THE USE OF ACOUSTIC DOPPLER CURRENT PROFILER DATA FOR MICROHABITAT MODELLING IN A SMALL-SCALE STREAM

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This study aims to demonstrate how acoustic Doppler current profiler (ADCP) data can be used for modelling microhabitats of freshwater fish in a small stream in Japan. An instream habitat survey was conducted using an ADCP equipped with RTK GPS in a 75-m reach, based on which 2D maps of water depth and depth-averaged flow velocity were created. Fish were sampled at three points in a cross section arranged at 3-m intervals longitudinally, resulting in total of 75 sampling points. At each sampling point, instream habitat conditions within a 1.5 m radius were extracted using QGIS. Of these data including 13 fish species with different prevalences (i.e. proportion of presences in the entire data points), habitat models were constructed using Random Forests for its predictive capability. Results revealed the microhabitat uses by different species with different body sizes. Model accuracy can be discussed with reference to data quality.

1 INTRODUCTION

Innovative measurement techniques such as acoustic Doppler current profiler (ADCP) allow for seamless mapping of fine-scale instream habitat conditions in a shorter period time compared to a conventional field survey. Such detailed information can be used to quantify the importance of habitat heterogeneity (or environmental diversity) which is believed to be important in ecology but difficult to quantify. Habitat suitability modelling is a way to illustrate how a target species responds to a given habitat condition. While we observed tremendous development in modelling approaches using predictive machine learning methods, there still exist some issues in data quality affecting model performance and habitat information retrieved from the models. Given the aforementioned advanced techniques, it should now be possible to use field-observed large and precise instream habitat data. This study, therefore, examines how ADCP-derived physical habitat data can be used for microhabitat modelling in a small-scale agricultural canal in Japan.

2 METHODS

2.1 Physical habitat survey

We established a 75 m long and approximately 6 m wide study reach (Figs. 1a–1b) in the Fuchu Yosui irrigation system in Kunitachi, Tokyo, Japan. An instream habitat survey was conducted using an ADCP equipped with RTK GPS (M9, Sontek, USA; Fig. 1c). The ADCP moved across the target reach in order to cover the entire reach. For a better observation of bathymetry, intensive measurement was additionally made in the areas with dense aquatic vegetation. The survey results were used to create 2D maps of water depth (henceforth referred to as depth) and depth-averaged flow velocity (henceforth referred to as velocity). At each fish sampling point (see below), instream habitat conditions (i.e., depth and velocity) within a 1.5 m radius were extracted using QGIS [1], from which descriptive statistics (e.g., minimum, mean, median, maximum, etc.) of depth and velocity were derived. In addition, dominant substrate and vegetation coverage were observed visually as habitat variables characterizing fish microhabitats in the reach.

2.2 Fish sampling

After the physical habitat survey, fish sampling was conducted at three points along a cross section, which were arranged at 3-m intervals longitudinally, resulting in 75 sampling points. A cast net and hand net were used twice each to keep sampling effort constant across the survey points. Sampling was done moving from downstream to upstream, one point in a cross-section at a time and with at least 10 minute interval before the consecutive sampling in order not to disturb fish. For each point, all fish caught were identified at species level with body size measurement, and returned to the same point where they were captured.

(a) **(b)** **(c)**

Figure 1. Target reach: (a) view from upstream, (b) downstream end, (c) an ADCP (M9)

2.3 Data analysis

Prior to microhabitat modelling, multicollinearity between all habitat variables as well as presence/absence of fish species was tested to avoid inclusion of redundant habitat variables. Correlation analysis on species occurrences was examined to understand possible co-occurrence of two species in a sampling point, in which fish species with low prevalence (e.g., less than 10%) were omitted. In addition, relationships between habitat variables and abundance of fish species were also investigated to understand habitat use of target fish. Data-driven microhabitat models were then developed using Random Forests [2] for its high predictive capability. The models were built using 10 different sets of initial conditions.

3 RESULTS & DISCUSSION

In total, 13 species were observed in the target reach (Table 1). Of these, six species were found in more than 10% of the sampling points during the survey. Considering the impacts of data prevalence in assessing species responses, these six species were examined for further analyses. Correlation analysis revealed that crucian carp co-occurred with pale chub, Japanese barbel and topmouth gudgeon, while Japanese barbel co-occurred with pale chub and topmouth gudgeon.

Table 1. Species list with prevalences

Species name	Scientific name	Prevalence
Topmouth gudgeon	*Pseudorasbora parva*	0.84
Crucian carp	*Carassius sp.*	0.71
Pale chub	*Zacco platypus*	0.48
Japanese medaka	*Oryzias latipes*	0.33
Japanese barbel	*Hemibarbus barbus*	0.20
Common carp	*Cyprinus carpio*	0.11
Tamoroko	*Gnathopogon elongates*	0.09
Kamatsuka	*Pseudogobio esocinus*	0.09
Striped shiner	*Pungtungia herzi*	0/03
Small-mouth bass	*Micropterus dolomieu*	0.03
Amur Minnow	*Rhynchocypris logowskii steindachneri*	0.01
Japanese common catfish	*Silurus asotus*	0.01
Dark chub	*Nipponocypris temminckii*	0.01

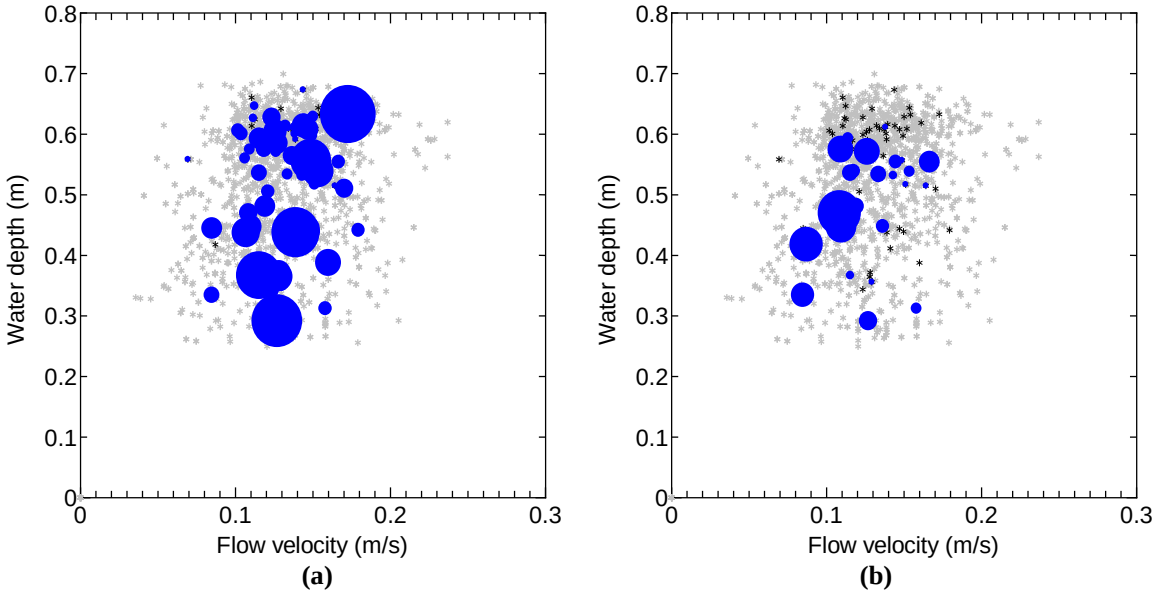

Figure 2. Habitat use for depth and velocity: (a) topmouth gudgeon and (b) Japanese medaka. The size of blue mark indicates the abundance of respective fish at a sampling point.

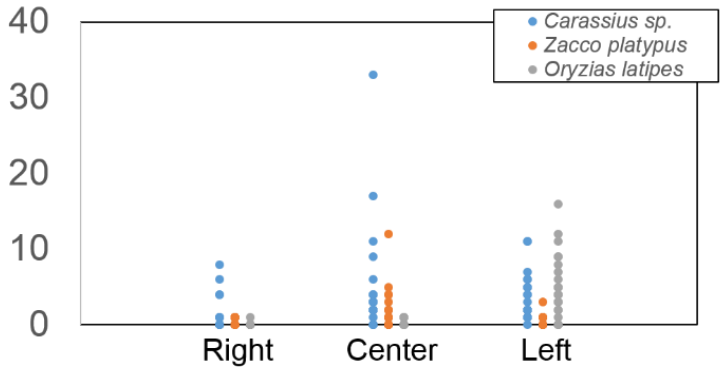

Figure 3. Abundance of crucian carp (blue), pale chub (orange) and Japanese medaka (grey) in different sampling points: right-hand side, center and left-hand side of the target reach.

Different species showed different habitat uses (e.g., Figs. 2–3). For instance, topmouth gudgeon exhibited wider habitat use for depth compared to that of Japanese medaka, while habitat use for velocity were similar between the two species (Fig. 2). This habitat use corresponds to the differences in sampling points (e.g., Fig. 3). That is, topmouth gudgeon occurred across the reach (i.e., right, center and left), whereas Japanese medaka mostly used the left-hand side of the reach (Fig. 3) where water depth is smaller than the others. Similar to topmouth gudgeon, crucian carp showed no trend in lateral habitat use, while pale chub specifically used the center of the reach. This may also correspond to the differences in microhabitat uses for depth, velocity and vegetation. Indeed, left-hand side as well as center of the study reach can be characterized by deeper and faster flowing water. Further analyses using data-driven microhabitat models and ecological information derived from these models shall illustrate ecological features of the target fish species under a given condition. Future study includes additional surveys at different water bodies to cover a wider range of habitat conditions that can be observed in the irrigation system. Incorporation of hydrodynamic models may also allow for better modelling and understanding of habitat use by the target species.

ACKNOWLEDGEMENTS

This study was supported in part by the Grant-in-aid for Young Scientists A (25712026) and Grant-in-Aid for Challenging Exploratory Research (26660190) of the Ministry of Education, Culture, Sports, Science and Technology (MEXT), Japan.

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