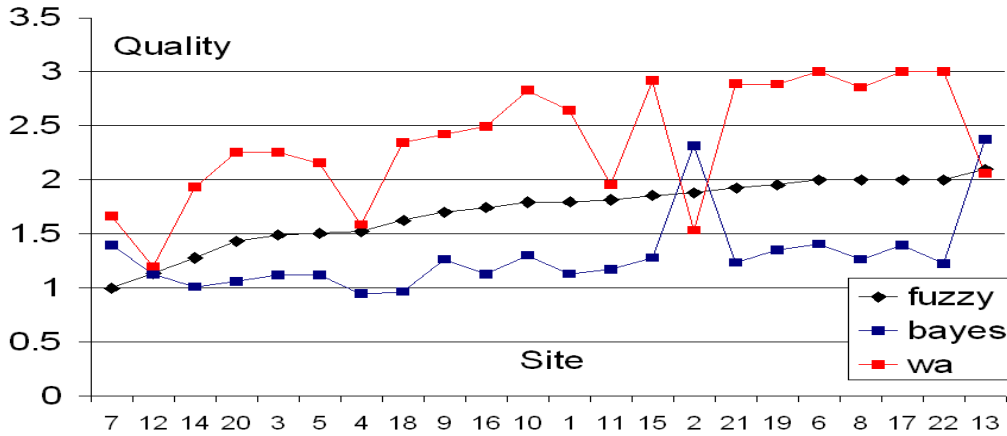

Figure 3. Quality by site for each model (ordered by Fuzzy)

A more detailed look at site 2 and site 21, which has a similar quality score by the Fuzzy model, reveals how the models differ. Figure 4 shows the quality scores along the cross-sections. Site 2 is wider and shallower than site 21 and the velocity is lower. At site 2, velocity is medium and depth is poor/medium. At site 21 velocity is poor while depth is good. The improvement in velocity more than compensates for the poorer depth in the Bayes model but not the WA.

Figure 5 shows utility per site for each model, sorted by Fuzzy. Considering utility, the models agree more on the best and worst sites. Site 13 is ranked highest by all 3 models. The worst are 14 and 12 (Fuzzy), 14 and 18 (Bayes) and 14 and 12 (WA). At sites 12, 13 and 14 there is a big change in width that damps the quality differences and that explains the change in utility values and accounts for the agreement between the models (Table 3).

Table 3. Range of Quality and Utility scores for each model

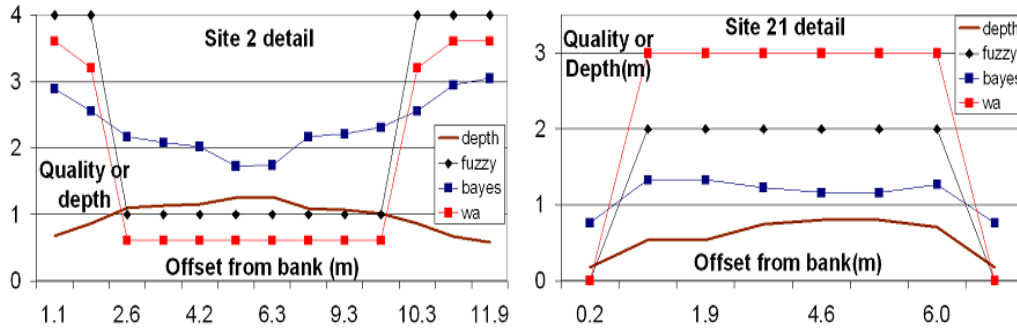| Site	Width	Fuzzy		Bayes		WA	
		Quality	Utility	Quality	Utility	Quality	Utility
12	6.51	1.14	7.41	1.13	7.33	1.20	7.79
13	15.60	2.1	32.73	2.37	37.03	2.02	32.09
14	6.03	1.28	7.71	1.01	6.1	1.93	11.65

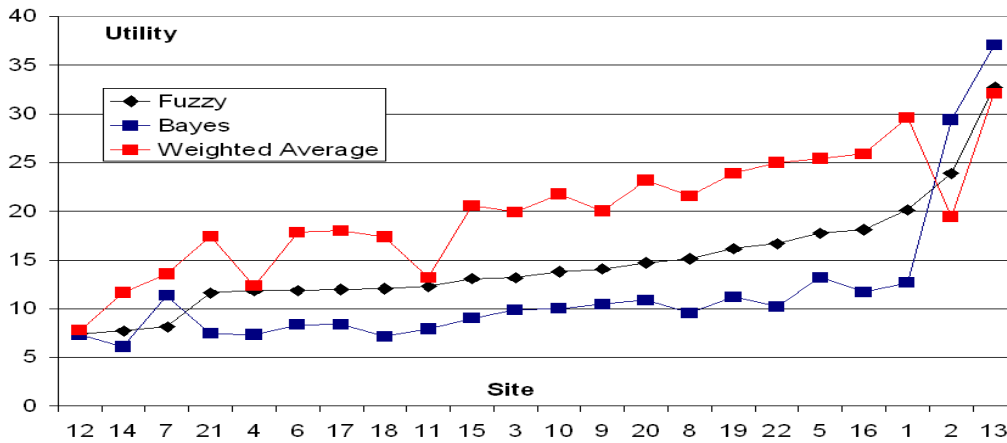**Figure 4.** Comparison of details for site 2 and site 21

Figure 5. Utility calculated by Fuzzy, Bayes and Weighted Average - (ordered by Fuzzy)

5   CONCLUSION AND RECOMENDATIONS

Looked at broadly, the models appear to agree, but in detail there are some big differences. Notably two models generated almost completely opposite quality results for one site. The models are very sensitive to the physical characteristics of the sites, as implied by site 2. Differences between the models are greater with respect to quality than utility because of the masking effect of width. In each model the sites with highest and lowest utility are consecutive sites on the river so although the different models do not agree in detail for each site, they do direct attention to the same part of the river.

Model implementation is a source of uncertainty and different formulations could lead to different decisions. This uncertainty should be conveyed to the end user. Standard statistical error modelling expresses both a range of values and confidence that the true value lies within that range. While the Bayes and Fuzzy models represent and propagate uncertainty in habitat requirements their output classifications and the WA scores do not convey uncertainty in the output. Taken together, the range of outputs produced by the three implementations indicates a range of possible outputs. This approach should be extended, using Monte-Carlo or similar methods, to generate a range of outputs in response to uncertainties in data, habitat requirements and model formulation. Models should output as much information as possible so that users can examine what leads to particular results. This would help users to assess the confidence in the outputs.

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