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Monitoring and estimating the flow conditions and fish presence probability under various flow conditions at reach scale using genetic algorithms and kriging methods

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ABSTRACT

The combination of current velocity and water depth influences stream flow conditions, and fish activities prefer particular flow conditions. This study develops a novel optimal flow classification method for identifying types of stream flow based on the current velocity and the water depth using a genetic algorithm. It is applied to the Datuan stream in northern Taiwan. Fish were sampled and their habitat investigated at the study site during the spring, summer, fall and winter of 2008–2009. The current velocity, water depth and maps of the presence probability of fish were estimated by ordinary and indicator kriging. The optimal classification results were compared with the classification results obtained using the Froude number and empirical methods. The flow classification results demonstrate that the proposed optimal flow classification method that considers depth–velocity and optimally identified criteria for classifying flow types, yields a current velocity and water depth of 0.32 (m/s) and 0.29 (m), respectively, and classifies the flow conditions in the study area as pool, run, riffle and slack. The variography results of the current velocity and the water depth data reveal that seasonal flows are not spatially stationary among seasons in the study area. Kriging methods and a two-dimensional hydrodynamic model (River 2D) with empirical and optimal flow classification methods are more effective than the Froude number method in classifying flow conditions in the study area. The flow condition classifications and probability maps were generated by River 2D, ordinary kriging and indicator kriging, to quantify the flow conditions preferred by *Sicyopterus japonicus* in the study area. However, the proposed optimal classification method with kriging and River 2D is an effective alternative method for mapping flow conditions and determining the relationship between flow and the presence probability of target fish in support of stream restoration.

1. Introduction

To protect native biodiversity and the evolutionary potential in riparian ecosystems, a suitable flow paradigm emphasizes the need to partially or fully maintain, or restore, the range of natural intra- and interannual variation in hydrologic regimes (Jowett and Biggs, 2009; Poff et al., 1997). The hydrological processes in stream systems may be differentiated by the spatial-temporal scale relative to the current velocity, water depth, substrate and other variables into (1) those occurring at the microhabitat, mesohabitat (reach) scale; and (2) those at larger spatial scales, commonly referred to as reaches and/or segments depending on the classification system (Frissell et al., 1986; Moir and Pasternack, 2008; Thompson et al., 2001). Therefore, knowing the habitat available in a stream is useful for modeling and mapping the distribution and production of fish (Kratzer et al., 2006). Specifically, the term “microhabitat” refers to the localized depth, velocity, temperature, and substrate at one point in a river section (Moir and Pasternack, 2008). On the other hand, the term “mesohabitat” refers to the interdependent set of the same hydrological variables (e.g., water depth, current velocity, and others) over discernible landforms, known as flow condition classifications (e.g., pools, riffles, runs and slack areas). However, relatively studies have linked the ecological functions and hydrological characteristics in each section of a river system (Jackson

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and Fureder, 2006; Jowett and Biggs, 2009; Jowett and Duncan, 1990; Monk et al., 2006; Poff and Ward, 1989; Poff and Allan, 1995).

Complex physical variables on the reach scale must be demarcated by current velocity and water depth; however, joining river cross-sections, slope, and substrate composition are more appropriate for explaining a greater proportion of the variation than a single variable alone. In many studies, the habitat models often used to predict ecological functions are commonly based on four key variables: water depth, current velocity, substrate composition and in-stream cover. The findings of several studies suggest that the combination of current velocity and water depth affects river plants, with some species preferring various flow conditions (Kemp et al., 2000). However, meso-habitats and stream biota have been shown to be associated with distinct combinations of these two variables, rather than responding to depth and velocity separately (Kemp et al., 2000; Statzner et al., 1988; Schweizer et al., 2007a,b). Hence, a definition such as one based on water depths and velocities is useful to biologists because it describes an aspect of those physical conditions (Jowett, 1993). Moreover, the classification of flow conditions based on current velocity and water depth has become the most important approach, and has resulted in multiple fish distributions. Based on the current's velocity and water depth, the empirical model (Aadland, 1993; Borsányi et al., 2004; Hauer et al., 2010; Wang, 2000) and the Froude number method (Azzellin and Vismara, 2001; Deborah and Dan, 2008; Jowett, 1993; Kemp et al., 2000; Moir and Pasternack, 2008; Schweizer et al., 2007a,b) have been widely used to classify flow conditions in studies of the association between fish distributions and flow conditions in their study sites.

Fish are one of the major vertebrates in aquatic communities whose distribution exist a hierarchical relation along streams, and their movements, spawning, and migratory behavior are affected by different flow conditions. Consequently, choosing an indicator species is important to clarify the links between the life-cycles of fish and the flow conditions. The distribution of *Sicyopterus japonicus* ranges from Taiwan to Fukushima Prefecture, Japan (Akihito et al., 2000), which is the northernmost distribution of the *Sicydiinae. S. japonicus* are widely distributed in Datuan stream located in the northern Taiwan. They spawn in freshwater, and the larvae migrate downstream to the sea where they have an oceanic larval life before migrating back to the rivers to mature and reproduce in winter and early spring (Abe et al., 2007). The distribution of *S. japonica* (goby larvae) tends to change with the diverse flow conditions resulting from seasonal precipitation, temperature changes and the relative location from upstream to downstream, which certainly impact the fishes' life-history.

To estimate the current velocity, water depth and the probability of fish, kriging, a geostatistical method, is adopted. Kriging is a linear interpolation procedure that provides the best linear unbiased estimator (BLUE) for the variables spatially (Cressie, 1993). At an unsampled location and for a given variogram, the kriging estimate of variables (e.g. current velocity and water depth) can be thought of simply as an optimally weighted average of the surrounding sampled data. Moreover, the results of kriging estimation can be presented by Arcview software to show how various hydrological factors impact the distribution of fish. Notable recent works that have used geostatistical approaches in freshwater fish and hydrological factor studies include Clark et al. (2008), Cressie et al. (2006), Durance et al. (2006), Ganio et al. (2005), Gresswell et al. (2006), Kratzer et al. (2006), Lin et al. (2010), Peterson et al. (2007), Torgersen and Close (2004), Torgersen et al. (2004), Vilizzi et al. (2005) and Ver Hoef et al. (2006).

Genetic algorithms (GAs), a multiple-criteria assessment methodology, are usually described for exploring uncertainty in the relationships between ecological theory and assessment data. They have been applied to various problems not amenable to traditional computational methods because the search space of all possible solutions is too large to search exhaustively in a reasonable amount of time (Anderson et al., 2003; Stockwell and Noble, 1992). Many researches indicated that genetic algorithms (GAs) proven especially successful in predicting species' potential distributions under a wide variety of situations (Anderson et al., 2002; Al-Zahrani and Moied, 2003; Elith and Burgman, 2002; Feria-A and Peterson, 2002; Reed et al., 2000). Consequently, genetic algorithms have been used in ecological assessment, management, and restoration applications. e.g., Chang and Hsiao (2002), Hsiao and Chang (2002), Mohan (1997), Peterson et al. (2008), and Wardlaw and Sharif (1999).

The hydrodynamic model has been widely used in studying stream flows and habitat simulation. This study used a combination of geostatistics, River 2D model and flow conditions classification (Jowett, 1993; Wang, 2000) to assess the requirements of fish in the Datuan Stream region. The objective of the study was fourfold; (i) use GAs to derive a new flow classification of the study area; (ii) determine which flow conditions could have the higher and lower preferences of *S. japonicus* in the reach scale; (iii) discover the relations between classifications of the flow conditions and *S. japonicus* in the spatial-temporal variations; and (iv) assess the suitability of the above classification methods for the study area.

2. Materials and methods

In this study, we use the empirical model proposed by Wang (2000), the Froude number method (Jowett, 1993) and optimal GA criteria to classify the flow conditions and develop a more suitable classification of the study area. We employ GAs to search for the best flow condition classification for comparison with other classifications the empirical model and the Froude number methods. The above three classifications and fish presences are mapped by using kriging and indicator kriging. Finally, the associations between flow conditions and fish presences are discussed.

2.1. Study area

The Datuan Stream in northern Taiwan (Fig. 1) stretches a total of 14.5 km and rises 1066 m above sea level. The size and mean slope of the catchment area are 16.6 km^2 and 0.075°, respectively. The stream substrate is comprised mainly of cobbles and boulders in the upper- and mid-sections, and silt and sand mixed with cobble in the down-stream section. The geological formations of the substrate are Andesite in the upstream section, and Andesitic Pyroclastics in the mid- and down-stream sections. The study reach is 50 m long and approximately average 6.3 m wide (Fig. 1). In the reach, the right bank is protected with concrete thus the vegetation is ill-covered. Sandbanks with grass plant cover appear at the slower-flow condition. In contrast, the concrete protection is only built at the most erosive parts of the left bank, and the others remain in natural state. The substrate is majorly composed of the cobbles with the average diameter of 28.06 cm. Woody and grass plants are covered through and around the bank. And the inflow contains the irrigational water entering the stream through the drains.

The region's climate is subtropical with a mean average annual air temperature of 22.0 °C, and mean monthly temperatures of 15.0 °C in January and 28.7 °C in July. The rainy season lasts approximately three months (June–August) with occasional monsoons, and the mean annual rainfall is 3000 mm.

2.2. Field surveys of fish and velocity/depth investigation

Sites for data collection were distributed systematically along the Datuan Stream study section and were sampled for fish in the

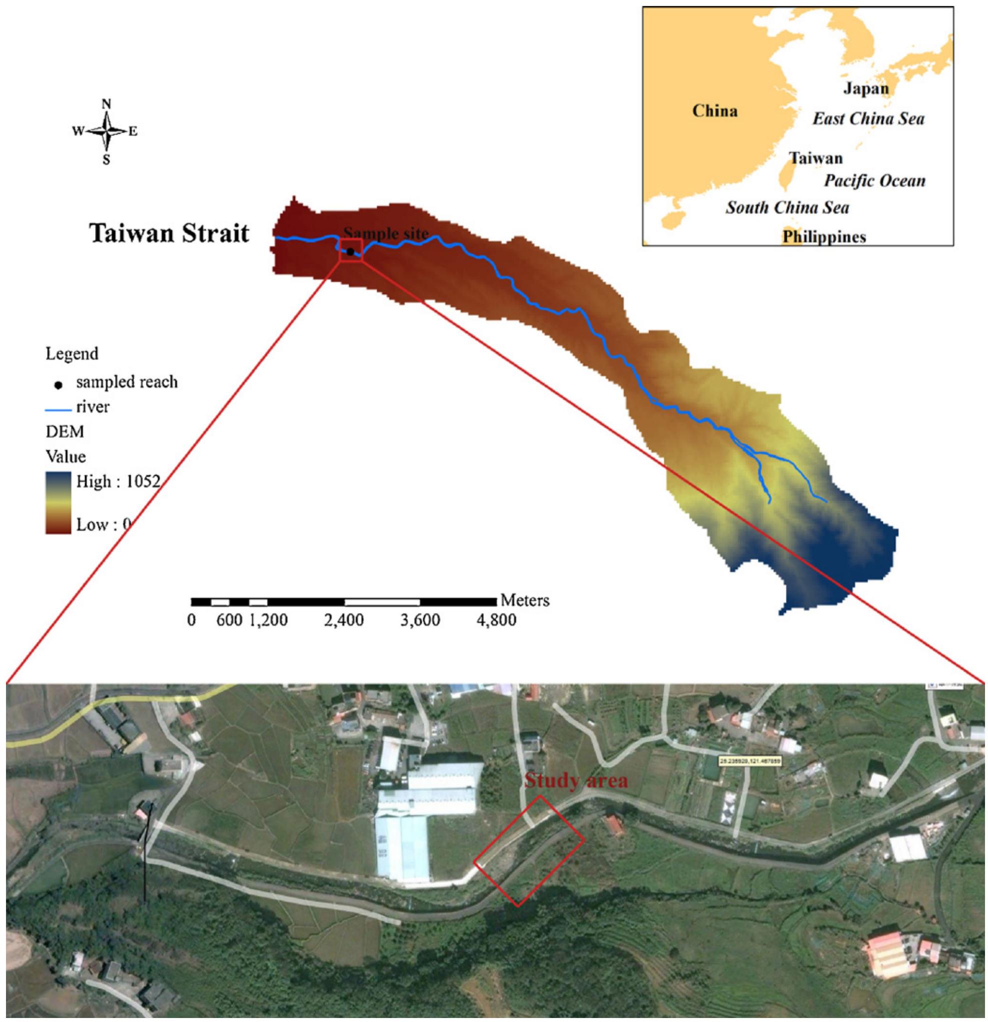

Fig. 1. Study area and reach.

fall and winter of 2007, as well as the spring and summer of 2008. Sampling locations with fish, velocity and water depth data are shown in Fig. 2. To locate fish positions, we used backpack electrofishing. Direct observation via snorkeling was difficult because of water turbulence and turbidity, and direct stream bank observation was difficult due to the lack of suitable observation points (i.e., bridges, and other ecological engineering facilities). Following Bain et al.'s (1985) approach, point electrofishing was performed moving upstream, in order to minimize the time spent in the water by the sampling team at each fish catch, and while moving. To minimize disturbance, sample locations were spaced sufficiently far apart, so that the fish were not unduly disturbed by the previous sample (Azzellin and Vismara, 2001). The fish were kept in aerated buckets for identification, enumeration, and measurement. Species that could not be identified in the field were preserved in 10% formalin, and subsequently identified in the laboratory. The fish survey methods were based on the U.S. EPA Rapid Bioassessment Protocol (RBP) (Barbour et al., 1999) and freshwater bio-monitoring protocols (Liang, 2005). The investigation of water depth and current velocity was conducted according to the standard operating procedures of the NIEA (National Institute of Environmental Analysis) published by the Environmental Protection Administration (EPA) of the Executive Yuan. The current meter shows the current velocity and the water depth. During the electrofishing operation, one person holds the meter and records the values at every point fish are captured.

2.3. Genetic algorithms

Genetic algorithms (GAs) are heuristic programming methods capable of locating near global optimal solutions to complex problems (Goldberg, 1989). The steps of the GA procedure are as follows (Mitchell, 1998):

(1) Randomly generate a population of n chromosomes (candidate solutions to the problem).
(2) Calculate the fitness of each chromosome in the population.
(3) Repeat the following steps until n offspring have been created.
  (a) Select a pair of parent chromosomes from the current population. The probability of selection is an increasing function of fitness.
  (b) Based on the crossover probability, cross over the pair at a randomly chosen point to form two offspring.
  (c) Mutate the two offspring at each locus based on the mutation probability, and add the resulting chromosomes to the new population.
(4) Replace the current population with the new population.
(5) Repeat steps 2–5 until the required number of generations are obtained.

In this study, we combine GAs with the Kappa coefficient for classification accuracy to optimize the criteria of habitat

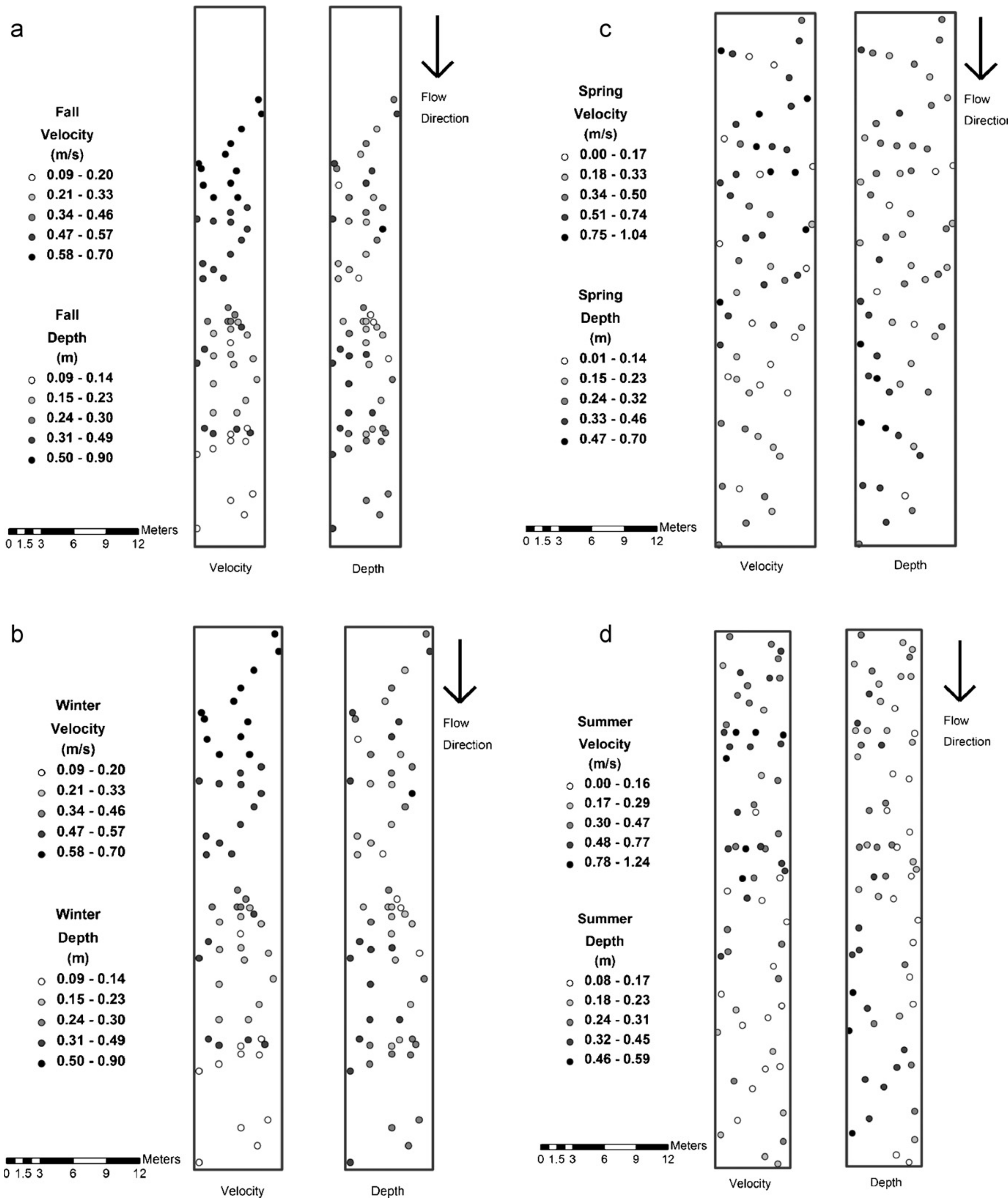

Fig. 2. The local velocity and water depth map of (a) fall, 2007 (b) winter, 2007 (c) spring, 2008 (d) summer, 2008.

classification based on the velocity/depth. The current velocity, water depth and flow conditions were randomly investigated at 90 points in the study reach. In this study, 90 samples (Fig. 2) with velocity and water depth data collected from fall 2007 to summer 2008 are set as training data in GA flow classification. In addition, 101 samples with velocity and water depth data collected on May 2010 are set as testing data in GA flow classification.

The objective function for optimizing the criteria is formulated as follows:

Objective function

$$Z = \underset{D_b, V_b}{\mathrm{Max}}\{\mathrm{Kappa\_Value}\} \tag{1}$$

Table 1
The classification of habitat types (Jowett, 1993).

Habitat type	Froude number (Fr)
Pool	Fr < 0.18
Run	Fr = 0.18–0.41
Riffle	Fr > 0.41

subject to the criteria for habitat classification based on the velocity/depth:

If $V(I) > V_b; D(I) > D_b$ $C(I) = 1$ classify as a run

If $V(I) > V_b; D(I) < D_b$ $C(I) = 2$ classify as a riffle

If $V(I) < V_b; D(I) > D_b$ $C(I) = 3$ classify as a pool

if $V(I) < V_b; D(I) < D_b$ $C(I) = 4$ classify as a slack

for $I = 1 \sim N$
The error matrix X:

If $C(I) = i; E(I) = j$ $X_{ij} = X_{ij} + 1$ for $I = 1 \sim N$

		Objective identification by expert $E(N)$				Row total
		Round(1)	Riffle(2)	Pool(3)	Slack(4)	
Classification via velocity/depth $C(N)$	Run(1)	X_{11}	X_{12}	X_{13}	X_{14}	Row_1
	Riffle(2)	X_{21}	X_{22}	X_{23}	X_{24}	Row_2
	Pool(3)	X_{31}	X_{32}	X_{33}	X_{34}	Row_3
	Slack(4)	X_{41}	X_{42}	X_{43}	X_{44}	Row_4
	Column total	Col_1	Col_2	Col_3	Col_4	N

The kappa coefficient:

$$\text{Kappa\_Value} = \frac{N\sum_{i=1}^{n} X_{ii} - \sum_{i=1}^{n}(X_{ij} \times X_{ji})}{N^2 - \sum_{i=1}^{n}(X_{ij} \times X_{ji})} \times 100\% \tag{2}$$

where Kappa_Value is the kappa coefficient; D_b is the depth bound of the habitat classification based on the velocity/depth; V_b is the velocity bound of the habitat classification based on the velocity/depth; C is the set of classification via velocity/depth; E is the set of objective identification by experts; D is the set of depth measurements; V is the set of velocity measurements; X is the population error matrix; N is the total number of survey data; n is the number of rows and columns in the error matrix.

2.4. The classification standards of flow conditions

The classifications of Jowett's Froude number criteria (Jowett, 1993) and Wang's empirical method (Wang, 2000) are listed in Tables 1 and 2. The Froude number is a common hydraulic index that describes the mean flow conditions of an entire water column. The index is used to calculate the open surface flow in channels based on the velocity and depth of each unit. The Froude number (Fr), which relates the inertial and gravitational forces in flows, is a measure of flow criticality. It is given by

$$\mathrm{Fr} = \frac{V}{\sqrt{gd}} \tag{3}$$

Table 2
The standard classification of a stream system (Wang, 2000).

Stream type	Riffle	Pool	Run	Slack
Velocity (m/s)	>0.3	<0.3	>0.3	<0.3
Depth (m)	<0.3	>0.3	>0.3	<0.3
Substrate	Sandstone, Cobble, Gravel	Laccolith, Boulder, Pebble	Boulder, Cobble, Pebble	Sand soil, gravel soil

where V denotes the mean velocity (ms^{-1}), d is the water depth (m) and g is the acceleration of gravity (ms^{-2}).

2.5. Data interpolation by geostatistical methods

An initial analysis of the data on fish abundance, current velocity and water depth was performed using experimental variograms, which show in graph form the semivariance calculated directly from the data for each lag distance. In an experimental variogram, the semivariance at lag h is denoted by

$$\gamma_{uu}(h) = \frac{1}{2n(h)}\sum_{i=1}^{n(h)}[u(x_i + h) - u(x_i)]^2, \tag{4}$$

where h denotes the lag distance that separates pairs of sampling sites (the asymmetric hydrologic distance); $u(x)$ is the fish count and assemblage value at location x; $u(x+h)$ denotes the number of fish at location $x+h$; and $n(h)$ represents the number of paired samples separated by the lag distance h.

The three main features of the typical variogram model are the *range*, *sill*, and *nugget effect*. The sill is the upper limit that a variogram approaches at a large distance, and is a measure of the variability of the investigated variable: a higher sill corresponds to greater variability in the population (Lin et al., 2007). The range of a variogram model is the distance lag at which the variogram approaches the sill, and can reveal the distance above which fish counts become spatially independent (Durance et al., 2006; Ganio et al., 2005; Lin et al., 2007) and are more likely to be random (Durance et al., 2006). Paired samples separated by a distance greater than the range are uncorrelated. The nugget effect is exhibited by the apparent non-zero value of the variogram at the origin, which may be due to the small-scale variability of the investigation process and/or measurement errors.

We used ordinary kriging to estimate the velocity/depth of the stream when catching fish in the study 50 m reach. We use kriging to estimate the value of the investigated variables at an unsampled location x_0 based on the measured values in the linear form:

$$u^*(x_0) = \sum_{i=1}^{N}\lambda_{i0}u(x_i), \tag{5}$$

where $u^*(x_0)$ is the estimated value at location x_0; λ_{i0} is the kriging estimate of the weight of $u(x_i)$; x_i is the location of the sampling site of the variables u; and N is the number of variables u involved in the estimation.

By using non-biased constraints and minimizing the estimation variance, the kriging estimation variance (σ^2) can be calculated by

$$\sigma^2_{\text{kriging}} = \sum_{i=1}^{N}\lambda_{i0}\gamma_{uu}(x_i - x_0) + \mu \tag{6}$$

where μ is a Lagrange multiplier.

To obtain adequate indicators of the *S. japonicus*' status, the probability of fish being present in each reach was estimated by indicator kriging (Burrough and McDonnel, 1998; Seijo and Caddy, 2000). Specifically, we defined 1 as the maximum value when *S. japonicus* samples were caught and 0 as the minimum value when no samples were caught in the study area in each season. We transformed the fish data from a continuous scale to a binary scale in order to apply ordinary indicator kriging ($i(x_i)$) (Goovaerts, 1997) as follows:

$$i(x_i) \begin{array}{l} = 0 \quad \text{if } S.japonicus \text{ is captured} \\ = 1 \quad \text{if no one is captured} \end{array} \tag{7}$$

Indicator kriging is a non-linear form of ordinary kriging. Specifically, semi-variograms are computed for the binary data

Table 3
General information on sampling site.

Season	Stream width (m)	Total area (m^2)[a]	Average Current velocity (m/s)	Average Stream depth (m)
2007 fall	6.3	315	0.41	0.27
2007 winter	5.2	260	0.62	0.40
2008 spring	9.0	450	0.44	0.28
2008 summer	7.0	350	0.40	0.25

[a] The total area of the sampling reach varies with the seasons according to discharge.

in the usual way, and ordinary kriging proceeds with the transformed data (Burrough and McDonnel, 1998; Mario and Omar, 2003). The resulting maps display continuous data in the range 0–1, showing a contour of the fish probabilities in each reach.

2.6. River 2D model

In this study, the River 2D model, a hydrodynamic model, was used to simulate velocity and water depth using 1 m finite element mesh within the study reach. The River2D model is a two-dimensional, depth-averaged finite element model (Lee et al., 2010; Steffler and Blackburn, 2002). The River2D model uses the finite element method to solve the basic equations of vertically averaged 2D flow, which incorporate mass and momentum conservation in the two horizontal dimensions (Steffler and Blackburn, 2002). In the finite element solution regime, the user can vary the density of the computational mesh across various parts of the study area (Waddle, 2010). The conservation of mass of water (Eq. (8)) and the two components of the momentum vector (Eqs. (9) and (10)) are represented as follows (Lee et al., 2010; Steffler and Blackburn, 2002).

$$\frac{\partial H}{\partial t} + \frac{\partial q_x}{\partial x} + \frac{\partial q_y}{\partial y} = 0 \tag{8}$$

$$\frac{\partial q_x}{\partial t} + \frac{\partial (Uq_x)}{\partial x} + \frac{\partial Vq_x}{\partial y} + \frac{g}{2}\frac{\partial}{\partial x}H^2 = gH(S_{0x} - S_{fx}) + \frac{1}{\rho}\left[\frac{\partial (H\tau_{xx})}{\partial x}\right] + \frac{1}{\rho}\left[\frac{\partial (H\tau_{xy})}{\partial y}\right] \tag{9}$$

$$\frac{\partial q_x}{\partial t} + \frac{\partial (Uq_y)}{\partial x} + \frac{\partial Vq_y}{\partial y} + \frac{g}{2}\frac{\partial}{\partial y}H^2 = gH(S_{0x} - S_{fx}) + \frac{1}{\rho}\left[\frac{\partial (H\tau_{xx})}{\partial x}\right] + \frac{1}{\rho}\left[\frac{\partial (H\tau_{xy})}{\partial y}\right] \tag{10}$$

where H is the average depth of the flow; U and V are the averaged velocities in the x and y directions, respectively; g is the acceleration due to gravity; ρ denotes the density of water; S_{0x} and S_{0y} denote the bed slopes; S_{fx} and S_{fy} denote the friction slopes; and τ_{xx}, τ_{xy}, τ_{yx} and τ_{yy} are the components of the horizontal turbulent stress tensor.

3. Results

3.1. Basic information about sample site

According to Table 3, the average current velocities during the fall of 2007, as well as the spring and summer of 2008 were close to 0.4 m/s (0.41, 0.44, 0.40 m/s). It reached 0.62 m/s (maximum value) in the winter of 2008. Meanwhile, the average stream depth varied in a manner similar to the average current velocity (Table 3). The average depth in the fall of 2008, as well as the spring and summer of 2009 was approximately 0.26 m; only in the winter of 2008 did it reach 0.40 m. In summary, although the average current velocity and water depth varied little through the fall, spring and summer, both were significantly higher those in the winter. Accordingly, this study site was chosen to compare the distribution of *S. japonicus* across the four seasons.

3.2. Optimal classification of flow conditions in genetic algorithms

In this study, a genetic algorithm with 90 investigated points of flow that uses the tournament selection method to perform a uniform crossover operation. The crossover probability is 0.8; the mutation probability is 0.1, and the population size is 100. The stopping criterion is based on the difference between the value of the objective function. When the user-defined criterion is met or the maximum allowed number of generations is reached, the optimal procedure is terminated; otherwise, another cycle is performed. The termination criterion is that the discrepancy between the value of the objective function should not increase over 30 successive generations, and the population should propagate for more than 100 generations. The training data set was collected from fall of 2007 to summer of 2008 and the testing data set with a size of 101 was collected in May 2010. Therefore, the GA converges when the kappa coefficient (value of objective function) equals 77.04%, corresponding to the solution that V_b (current velocity) is 0.32 (m/s), and D_b (water depth) is 0.29 (m) for the flow classification criterion that is based on velocity/depth. The kappa value obtained in the test is 81.42%. The testing result suggests that the optimal criterion of classifying flow types is reliable. The kappa values obtained by the empirical method (Wang, 2000) and Froude number method (Jowett, 1993) are 74.94% and 52.66%, respectively. Fig. 3 shows the flows classified by Wang's empirical method, Jowett's Froude number method and the proposed optimal method. This comparison result reveals the GA criteria for classifying flow are close to that were obtained from the empirical method (Wang, 2000). Additionally, the classifications of flow by the proposed optimal classification method are more accurate than those by the methods of Wang and Jowett.

3.3. Description of three classifications of flow conditions the four seasons

Variography reveals how measures such as the population density of fish vary in spatial or temporal scale. Tables 4 and 5 present the variogram models of measured current velocity, water depth and fish population data. The best-fit model was determined using the *R*-squared method with cross-validation. Figs. 4–7 show kriging estimated maps of the current velocity and water depth during the fall, winter, spring and summer.

Based on GA criteria (0.32 (m/s) for current velocity and 0.29 (m) for water depth), riffle occupied most of the stream area at this study site in the fall, while the remaining area was shared by pool, run, and slack (Fig. 4(a)). Owing to the various flow conditions, the density of *S. japonicus* was greatest in the Datuan stream. Slack was present only close to the upstream of the river bank. Fig. 4(b) reveals that pool and run covered most of the study site. Unlike in the empirical method, some of the riffle should be regarded as run. Although run covered most of the study site, some pool and riffle were found in the neighborhood of the river bank in winter (Fig. 5(a) and (b)). This phenomenon did not appear in any other season. The flow was highly heterogeneous in the spring, included all flow types (Fig. 6(a)). Slack always appeared close to the river bank, as confirmed by the description of slack in the empirical rule method (Fig. 6(b)). Eventually, riffle covered almost half of the stream area, while most of the remaining area was covered by pool and slack (Fig. 7(a)). According to Fig. 7(b), pool and run covered most of the

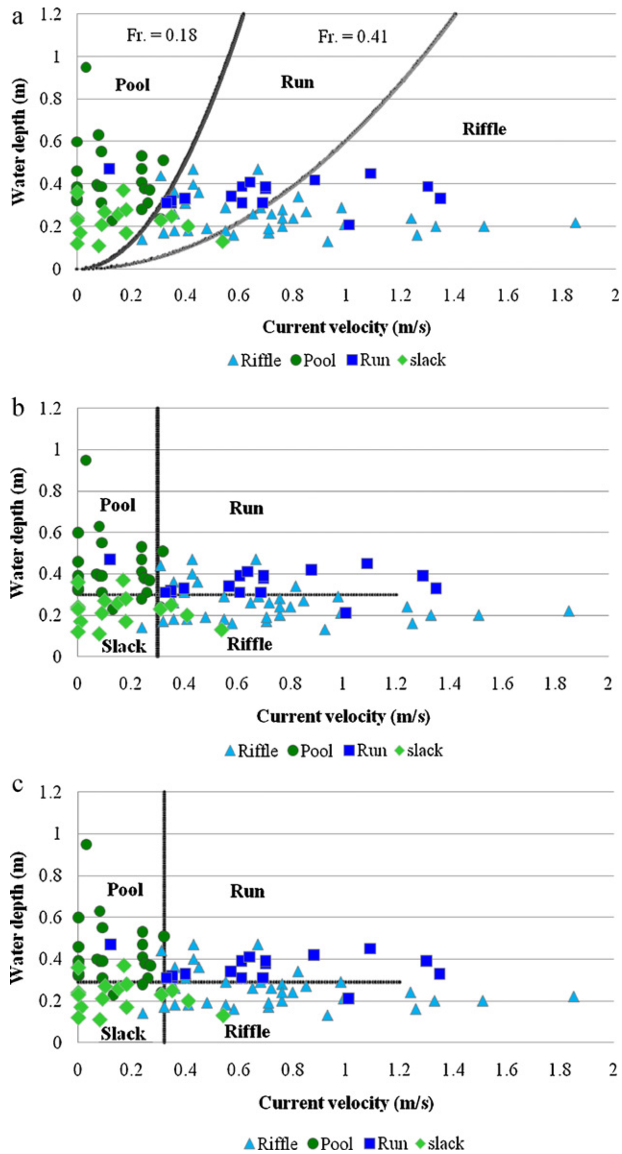

Fig. 3. The investigated flows versus the flows classified by (a) the Jowett's Froude number method, (b) the Wang's empirical method, (c) the optimal classification method.

study site. Therefore, most of the riffle and slack (Fig. 7(a)) should be regarded as run and pool (Fig. 7(b)).

This uses genetic algorithms (GAs) to identify the optimal flow conditions as a current velocity of 0.32 (m/s) and and a depth of 0.29 (m). Obviously, although the flow condition maps that are based on the GA criteria (Figs. 4–7(c)) in the seasons are very similar to those obtained using the empirical (Figs. 4–7(a)) method, the two

Table 4
Variogram model of the current velocity, water depth and fish data.

Season	Variable	Nugget	Model	Range (m)	Sill	R^2
Fall	Velocity	0.00687	Gaussian	25.15	0.05	0.828
	Depth	0.00745	Spherical	20.25	0.026	0.727
Winter	Velocity	0.0043	Spherical	11.19	0.06886	0.322
	Depth	0.00662	Exponential	27.39	0.01423	0.535
Spring	Velocity	0.0523	Exponential	25.16	0.0831	0.522
	Depth	0.00437	Exponential	28.65	0.02124	0.726
Summer	Velocity	0.0466	Exponential	28.314	0.08641	0.524
	Depth	0.00262	Exponential	16.8	0.01304	0.713

Table 5
Indicator variogram model of the fish data.

Season	Variable	Nugget	Model	Range (m)	Sill	R^2
Fall	Fish	0.017	Gaussian	1.68	0.148	0.886
Winter	Fish	0.0021	Gaussian	2.685	0.0692	0.544
Spring	Fish	0.0001	Spherical	2.69	0.1642	0.672
Summer	Fish	0.0017	Exponential	3.30	0.0914	0.525

classifications somewhat differed from each other. In Fig. 4(a) and (c), some of the run is regarded as pool in the fall. Some of the run and riffle in spring and summer turned into pool and slack in the spring and summer (Fig. 6(a) and 7(a)). These findings were evident in the cross-section of the study site under a range of flow conditions – run and pool or riffle and slack.

Fig. 8 shows River 2D maps of the current velocity and water depth in the fall, winter, spring and summer. The observed values of velocity and depth at the measurement locations in each season were compared with the simulated values. The coefficients of determination (R^2) between measured and simulated velocity in the fall, winter, spring and summer are 0.834, 0.803, 0.812 and 0.818, respectively. The coefficients of determination (R^2) of between measured and simulated water depths in the fall, winter, spring and summer are 0.801, 0.890, 0.846 and 0.885, respectively.

3.4. Maps of fish presence probability

The presence probability of fish was determined using indicator kriging. The results were represented as contours of presence probability of fish on the flow condition maps (Figs. 4–7). The contours congregated closely in the middle of the study site, where the presence probability of fish varied considerably (Fig. 4(a)–(c)). The presence probability of *S. japonicus in* most parts of the study site was between 0.8 and 1, indicating that the prevalence of *S. japonicus* was high. Only in three places close to the river bank did the probability fall outside this range (Fig. 5(a)–(c)). According to the maps in spring, although the low probability contours were bund at the bottom of the study site, the area of high probability in the upper study site is large (Fig. 6(a)–(c)). Most of the area has a probability of finding *S. japonicus* from 0.8 to 1, indicating that the presence probability of *S. japonicus* was high in the study site (Fig. 7(a)–(c)). The presence probabilities of fish were also mapped as contours on the flow condition maps that were simulated by River 2D (Fig. 8).

3.5. Area ratios of fish presence to the study area

The relationship between the presence probability of fish and the flow conditions was determined using the ratio of the area of a specific flow condition with a certain presence probability of fish to the total area of the study site. The area ratio is the area of a flow condition under a fish presence probability divided by the area of total area of study site. According to bar graphs, *S. japonicus* exhibits strong preferences for particular flow conditions (Figs. 9–12). The study site was divided into areas of pool, run, riffle, and slack. Riffle is the most favorable habitat for *S. japonicus* and the area ratio of a riffle, associated with probability 0.8–1, was 55.0% (Fig. 9(a)). In the study site, the area ratios of the various flow conditions (Fig. 9(b)) are not similar to those in Fig. 9(a). During the various seasons, run was the only flow condition (Fig. 10(a)). Additionally, the area ratio was increased with the presence probability of fish. According to the Froude number method, the appearance of run in the study site in Fig. 10(b) was similar to that in Fig. 10(a). The area ratios of the flow conditions in Fig. 9(a) and Fig. 11(a), in which riffle dominated, were also similar. In Fig. 12(a), run and pool were

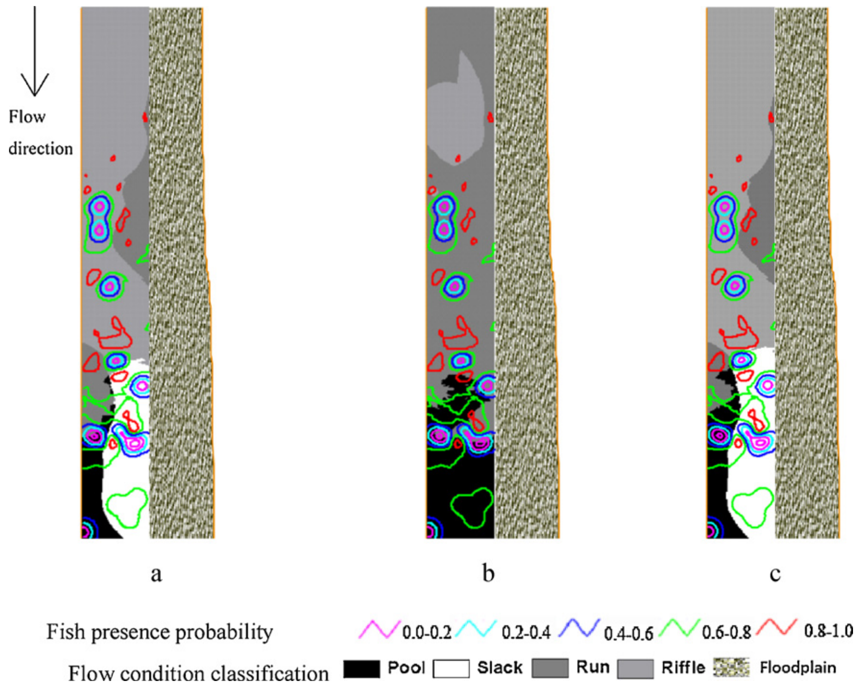

Fig. 4. The flow conditions and fish presence probability overlapped mapping in fall. (a) The Wang's empirical method; (b) the Jowett's Froude number method; (c) the optimal classification method.

the two most important flow conditions in the reach. This situation is dissimilar to that in Fig. 12(b). Additionally, the area ratios of the flow conditions obtained by the empirical method were identical to those obtained by the optimal method in fall, winter and spring (Figs. 9–11), but were very different in summer (Fig. 12). Therefore, the disagreement between the empirical rule method and the Froude method in flow classification is obvious.

4. Discussion

Patterns of velocity and depth significantly influence the structure and functions of a stream ecosystem (Schweizer et al., 2007a,b). Fish play an important role in streams and their actvitiies substantially are affected by the flow conditions of freshwater systems (Abe et al., 2003; Inoue and Miyayoshi, 2006; Wooster and

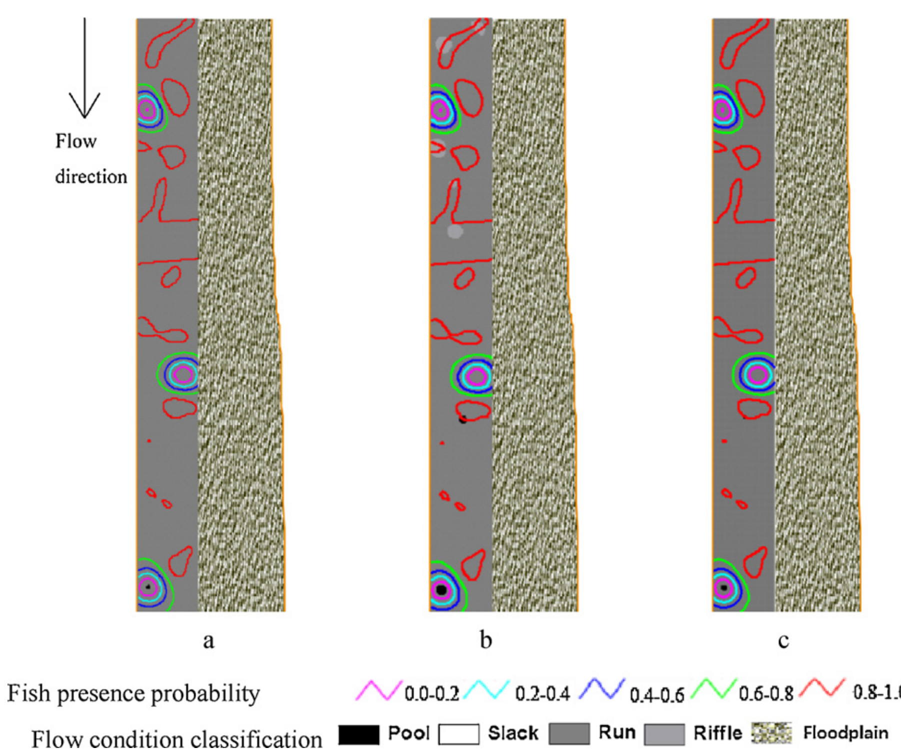

Fig. 5. The flow conditions and fish presence probability overlapped mapping in winter by (a) the Wang's empirical method; (b) the Jowett's Froude number method; (c) the optimal classification method.

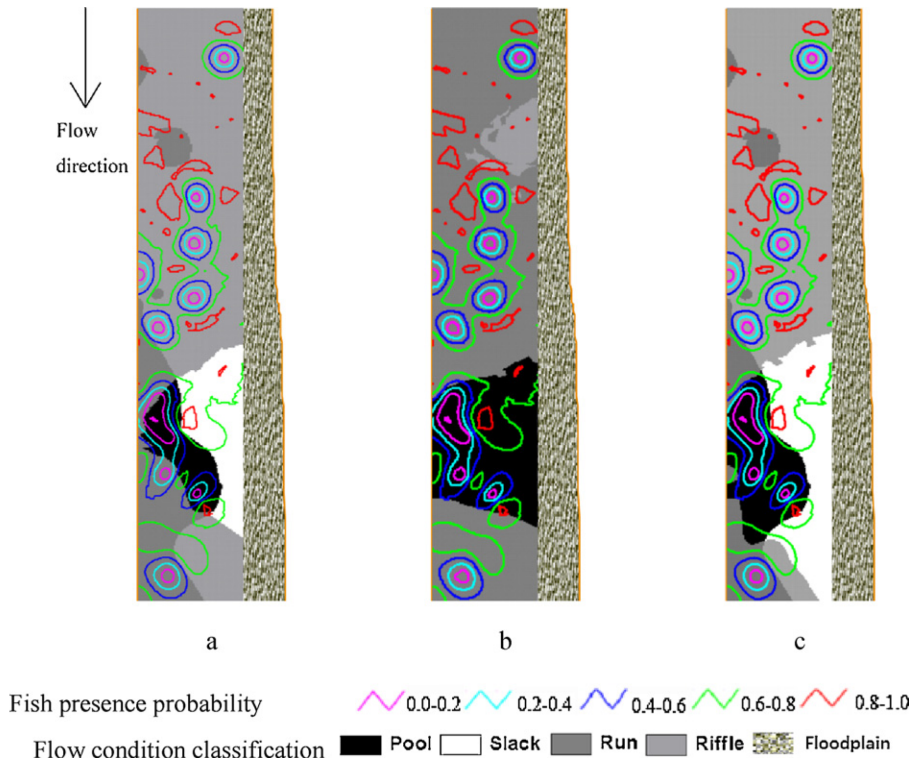

Fig. 6. The flow conditions and fish presence probability overlapped mapping in spring by (a) the Wang's empirical method; (b) the Jowett's Froude number method; (c) the optimal classification method.

Sih, 1995). In the estimation of the joint frequency distributions of depth and velocity to evaluate an instream habitat (Schweizer et al., 2007a), the joint, rather than independent, representation of velocity and depth represents a significant advancement. Schweizer et al. (2007b) indicated that such representation not only yields a more realistic description of hydraulic conditions, but also improves ecological assessments. Fish seek a suitable combination of current velocity and water depth. Gore (1978) indicated that the con-

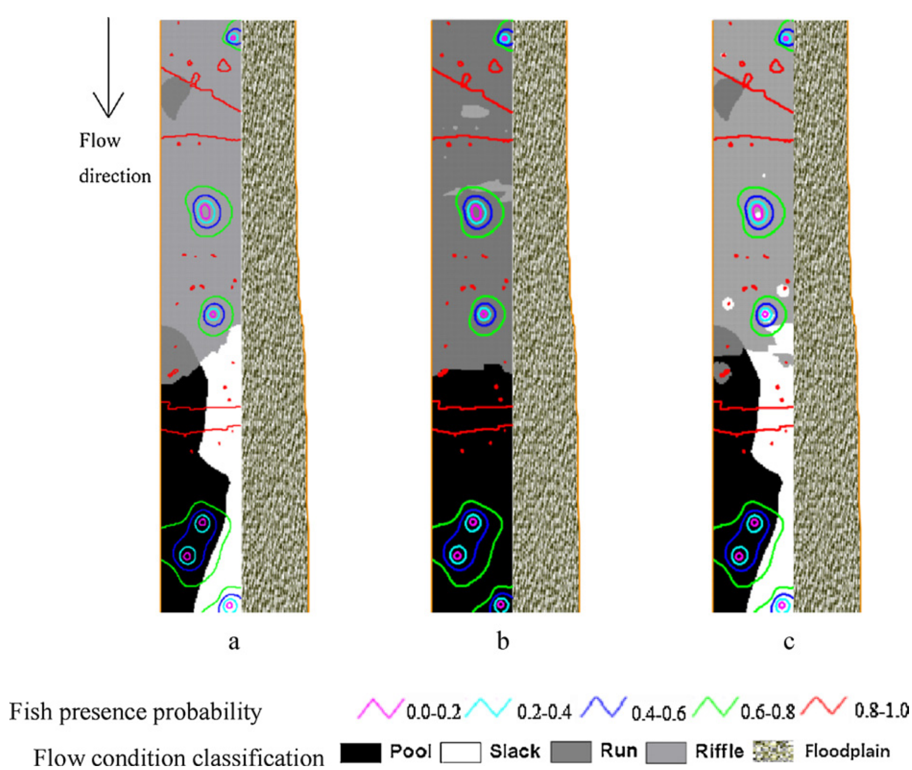

Fig. 7. The flow conditions and fish presence probability overlapped mapping in summer by (a) the Wang's empirical method; (b) the Jowett's Froude number method; (c) the optimal classification method.

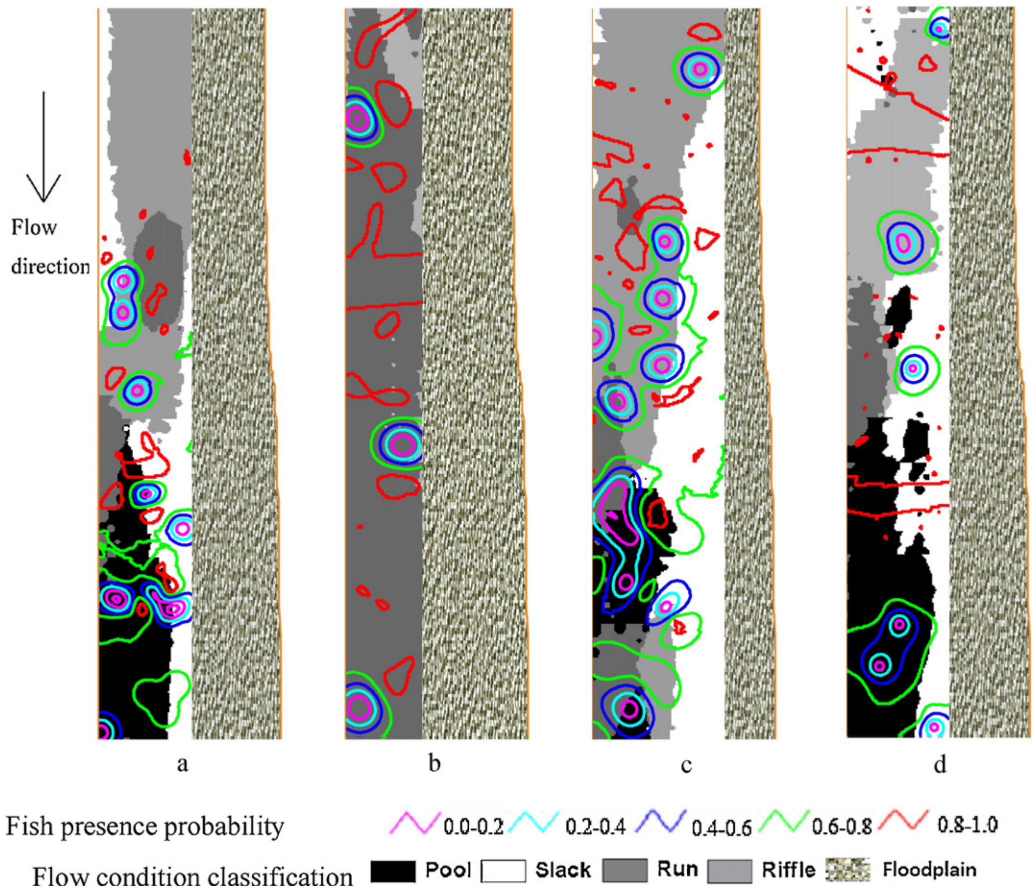

Fig. 8. The simulated flow conditions of River 2D and fish presence probability of (a) fall (b) winter (c) spring (d) summer.

ditions that maximized faunal diversity were a current velocity of 75–125 cm/s and a depth of 20–40 cm. The optimal condition was a current velocity of 76 cm/s at a depth of 28 cm over cobble substrates (Gore, 1978). The relationships among fish abundance, current velocity and water depth from fresh water to sea are complex. The preferences of fish are mostly for particular current velocities and stream depths. Previous studies have classified flow conditions to estimate the need of *S. japonicus* for pool/riffle (Inoue and Miyayoshi, 2006; Wooster and Sih, 1995). In this study, GA was successfully used with 90 sampled data to determine the criteria for classifying flow. The optimal criteria were successfully tested with additional 101 sampling data. The optimal flow classification criteria are close to those used in the empirical method. Additionally, flow conditions were classified and mapped using kriging and the empirical rule (Wang, 2000), the Froude number and optimal criteria method (Jowett, 1993). Many studies have demonstrated the application of the empirical rule and Froude number methods to streams, and have discussed the advantages and disadvantages of using these methods (Azzellin and Vismara, 2001; Deborah and Dan, 2008; Gordon et al., 1994; Jowett, 1993; Kemp et al., 2000; Wang, 2000).

Spatial variation in velocity and depth over a stream reach importantly determines the structure and function of a stream ecosystem (Allan, 1995; Schweizer et al., 2007a). This study evaluated the spatial variation of velocity and depth using a variogram model. A typical variogram model is characterized by range, sill and nugget effect variogram, the sill is a measure of the variability of the investigated variable a higher sill implies greater variability in the measurement data. The range of a variogram model and the distance lag at which the variogram approaches a sill can reveal the distance above which measured data become spatially independent. The nugget effect is exhibited by the apparent non-zero value of the variogram at the origin, possibly attributed to the small-scale variability of the investigated process and/or measurement errors. The variogram results herein reveal that water depth data fall consistently in the range 16.8–28.65 m in all four seasons. Water velocity data varied in the range 11.9–28.31 m. Fish prevalence data fell stably in the range 1.68–3.30 m. Sill values of variogram models reveal that the water velocity in the spring varies more than that in the other seasons. The variography results reveal that flows in the winter and summer are less discontinuous than those in the fall and summer in the study area. Different variogram models were fitted to seasonal current velocity and water depth data. The various variogram models reveal that seasonal flows are not spatially stationary in the study reach among the seasons.

The study seeks to establish the feasibility of both classifications of data from the Datuan stream. Indicator kriging estimation was used to map the distribution of fish presence in the autumn, winter and spring, and the relationship between the presence of fish and flow conditions in the study area (Carroll and Pearson, 2000; Durance et al., 2006; Lin et al., 2010; Thompson et al., 2001; Torgersen et al., 1999, 2004; Torgersen and Close, 2004).

In this study, the flow condition classifications of Wang (2000), Jowett (1993) and the GA optimal criteria were used to analyze the distribution of *S. japonicus*. The results of these three methods indicate that the classifications of flow conditions by the empirical and optimal methods differ substantially from those by the Froude number method of Jowett (1993). In the study of Moir and Pasternack (2008), the Froude number method adequately differentiated morphological units in most cases, but the most effective hydraulic classification approach was based on joint depth–velocity distributions. Fig. 3 shows that the Froude number

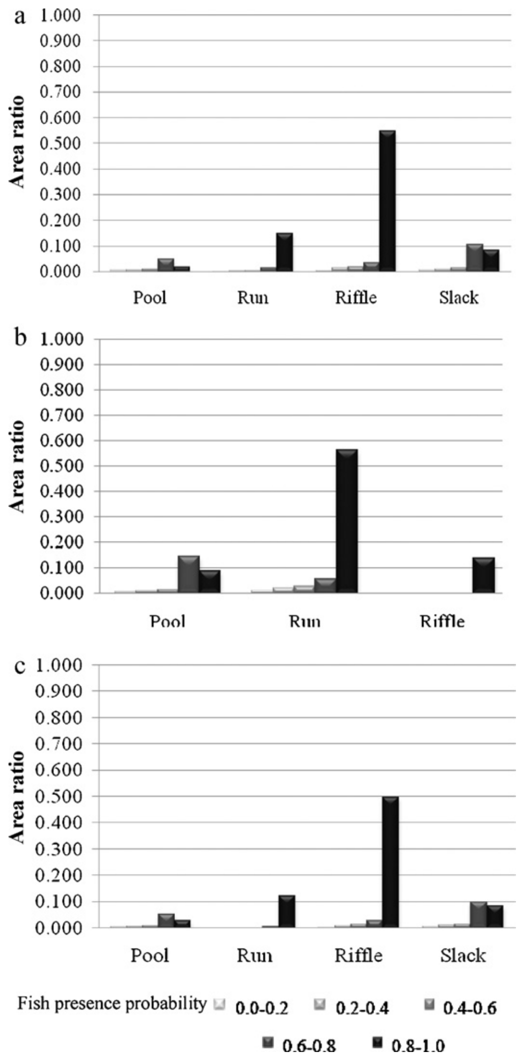

Fig. 9. The histogram of area ratio with a certain range of fish presence corresponds to each flow condition (a) the Wang's empirical method; (b) the Jowett's Froude number method; (c) the optimal classification method. (Area ratio = the area of a flow condition under a fish presence probability/the area of total area of study site.)

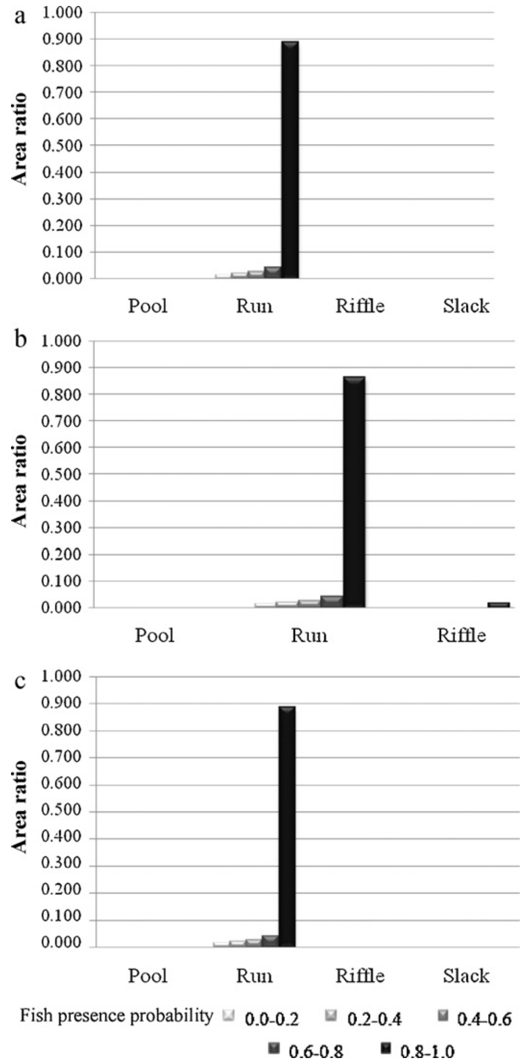

Fig. 10. The histogram of area ratio with a certain range of fish presence corresponds to each flow condition in winter by (a) the Wang's empirical method; (b) the Jowett's Froude number method; (c) the optimal classification method. (Area ratio = the area of a flow condition under a fish presence probability/the area of total area of study site.)

(TRY method) clearly identified pool (Fr. < 0.18), but could not distinguish between riffle and run. This result is similar to that of Moir and Pasternack (2008), who found that the Froude number method classify flow conditions such as pool, run, riffle and others poorly, and was particularly poor at distinguishing between riffle and run.

Jowett (1993) found that the pool habitat was associated with a Froude numbers of less than 0.18 and a velocity/depth ratio less than 1.24 s^{-1}; the riffle habitat with a Froude number of greater than 0.41 and a velocity/depth ratio of greater than 3.20 s^{-1}, and the run habitat with intermediate values. The proposed optimal method confirms that the empirical method can effectively classify the flow conditions in the study area. The empirical rule was established by Wang (2000) and has been subsequently applied to many rivers in Taiwan to estimate the pool/riffle series (Wang, 2000). However, according to the empirical rule, the limits of water depth and current velocity are 0.3 m and 0.3 m/s, respectively. Aadland (1993) and Borsányi et al. (2004) defined the limits of water depth for flows as 0.6 m and 0.7 m and the limits of current velocity as 0.5 m/s and 0.3 m/s. Despite the shortcomings of the empirical rule, many ecologists still apply it because of its convenience (Aadland, 1993; Borsányi et al., 2004; Hauer et al., 2010; Kemp et al., 2000; Statzner et al., 1988). This study develops an optimal classification method which supports classification by the empirical method. However, the optimal classification method considers depth–velocity relations and is the most effective flow classification method. The flow maps (Figs. 4–7) indicate that the optimal velocity and water depth, determined by GA, can affect the spatial patterns of classified flows.

The hydrodynamic model has been widely used in studying stream flows. Recently, some studies in this field have used kriging to map flow conditions. However, River 2D-simulated seasonal flows are slightly different from seasonal flows estimated by kriging (Figs. 4–8), particular at the boundary of the study reach. The differences between River 2D-simulated flows and kriging-estimated flows are caused by differences between numerical methods and estimated methods. River 2D simulates flows using deterministic equations with boundary conditions, whereas kriging estimates flows by making linear unbiased estimates. More complex flows are associated with greater differences between the simulation using River 2D and the estimation using kriging. Moreover, the effect of flow simulation outliers on potential habitat outcomes must be considered when using 2D models for habitat simulation (Waddle, 2010). Therefore, the weak tendency to under-predict lower and over-predict higher velocities should be addressed

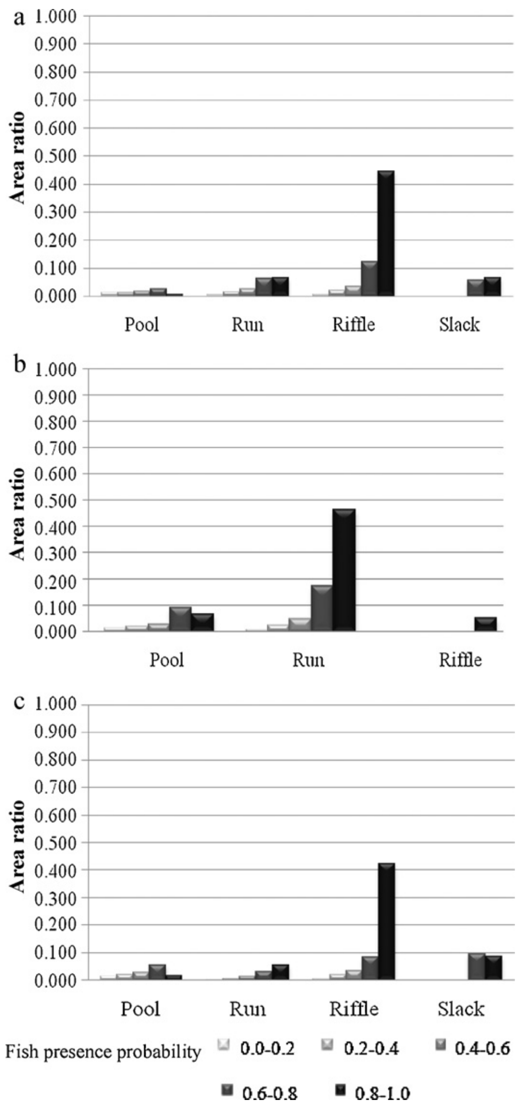

Fig. 11. The histograms of area ratio with a certain range of fish presence corresponds to each flow condition in spring by (a) the Wang's empirical method; (b) the Jowett's Froude number method; (c) the optimal classification Method. (Area ratio = the area of a flow condition under a fish presence probability/the area of total area of study site.)

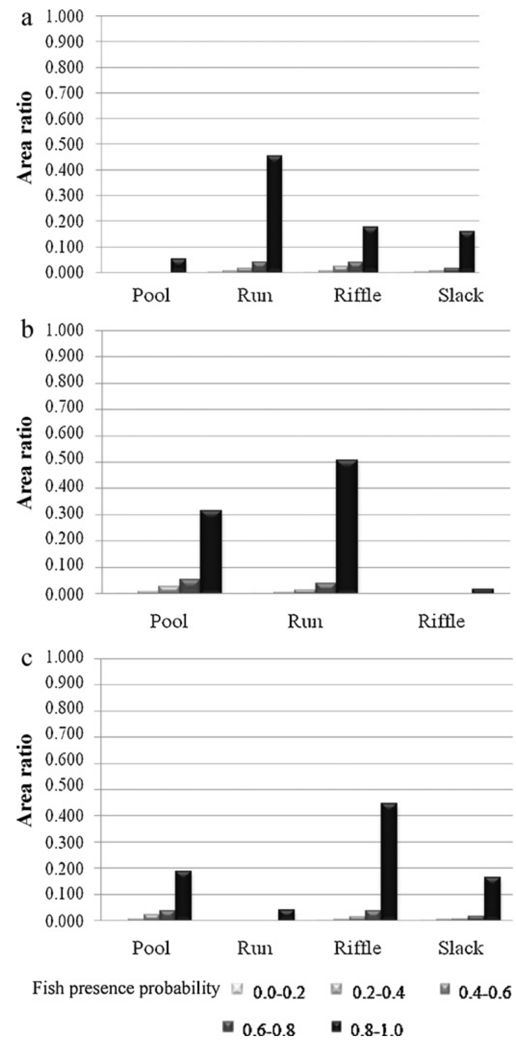

Fig. 12. The histograms of area ratio with a certain range of fish presence corresponds to each flow condition in summer by (a) the Wang's empirical method; (b) the Jowett's Froude number method; (c) the optimal classification method. (Area ratio = the area of a flow condition under a fish presence probability/the area of total area of study site.)

in other, uniform channels to determine if the River 2D model introduces systematic bais into the velocity simulations (Waddle, 2010).

4.1. Preference of fish for stream conditions on a temporal scale

Velocity of flow and depth significantly influence the quality of a habitat for aquatic biota (Schweizer et al., 2007b). Nykanen and Huusko (2004) suggested that larval grayling may universally exhibit a preference for a particular range of water velocities. This preference may be considered alone in the hydraulic modeling of habitats when estimating the suitability of such habitats for larval grayling. In this study, the flow conditions varied from mixed in the fall to simple run flow conditions in the winter, returning to mixed flow conditions with run in spring of the following year, according to measurements made herein and both optimal and the empirical classification methods. The copious precipitation that was caused by the northeasterly monsoon during the cold season in this area explains why the stream conditions were mainly run conditions. Boulders and cobbles were randomly stacked by adjacent to each other by artificial engineering, forming many combinations of water depth and current velocity (Dahl and Greenberg, 1996; Dahl, 1998). For instance, in riffles that appear in fall and spring, a higher concentration of dissolved oxygen in the water suggests the presence of more algae (Madsen and Sondergaard, 1983; Madsen et al., 1993), which are food for *S. japonicus*. The Froude number method yielded significantly different classification results from those obtained using the empirical method (Wang, 2000) and the optimal method. Jowett's classification standards yielded mixed stream conditions in the autumn, run in the winter, and mixed stream conditions again in the following spring.

As also suggested by the results of Abe et al. (2003), *S. japonicas* stays in the pool/riffle sequence more often in some seasons than in others, according to the simulation herein. Stream fish use velocity refugia to maximize energy intake and minimize the energetic cost of swimming. For instance, boulders provide energetically suitable locations for fish, and are therefore associated with greater population. The heterogeneity of dry season refugia may still contribute to the persistence of at least some species with different habitat requirements. The kriging results herein reveal that, in reaches, *S. japonicus* was populous in areas with a high water velocity in the spring and summer, but relatively un-populous in areas with a low water depth in the fall and winter. Accordingly, deep pools provide an excellent environment in which *S. japonicus* can rest and conserve energy (Abe et al., 2003) in fall and winter. Furthermore, *S. japonicus* feed on benthic diatoms and cyanobacteria that are attached to stony substrates and frequently exhibit intra- and inter-species aggression in an attempt to consume algal food exclusively (Abe et al., 2007), particularly in reaches where the Datuan stream has a substrate of cobbles and boulders.

5. Conclusion

To confirm the preference of *S. japonicus* for particular flow conditions, researchers, biologists, and river managers have attempted to classify stream conditions (pool, riffle, run, slack), and compare areas to identify those of higher abundance and heterogeneity. This study develops a novel optimal classification method that successfully identifies the criteria for classifying flow in the study area. The proposed optimal classification method considers depth–velocity relations and is proven to be the most effective flow classification approach. To the best of our knowledge, this study combines, for the first time, kriging methods and River 2D with the empirical, Froude number and optimal flow classifications in a study of the flow conditions associated with the presence of *S. japonicus* in a stream catchment area in Taiwan. The flow classification results reveal that the proposed optimal classification is more appropriate for the Datuan stream than is the Froude number method. The above optimal flow criteria are successfully used to classify hydraulic data (current velocity and depth) that are interpolated using ordinary kriging and simulated by River 2D. The variography results concerning flow conditions reveal that seasonal flows are not spatially stationary among seasons in the study area. A layer of probability of finding *S. japonicus*, identified by indicator kriging, in the estimated flow map overlaps that in the simulated flow map, revealing the flow conditions preferred by *S. japonicus* capturing seasonal changes in the study area. Therefore, the proposed optimal classification method can be easily applied, if enough samples are collected, to determine criteria for classifying flows. The results herein confirm the results of Schweizer et al. (2007a), who demonstrated that Jowett's definitions of flow condition may be site-specific. The proposed classification methods with presence probability maps are based on kriging, River 2D and indicator kriging, effectively yield the preferences of *S. japonicus* in various seasons in the study area. The results obtained using the proposed methods can be used in the stream restoration act. The proposed method is useful for classifying and mapping flow conditions, and obtaining relations between flow conditions and the presence of fish. We recommend that a future study should undertake the effect of substrate on optimal flow classifications. A large set of data should also be sampled to confirm and improve the optimal criteria for classifying flow conditions. However, the optimal velocity and water depth, determined by GA, can affect the spatial patterns of classified flows. Therefore, future work should consider in detail analyses spatial flow patterns, such as by habitat patch analysis.

Acknowledgments

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