A Preliminary Analysis for Improving Model Structure of Fuzzy Habitat Preference Model for Japanese Medaka (*Oryzias latipes*)

Shinji Fukuda[1]

1. Institute of Tropical Agriculture, Kyushu University
Fukuoka, Japan
Email: shinji-fkd@agr.kyushu-u.ac.jp

Abstract*—The present study examined a preliminary analysis for improving model structure of fuzzy habitat preference model for Japanese medaka (Oryzias latipes) dwelling in agricultural canals in Japan. The present model employed a simplified fuzzy reasoning method for evaluating habitat preference of the fish based on the relationship with physical habitat characteristics observed in the field survey. The model parameter was optimized by using a simple genetic algorithm, in which number of fuzzy membership function was fixed. In the present analysis, number of fuzzy membership function was changed while the other methods were fixed as the original model. The model performance was evaluated based on mean square error between observed and predicted fish population density, and by using two different data sets. As a result, there was no clear tradeoff between number of fuzzy membership functions and prediction accuracy. By contrast, calibration and validation results showed a slight tendency of tradeoff. Further studies on clarifying the tradeoffs would be necessary for improving the model structure in an effective way.*

Keywords— fish habitat, genetic algorithm, habitat modelling, simplified fuzzy reasoning

1 Introduction

Since anthropogenic impacts largely affect and degrade aquatic environments, assessment based on geomorphologic and ecological data is the basis for evaluating the state of the environment and its management planning [1]. In the evaluation, a habitat preference approach, such as habitat evaluation procedure (HEP) [2, 3] and Instream Flow Incremental Methodology (IFIM) [4], is often applied for its simplicity and intuitiveness. Habitat suitability index (HSI), which was originally proposed for HEP and IFIM, is usually classified into three categories: Category I—professional judgements; Category II—habitat use indices; Category III—habitat preference indices [5]. Despite its generality, some studies concluded that HSI cannot describe habitat uses [6, 7, 8, 9]. This failure would be ascribed to non-linear and complex interactions between environmental factors affecting the habitat use and to uncertainty in ecology.

The uncertainty is increasingly recognized and gaining public interests in natural ecosystem research. In ecological modelling, the uncertainty of the model is caused by both the lack of knowledge (i.e. data imperfection) and the variability of models and parameters (models' sensitivity) [10]. For coping with the data imperfection, an approach using fuzzy logic was proposed and widely applied to expressing expert knowledge and dealing with incomplete and/or subjective information [11, 12, 13, 14, 15, 16]. This approach enables qualitative information consisting of linguistic terms to be used for quantitative evaluation of target systems that are required for decision-making at an ecosystem level. By contrast, [17] introduced fuzziness as a reliability bound so as to consider the subjective uncertainty in habitat evaluation by different interpretation. The author also applied fuzzy set theory to habitat evaluation for considering the vagueness of fish behaviour, measurement errors and dispersions of physical environment, in which models showed high ability to represent habitat use of the target fish by integrating fuzzy rule-based model with model optimization techniques of genetic algorithm (GA) [18, 19, 20, 21, 22, 23, 24] or artificial neural network [25, 26]. By applying GA, all the model parameters can be simultaneously optimized, which enables us to assess the nonlinearity in fish habitat preference [23]. This emerging property clarified from the modelling would make an appeal to researchers for applying artificial intelligence techniques. However, as reported in [22], the fuzzy habitat preference model showed weakness in terms of transferability which might be ascribed to the complexity of the models. Therefore, to assess the relationship between models' complexity and accuracy would be necessary for the model improvement without losing its accuracy. This could also promote the application of genetic fuzzy systems in ecological research.

The present study aims to examine a preliminary analysis for improving model structure of fuzzy habitat preference model (FHPM) for Japanese medaka (*Oryzias latipes*) dwelling in agricultural canals in Japan. Field surveys were conducted in the agricultural canals to establish a relationship between fish habitat preference and physical environments of water depth, current velocity, lateral cover ratio and percent vegetation coverage. All the FHPMs of different model structure were compared focusing on the tradeoffs between complexity of the model and accuracy of habitat prediction.

2 Methods

In this section, the author first gives a brief review on the application of fuzzy systems to ecological research. Second, an overview of the study site and target fish is described. And then, the author explains the field surveys and the modelling procedure of habitat prediction models together with the explanation on assessment and comparison of the models.

2.1 *Fuzzy Modelling in Ecological Research*

The pioneer work of fuzzy logic application to ecological study would be [27] in which fuzzy set theory was introduced to habitat quality evaluation, classification of wetlands, and formation of compartments of ecosystem components. Since

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then, many researchers have employed fuzzy logic-based approaches in ecological research (e.g., population dynamics [28, 29, 30, 31], cluster analysis [32], elicitation of expert knowledge [33], human decision behaviour [34]). Reference [35] reviewed applications of fuzzy logic for decision support in ecosystem management with focus on the identification, optimization, validation, interpretability and uncertainty aspects of rule-based models. As mentioned earlier, fuzzy modelling has also been applied to habitat assessment. This can be classified into two categories of knowledge-based modelling [12, 13, 14, 15] and data-driven modelling [16, 18, 19, 20, 21, 22, 23, 24, 25, 26, 36]. The former cannot optimize model parameters, while the latter can do it. Several approaches were employed for data-driven optimization of model parameters. For instance, [16] employed a nearest ascent hill climbing algorithm, [22, 25, 26] incorporated fuzzy membership function into artificial neural network, and the others employed GA [18, 19, 20, 21, 22, 23, 24, 36]. According to [37], the latter two approaches can be classified into genetic fuzzy systems. The genetic fuzzy systems would gain more attentions in ecological research because of its interpretability and learning ability.

2.2 Study Site and Target Fish

The survey was carried out in an agricultural canal located in Kurume City, Fukuoka, Japan (33˚20’ N, 130˚42’ E; Fig. 1). The spring-fed canal runs through paddy fields, and is used for both irrigation and drainage purposes. It flows into the Kose River, which is a tributary of the Chikugo River.

The target fish, Japanese medaka (*Oryzias latipes*), is one of the most common freshwater fish in Japan. This fish has been considered as one of the symbols of rural environmental conservation and restoration because of the vulnerability to alterations of physical environment such as concrete lining of the earthen canal. For instance, Japanese medaka generally grows up to approximately 2 cm in length and thus is vulnerable to fast flowing water.

2.3 Field Survey

The field surveys were conducted on 14 October, and 5 and 9 November 2004. The surveys were conducted during a non-irrigation period, thus the discharge in the study reaches remained stable. Therefore, the habitat uses of Japanese medaka were not affected by any agricultural activities or agricultural chemicals. The water temperature remained stable (16.1–20.3˚C) during the surveys.

The habitat uses of Japanese medaka and the physical habitat characteristics of water depth (henceforth referred to as depth), current velocity (velocity), lateral cover ratio (cover), and percent vegetation coverage (vegetation) in the study reach were surveyed on sunny days. The four physical environments are found to be the primary factors affecting spatial distribution, i.e., habitat use, of the fish [20]. After mapping the reach, habitat use of the fish was first observed (11:00–14:30) and then the physical habitat characteristics within the reach were surveyed.

The habitat use of Japanese medaka was observed visually from the bank; the observer moved slowly and carefully to avoid disturbing the fish. The number of the fish was counted in units of five to take into consideration the habit of school formation, i.e., fish in a small school (less than five) were not counted. Observations were repeated eight times and the results were averaged to reduce observational error.

Immediately after completing the fish observation, the four physical habitat characteristics of depth, velocity, cover, and vegetation were surveyed to establish a relationship between physical environment and habitat preferences of Japanese medaka. First, depth and velocity were measured to divide the study reach into small water bodies having similar condition with regard to these two physical parameters. Depth was measured with a stainless steel ruler, and velocity with a portable propeller current meter (KENEK, V-303) at three lateral points comprising a midpoint and two near-shore points at longitudinal intervals of 1 m. By using the measurements of depth and velocity, the reach was divided into water bodies. Next, the other two factors of cover and vegetation were calculated from the schematic diagrams of the water bodies. The lateral cover ratio is defined as a function of the presence of lateral cover, which comprises the water’s edge, a dike, or anything that emerges from the water surface and surrounds the water body. The cover thus consists of four components (four lateral sides). The maximum cover ratio is 100%, and each of the cover components is assigned a score of 25%. In the definition of the cover, objects attached to more than 90% of the boundary between water bodies were regarded as cover components. That is, only instream and undersurface cover structures were considered as cover component because they may have had the same effects as the margin of the stream. Percent vegetation coverage is defined as the percentage of the area covered with aquatic vegetation in each water body. Both submerged and emergent vegetation were pooled because of their same roles in providing food and shelter from predators and fast-flowing currents.

Figure 1: Study reach

The habitat use data used in the following analyses were the observed fish population density obtained for the i^{th} water body $\rho_{o,i}$ (individuals per square metre), where i (i=1, 2, …, n) denotes the index of the water body and n the total number of water bodies.

2.4 Fuzzy Habitat Preference Model

In fuzzy habitat preference model (FHPM), a simplified fuzzy reasoning was introduced to relate physical habitat characteristic to habitat preference with the consideration of the uncertainties (Fig. 2), and a simple GA to optimize the

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model structure. GA was employed because it enables us to simultaneously optimize all the parameters in FHPM even under the nonlinear, complex interactions between physical environment and fish habitat preference. The premise part of FHPM (Fig. 2(i)), i.e. fuzzy membership functions, is defined for the purpose of reflecting the ecology of Japanese medaka. For instance, because the body length of an adult medaka is approximately 2 cm, the critical requirements for Japanese medaka with regard to depth and velocity thus would be relatively shallower and slowly flowing water. The habitat preference is calculated by taking the weighted mean of singletons in the consequent part (Fig. 2(ii)) by the membership value μ_i. That is,

$$P_j = \frac{\sum_{i=1}^{n_m} \mu_{j,i} \cdot c_{j,i}}{\sum_{i=1}^{n_m} \mu_{j,i}} \tag{1}$$

where P_j denotes the habitat preference to the environmental factor j (=depth, velocity, cover, and vegetation), c_i is the value assigned to each singleton (i.e., degree of habitat preference assigned to the corresponding membership function in the premise part), μ_i is the membership value (i.e., degree of fitness to the membership functions in the premise part), i is the index of the membership functions, and n_m is the number of membership functions (Fig. 2). By taking the weighted mean (1), the results are given in a simple linear form. The singletons in the consequence part are determined by using GA so as to minimize mean square error (MSE) between predicted and observed fish population density. The optimization procedure is summarized as follows.

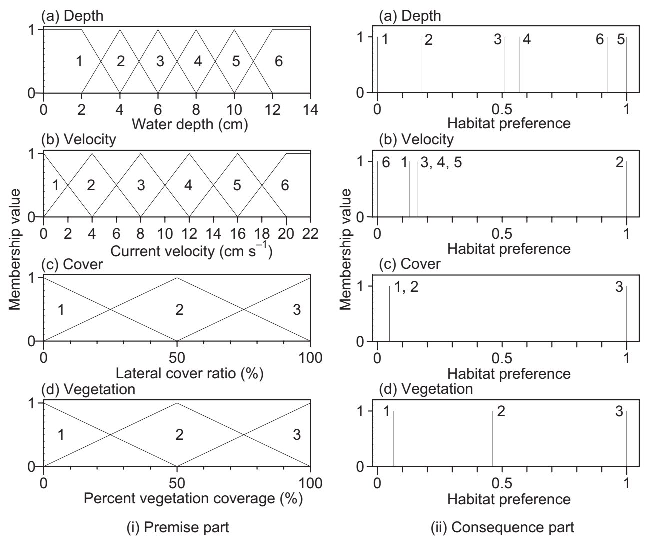

Figure 2: Membership functions of FHPM

First, GA proposed a set of initial model structures (i.e., consequence part) of FHPM. Second, the environmental measurements were given as input values. The input values, i.e., four physical environmental variables, are represented by symmetric triangular fuzzy numbers for considering the uncertainty originated from measurement errors and spatial dispersions. The fuzzy inputs are expressed by its centre a^c_j and spread a^s_j as (a^c_j, a^s_j), where j denotes the environmental factors of depth, velocity, cover, and vegetation. The spread a^s_j is determined from allowable variance when dividing the reach into water bodies: 1 cm is given for the spread of depth a^s_d, 2 cm s^{-1} for velocity a^s_v, 10% each for cover a^s_c and vegetation a^s_{veg}. Of these, the abbreviations of d, v, c, and veg indicate depth, velocity, cover, and vegetation, respectively. Third, habitat preferences for each environmental factor were calculated. Fourth, the habitat preferences to the four environmental factors were combined using (2).

$$P_i = P_{d,i} \times P_{v,i} \times P_{c,i} \times P_{veg,i} \tag{2}$$

Fifth, the habitat use of Japanese medaka was predicted by using (3).

$$\rho_{c,i} = \left(P_i \Big/ \sum_{i=1}^{n} P_i \right) \cdot \sum_{i=1}^{n} \rho_{o,i} \tag{3}$$

Table 1: Condition of GA optimization

Operation	Condition & Remarks
Selection	Elite preservation strategy
Crossover	Uniform
Mutation	0.05%
Number of individuals	100
Number of iteration	5000
Length of binary strings	6 bits per parameter

Table 2: Condition of model structure modification, in which filled circles indicate the factors modified.

Factor	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Depth	●				●	●	●				●	●	●		●
Velocity		●			●			●	●		●	●		●	●
Cover			●			●		●		●	●		●	●	●
Vegetation				●			●		●	●		●	●	●	●
Number*	1	1	1	1	2	2	2	2	2	2	3	3	3	3	4

*Number of membership functions modified.

Next, MSE between the predicted and observed fish population density was calculated, and then GA repeatedly modified the singletons so as to minimize MSE. Finally, the optimized FHPM was obtained. The basic condition of GA optimization is summarised in Table 1. In the original setting, totalled 17 parameters were optimised (5 for depth, 6 for velocity, and 3 each for cover and vegetation). The number of parameters to be modified differed by the condition of model structure modification (see Table 2).

2.5 Model Development and Analysis

In the present study, a data set collected on 14 October and 5 November 2004 was used for calibration while the other data set collected on 9 November was used for validation. The condition given for comparing the results of model structure modification is summarised in Table 2. Totalled 31 sets of the condition were given in which one is given for original model, and 15 each for reducing and adding membership functions to the original model. Since model structures of the models vary in accordance with their initial conditions in the optimization, 20 different initial conditions

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were thus given to each model so as to evaluate the variance of model structure developed. For the comparison, MSE between predicted and observed fish population densities was calculated. Average and standard deviation of MSE on all the models were then used for the comparison. The relationship between MSE and number of fuzzy membership functions was compared in order to clarify the accuracy-complexity tradeoffs in FHPM.

3 Results

The results of field surveys on 14 October and 5 November 2004 were pooled and used for model calibration (Fig. 3(i)), while the result of survey on 9 November was used for model validation (Fig. 3(ii)). All the models were developed by using raw data shown in Fig. 3.

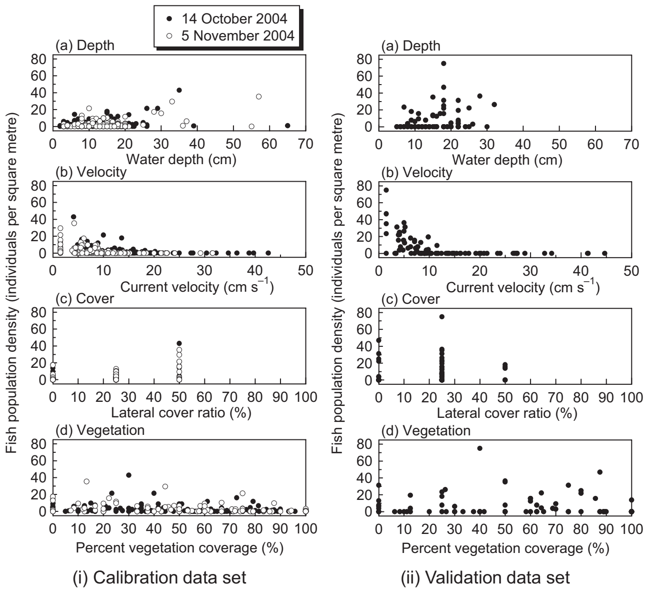

Figure 3: Result of field survey

Habitat preferences evaluated by all the models reflected their model structure, in which the variance in habitat preference curves would be ascribed to the difference in model structure among 20 different initial conditions. Of these, three habitat preference curves evaluated by the models of no modification (original), four-factor reduced and four-factor added are shown as an example (Fig. 4). Despite of the similar tendency in habitat preference, the larger variance in model structure was found in the case of four-factor added model.

By using the habitat preference models together with (2) and (3), habitat uses of Japanese medaka were predicted, of which MSE between predicted and observed fish population density (i.e., habitat use) were used for the comparison. Because some calibration turned out to be failure (especially in the case of adding fuzzy membership function), the best result (i.e., model) achieved at each condition was used in the following analysis. Fig. 5 shows the scatter diagrams of the averaged MSE and number of fuzzy membership functions in both calibration and validation, in which the number of 17 indicates the original model. The model structure could not be improved by modifying the number of fuzzy membership functions in calibration. By contrast, reducing number of fuzzy membership functions resulted in deterioration of prediction ability of the models. The degree of deterioration differed by factors that was modified. As a result, no tradeoff was found between prediction ability of the models (i.e., MSE) and number of fuzzy membership function (i.e., model complexity).

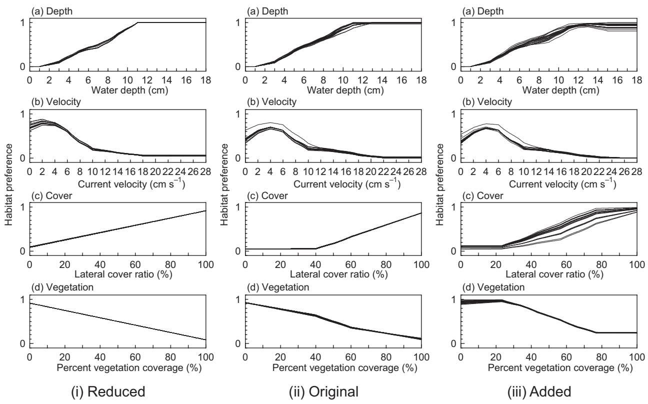

Figure 4: Habitat preference curves evaluated by three models of four-factor reduced (i), no modification (original) (ii), and four-factor added (iii).

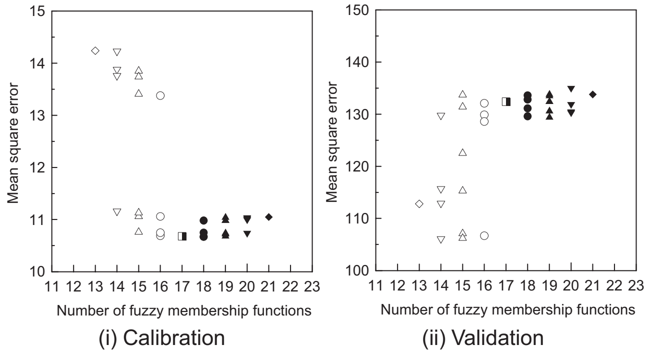

Figure 5: Scatter diagram between minimum mean square error and number of fuzzy membership functions in calibration (i) and validation (ii), in which open marks represent the case of reduced number of fuzzy membership function while filled marks represent that of added.

The MSEs of calibration and validation were compared for the deeper understandings of the relationship between prediction ability and model structure of FHPM. In Fig. 6, there were slight tradeoffs between calibration and validation results. For instance, models with smaller MSE in calibration resulted in larger MSE in validation. Fig. 6 also indicated that no improvement was achieved by adding fuzzy membership functions to the original one.

4 Discussion

The complex interactions between physical environment and habitat preference of the fish made it difficult to clarify the tradeoffs in FHPM. All the habitat preference curves of 31 different conditions showed similar trend of larger water depth, slower velocity, larger cover and smaller vegetation (Fig. 4). However, the prediction result differed between models (Figs. 5 & 6). In Fig. 5, reducing fuzzy membership

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function resulted in better prediction in the validation data set while prediction in the calibration data set resulted in deterioration. On one hand, this clearly indicates the effect of over-fitting to the data used in model calibration. This could be improved by modifying the conditions of GA optimization such as number of iteration and number of data used in model development. On the other hand, this would be ascribed to the different distribution of the physical environment and habitat use of the fish (Fig. 3). This is one of the major problems in habitat modelling and is often discussed as “transferability” of the habitat models [8, 9]. Adding fuzzy membership function thus could not improve prediction ability of the model. To achieve the model transferability, it is necessary to develop habitat models by using sufficient data which satisfy generality of the habitat use of the fish. In the present case, an approach to achieve generality would be the use of different sub-sets of data in model optimization. For instance, [38] employed different subsets of data to cope with the problems of overtraining and high sensitivity to outliers in the application of artificial neural network model. Reference [16] also applied similar approach in the optimization of fuzzy rule-based habitat model. Another approach would be to modify the fuzzy membership function into less precise definition as often applied in habitat modelling of riverine fish [12, 13, 14, 15, 16]. In this case, the advantage of consideration of critical requirement into model structure would however be lost at the same time. Besides the discussion on complexity and improvement of the model, the present result may suggest the significance of cover in the habitat use of the fish. In [20], the significance of cover was also supported by an approach using Akaike Information Criterion (AIC).

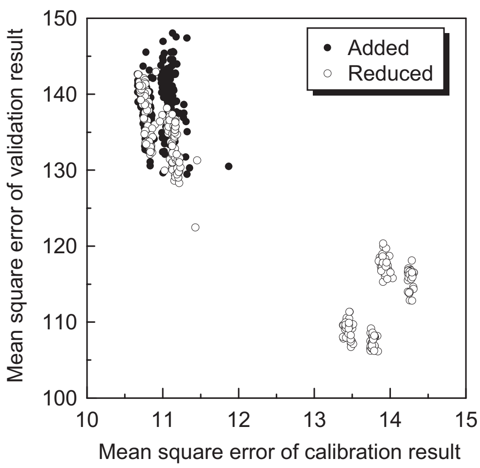

Figure 6: Scatter diagram between mean square errors of calibration and validation results, in which open circles represent the case of reduced number of fuzzy membership function while filled circles represent that of added.

As a concept, adding fuzzy membership function would improve model performance by precisely describing habitat preference of the fish. By contrast, increasing number of parameters to be optimised would put searching loads on GA. Although no clear trend was found between accuracy of the habitat prediction and model structure (i.e., number of fuzzy membership functions), further analyses should be carried out to assess the complex combination such as reducing and adding fuzzy membership functions at the same time. The use of AIC would be appropriate for the quantification of the complex relationship between model structure and prediction ability. In addition, different performance measures such as correctly fuzzy classified instances (%CCFI) and average deviation (AD), and interpretability-preserving optimization of the fuzzy models as presented in [36], can be a pathway for the accuracy improvement of the present model. Further studies would be needed to quantitatively understand the complexity-accuracy tradeoff of FHPM .

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