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Research Article

Modeling habitat requirements of riverine stone loach, *Paracobitis hircanica* (Teleostei: Nemacheilidae) in the Zarin-Gol River, Caspian Sea basin, Iran

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Abstract: For sustainable exploitation and conservation of biodiversity in riverine ecosystems which have been exposed to considerable modifications by human activities, it is necessary to understand the habitat requirements of the species inhabiting these ecosystems. The Zarin-Gol River in the east of Alborz Mountains, Golestan province, is one of the environments inhabited by the native Hircanian stone loach, *Paracobitis hircanica*. This stream has been exposed to human activities such as rural discharges, agriculture, fish farm effluents and ecotourism. Habitat requirements of this species and the impacts of human activities were determined in 17 stations along the Zarin-Gol River. Binary Logistic Regression was implemented to develop the distribution model of *P. hircanica* according to habitat variables. Finally, according to the best model selected by the Akaike Information Criterion (AIC), stream surface width, depth, vegetation cover, altitude and discharge were determined as the most significant parameters for the presence of *P. hircanica*. Also, other suitable models according to AIC values showed that the stream surface width and depth are the most important independent variables affecting the presence of this loach. Therefore, it was concluded that most significant factors affecting the presence and distribution of *P. hircanica* are stream surface width, depth, substrate and flow rate.

Keywords: Presence and absence, Binary logistic regression, Akaike information criterion, Human impacts, Loaches.

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Introduction

Knowledge of habitat requirements is crucial in managing and protecting animals including fishes. Fish species need a proper habitat for their survival and growth and various habitat descriptors can influence the biodiversity and population structure of riverine fishes. Recently, several studies have focused on non-biological descriptors (e.g., Zalewski et al. 1990; Jin-rong et al. 2014) with particular emphasis on stream hydraulic characteristics effects on presence and distribution of native riverine fishes (see Moyle et al. 2010). Most of the ecological studies pointed to the relative significance of physical and biological factors on the population structure of riverine fishes. These studies reported habitat complexity (Gorman & Karr 1978), physical and chemical properties, competition and predatory as the significant regulating factors of fish population structure (Tejerina-Garro et al. 2005).

In the recent years, explosion in human

population, exploitation of freshwater sources and anthropogenic environmental changes imposed threats to riverine fishes. Therefore, knowledge of habitat requirements of fishes and impacts of environmental changes are crucial in effective management of sustainable exploitation. Human activities such as impounding water by damming, diverting water away for irrigation, unsustainable agricultural systems, and excessive residential and industrial water consumption affect natural water current and can damage or destroy the suitable biological conditions for occurrence of native aquatic species (Hancock 2002) including fishes. In order to conserve and protect the natural water current and habitat conditions and structures, it is necessary to protect at least a part of the stream from anthropogenic changes to sustain the natural intra-stream conditions (Maloney et al. 2013). Therefore, managing human activities along the stream and protecting aquatic biodiversity demands inclusive knowledge of species distribution range and habitat requirement model especially for species which are native/endemic, endangered or sensitive to human activities such as agriculture, urbanization, and deforestation (see Porter et al. 1999).

Recently, modeling distribution structure of fishes is emphasized in the ecological literature (e.g., Palialexis et al. 2011). Since the presence of a species depends on environmental factors and intra-species relationships, therefore the study of effective factors in distribution of a particular species and knowledge of its response to environmental variables help to predict distribution models, develop managing and protecting programs and detect habitat requirements (Palialexis et al. 2011). Statistical models are employed in the study of fish species distribution for representing relationship between presence and absence of species as dependent variables and environmental factors as independent variables. Regression models are mostly used in aquatic ecology for estimating optimal values, determining the ecological range of aquatic species and predicting species response (presence, absence or abundance) to environmental factors (Wang et al. 2003).

The stone loach, *Paracobitis hircanica* Mousavi-Sabet, Sayyadzadeh, Esmaeili, Eagderi, Patimar & Freyhof, 2015 inhabits the high velocity and gravel substrate from middle to up-streams (Abdoli 2000). It is considered as a nocturnal species which buries itself in the gravel or sand during the day. It is usually found in the habitat of Trouts (Holcik & Razavi 1992) and feed on their eggs (Vossughi & Mostajeer 1994). *Paracobitis hircanica* is found in tributaries of the Gorgan River: the Kalaleh, Zarrin-Gol, Madarsu streams as well as from the Qarasu, an endorheic river in the Gorgan River catchment area, in the south-eastern Caspian Sea basin. At the type locality, Zarrin-Gol River is about 2 m wide, with substrate consisting of coarse gravel and boulders, fast-flowing and semi-transparent waters and no submerged vegetations (Mousavi-Sabet et al. 2015; Esmaeili et al. 2017).

Lack of biological and ecological information about *P. hircanica* and increasing anthropogenic changes in the Zarin-Gol River emphasize the importance of studying habitat requirement of the species. Hence, the main purposes of this study were (i) estimate habitat suitability and (ii) identify factors that explain the distribution of *P. hircanica* in the Zarin-Gol River by developing a model that could predict the presence of the species with acceptable accuracy.

Materials and Methods

Study area: Gorgan River is one the main and important river in the Caspian Sea basin in the Golestan Province due to its significance in agriculture, aquaculture, aquatic biodiversity and supply of water of many lagoons and ponds (Abdoli & Rahmani 2001). The Zarin-Gol River is one of the tributaries of Gorgan River (36°50'39"N 54°58'24"E and altitude of 280 to 2800m about see level). Its length is about 22km with catchment area of 342.82m^2 and discharge of 75×10^3 to 150×10^6 m^3 (Ministry of Energy 1991; Afshin 1994).

Sampling: Sampling was conducted during the spring 2016 in 17 stations along downstream to upstream regions of the stream including 12 main stations in the main stream and 5 sub-branch stations with an approximate distance of 1-2 km from each other (Fig. 1). Habitat diversity, different land-use types and main sub-branches were considered for selecting sampling stations. Sample collection was carried out in the opposite direction that the water is flowing in 20m stretches per station and in three different regions in each station (Johnson & Arunachalam 2009). Finally, all samples were returned to the stream after evaluation.

Environmental variables: Based on the life history of *P. hircanica* and its ecological requirements (Patimar et al. 2009), the most important environmental variables for species habitat suitability were selected for species distribution modeling including seven hydrological variables, stream depth (cm), surface width (cm), slope (m/km), altitude (m), discharge (m^3/s), substrate structure (i.e. gravel average diameter (cm), and riverside vegetation cover effect (%) (riparian vegetation type was classified into unvegetated, grasslands or bog (˂10% tree cover), shrub/herb and deciduous forest).

Besides fish sampling, water temperature (˚C), dissolved oxygen (mg/l), electrical conductivity (mos/cm), turbidity (NTU) and pH were measured using portable digital water-checker model (HACH sensionTM 156-378 multiparameter meter). Nitrate and phosphate was measured following APHA methods (APHA 2005) in the laboratory in Gonbad Kavous University. Water discharge was measured by float method which determines the time taken by a floating object to travel a particular distance considering surface velocity.

Statistical Analysis: The simplest measurement of individual species populations is presence-absence, which is used when the objective is to verify the use of a habitat by a species (Ahmadi-Nedushan et al. 2006). Mathematical models can reduce complex hydro-ecosystems and managing activity results into measurable and clear criteria by employing accurate sampling data (De Kerckhove et al. 2008).

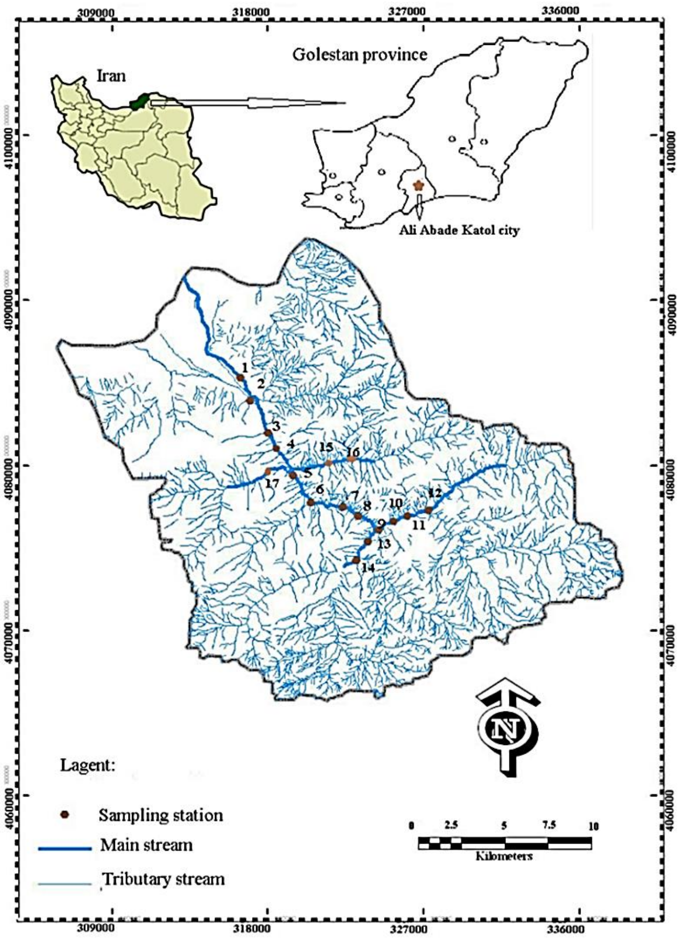

Fig.1. Location of sampling stations used in this study.

Regression models are widely used to predict species distribution and habitat preference (Aarts et al. 2012). Multiple linear regression model is considered as one of the most common methods for describing the relationship between a dependent or response variable (e. g. species richness) and independent or predictor variables (e. g. non-biological factors) in habitat priority models for fishes and relationship between habitat and species (abundance) in streams. Formally, for a given *n* observation, multiple linear regression model is as follows:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik} + \varepsilon_i, \quad i = 1,2,\cdots,n,$$

Where, Y_i is the response variable in i^{th} observation, $X_1, \ldots, X_n$ are the predictor variables, $\beta_1, \ldots, \beta_n$ is regression coefficient for each predictor variables, β_0 is regression intercept. The quantity ε is called the random error term and the most common assumption is that it follows a normal distribution with mean zero and constant variance.

However, multiple linear regression model is employed when both response and predictor variables are continuous. When modeling relation between a qualitative binary response variable (e. g. presence and absence) and qualitative or quantitative continuous predictor variables (e. g. environmental factors) logistic regression model should be used. Being widely employed in study of aquatic animals' habitat, logistic regression model has the advantage of simultaneous evaluation of categorical variables (e. g. bottom structure and riverside vegetation cover effect) and continuous variables (e. g. depth and velocity) (Palialexis et al. 2011).

Unlike the multiple linear regression in which the error term is considered normal distribution, but it is not normal in the natural ecological data and, therefore, more flexible models like logistic regression model should be employed here. Logistic regression model is the generalization of the generalized linear model. Let us assume $(\boldsymbol{x_i}, y_i), i = 1,2,\dots,n$, where $\boldsymbol{x_i} = (x_{0i}, x_{1i}, \dots, x_{ki})$, such that $x_{0i} = 1$, denotes a vector of $(k+1)$ assumed fixed the predictor variables for the i[th] subject and $y_i = 0,1$ denotes an observation of the outcome random variable Y_i. Under the multiple logistic regression model, the term $P(Y_i = 1|\boldsymbol{x_i}) = \pi(\boldsymbol{x_i})$ is the probability of presence in i[th] observation. The logit of the multiple logistic regression model is given as:

$$\mathrm{g}(\boldsymbol{x_i}) = \log\left(\frac{\pi(\boldsymbol{x_i})}{1-\pi(\boldsymbol{x_i})}\right) = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik} + \epsilon_i, \quad i = 1,2,\cdots,n,$$

or

$$\mathrm{g}(\boldsymbol{x_i}) = \boldsymbol{\beta}'\boldsymbol{x_i}$$

Where $\boldsymbol{\beta}' = (\beta_0, \beta_1, \dots, \beta_k)$ is the coefficients and $\pi(\boldsymbol{x_i})/1-\pi(\boldsymbol{x_i})$ denotes the odds ratio. The natural logarithm of odds ratio i.e. $\mathrm{g}(\boldsymbol{x_i})$ is called the logit function and may range from negative to positive infinity. Unlike multiple linear regression model which employs ordinary least squares method, logistic regression model uses maximum likelihood method for measuring regression coefficients (Ahmadi-Nedushan et al. 2006). For a sample of size *n*, the log likelihood for a binary logistic regression is given by:

$$l(\boldsymbol{\beta}) = \sum_{i=1}^{n} y_i \log(\pi_i) + (1-y_i)\log(1-\pi_i).$$

The values of $\widehat{\boldsymbol{\beta}}' = (\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_k)$ are given by the solution to above and is called the maximum likelihood estimator and the fitted values are $\hat{\pi}_i = \pi(\boldsymbol{x_i}, \hat{\beta})$. Maximum likelihood estimation finds estimates of model parameters that are most likely to give rise to the pattern of observations in the sample data. The dichotomous (binary) dependent random variable makes estimation using ordinary least squares inappropriate. The error term has neither a normal distribution nor equal variances for values of the independent variables. Therefore, the estimation procedure derived from the lease squares criterion (minimizing the sum of the squared deviations between the observed and predicted values of dependent variable) no longer gives efficient estimates for the logistic regression model.

Model evaluation tests: In practice, several statistical testes exist for determining goodness of fit test for logistic regression models including: the deviance, Pearson statistic, and Hosmer-Lemeshow statistic. In a theoretical sense, all three measures are equivalent (Hosmer & Lemeshow 1980).

Deviance and Pearson statistic: The likelihood ratio D (deviance) and Pearson chi-square (χ^2) statistics that compare observed values to those predicted by the fitted logistic regression model are, respectively (Fagerland et al. 2017),

$$D = -2\left\{\sum_{i=1}^{n} y_i \log\left(\frac{y_i}{\hat{\pi}_i}\right) + (1-y_i)\log\left(\frac{1-y_i}{1-\hat{\pi}_i}\right)\right\}, \quad \chi^2 = \sum_{i=1}^{n} \frac{(y_i-\hat{\pi}_i)^2}{\hat{\pi}_i(1-\hat{\pi}_i)},$$

Where their distributions are approximated by a chi-square distribution. Evidence for model lack-of-fit occurs when the values of these statistics are large.

G test: It measures the difference between the null model in which all the coefficients are 0 and alternative models with regression coefficients and intercept. The null hypothesis in G test is $H_0: \beta_1 = \cdots = \beta_k = 0$, in which all regression coefficients are zero (Alizadeh 2006). The G statistic is computed as:

$$G = 2\left\{\sum_{i=1}^{n}(y_i \, log(\hat{\pi}_i) + (1 - y_i)\, log(1 - \hat{\pi}_i)) - (n_1 \log(n_1) + n_0 \log(n_0) - n \log(n))\right\},$$

Where $n_1 = \sum_{i=1}^{n} y_i$ and $n_1 = \sum_{i=1}^{n}(1 - y_i)$. Its distribution is approximated by a chi-square distribution with k-1 degree of freedom. Larger difference in G-test shows more fitness.

Model selection: Increasingly, ecologists are applying novel model selection methods to the analysis of their data. Of these novel methods, information theory (IT) and in particular the use of Akaike's information criterion (AIC) is becoming widespread (Akaike 1973; Garamszegi 2010). Akaike information criterion (AIC) was used to select the best model (i.e. the model with highest congruence with obtained data). Akaike information criterion equation which provides a quantitative criterion for model selection is as below:

$$AIC = -2l + 2k,$$

Where l is the logarithm of likelihood function and k is the number of parameters in the model. Lower AIC values indicate more congruence between model and data. Furthermore, difference between AIC of each model and AIC of the best model (i.e. the minimum AIC value of all models) was measured by the following equation:

$$\Delta_j = AIC_j - \min_{1 \le j \le m} AIC_j\,, \qquad j = 1,2,\cdots,m,$$

Where, AIC_j is AIC of j^{th} model, min AICj is AIC of the best model and m is the number of models. Lower AIC difference shows more fitness. Generally, AIC difference values Δ AIC<2 indicates significant fitness, 2< Δ AIC<7 indicates significantly low fitness and Δ AIC>7 shows that there is no congruence (Burnham et al. 2011).

In this study, models with Δ AIC<2 were selected (Alizadeh 2006). Finally, Akaike weights were measured for each model using the following equation (Anderson et al. 2000):

$$w_j = \frac{e^{-\frac{\Delta_j}{2}}}{\sum_{r=1}^{m} e^{-\frac{\Delta_r}{2}}}, \qquad j = 1,2,\cdots,m.$$

Akaike weight of a model shows the probability of fitness. In fact, the w_j can be interpreted as the probability that j is the best model, given the data and set of candidate models. In other words, the weight, w_j is considered as the weight of evidence in favor of a model being the actual best model for the given data, given that one of the models must be the best model. Also, relative significance of each variable can be measured using sum of Akaike weights of models with that variable (Hermoso et al. 2015). Statistical analysis was carried out using Minitab V.14 and R 3.3.1 software packages.

Results

Sampling showed fish presence in 10 stations and absence in 7 stations. A correlation matrix was used to select one variable out of pairs of variable with correlation higher than 0.7. For example, electrical conductivity was selected out of water pH and electrical conductivity pair with correlation of 0.91 and riverside vegetation cover effect was selected out of electrical conductivity and riverside vegetation cover effect pair with correlation of 0.77. Selected variables were introduced into a binary logistic regression and variables with lower *P*-value and higher G test were selected as appropriate and significant variables in presence or absence of the species. Obtained results showed that stream depth and surface width were significant in all logistic models (*P*<0.05).

The best selected models were identified using

Table 1. The results of Akaike's information criterion to choose the best model.

ωi	P	ΔAIC	AIC	df	model
0.25	0.002	0	15.08	2	1
0.23	0.003	0.18	15.26	3	2
0.18	0	0.7	15.78	4	3
0.12	0	1.44	16.52	4	4
0.11	0.001	1.58	16.66	3	5
0.11	0	1.72	16.8	4	6

Table 2. Predictive parameters of each model and their regression coefficients.

Predictor variables
Model 1: $\hat{g}_1(\boldsymbol{x}) = -10.61 + 0.77 \times width + 16.23 \times depth$
Model 2: $\hat{g}_2(\boldsymbol{x}) = -17.18 + 1.44 \times width + 9.39 \times depth + 11.9 \times vegetation\ cover$
Model 3: $\hat{g}_3(\boldsymbol{x}) = -57.62 + 3.48 \times width + 1.77 \times depth + 20.15 \times discharge + 32.07 \times vegetation\ cover$
Model 4: $\hat{g}_4(\boldsymbol{x}) = -60.45 + 2.34 \times width + 34.99 \times depth + 10.76 \times discharge + 7.9 \times altitude$
Model 5: $\hat{g}_5(\boldsymbol{x}) = -12.23 + 0.79 \times width + 15.13 \times depth + 1.72 \times discharge$
Model 6: $\hat{g}_6(\boldsymbol{x}) = -178 + 10.39 \times width + 96.36 \times depth + 18.73 \times vegetation\ cover + 29.8 \times altitude$

Table 3. Results of G test and percentage of concordant (predicted model with sampling data).

Concordant %	P-value	df	G test	Log-Likelihood	Model
94.3	0.003	2	11.96	-5.54	1
95.7	0.003	3	13.77	-4.63	2
95.7	0.004	4	15.26	-3.89	3
95.7	0.000	4	14.05	-4.26	4
92.9	0.007	3	12.08	-5.33	5
99.99	0.000	4	23.03	-4.4	6

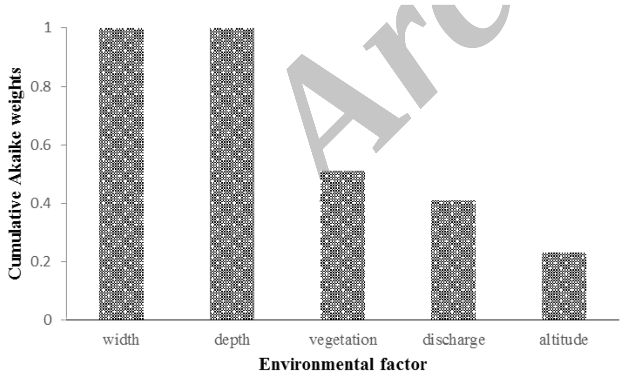

Fig.2. Compare cumulative Akaike weight for each variable in the most appropriate models.

AIC criterion among all the obtained generalized linear models. In this case, models with Δ AIC<2 were considered as the best models (Burnham & Anderson 2004). Among the six selected models shown in Table 1, the first model was considered as the best model due to its lower ΔAIC and higher Akaike weight (Garcia et al. 2010). Variable types in each model and regression coefficient results of variables in the selected models are presented in Table 2. The accumulative weight which indicates relative significance of each variable is also shown in Figure 2.

Logistic regression models were evaluated using G test. In G test, $P<0.05$ indicates that the introduction of environmental factors increases the accuracy of prediction of presence and absence of the species under study.

Pearson, Deviance and Hosmer-Lemeshow tests

Table 4. Results of Pearson, Deviance and Hosmer-Lemeshow.

P-value	DF	Chi-Square	Method	Model
0.507	14	13.24	Pearson	
0.68	14	11.07	Deviance	1
0.796	8	4.63	Hosmer-Lemeshow	
0.78	13	8.82	Pearson	
0.75	13	9.27	Deviance	2
0.67	8	5.75	Hosmer-Lemeshow	
0.89	12	6.52	Pearson	
0.8	12	7.78	Deviance	3
0.89	8	3.7	Hosmer-Lemeshow	
1	12	47.3	Pearson	
1	12	9.6	Deviance	4
1	8	16.4	Hosmer-Lemeshow	
0.49	13	12.37	Pearson	
0.61	13	10.96	Deviance	5
0.96	8	2.45	Hosmer-Lemeshow	
1	12	64.45	Pearson	
1	8	13.58	Deviance	6
0.78	13	8.82	Hosmer-Lemeshow	

were also employed to measure the association of models prediction and obtained data. According to Table 4, the results showed that the model could fit the data very well. When p value is significant (*P*<0.05) actual sampling data and model prediction are out of congruence and therefore, the model is not fit to the data.

Discussion

Identification of suitable habitat, distribution, abundance and also biological and ecological evaluation of aquatic animals are important issues in study of ecological and behavioral functions of a species but have not received deserving attention so far (Elith & Leathwick 2009). It has been suggested that compared to richness models, due to application of obtained data from inappropriate regions and determination of presence in terms of potentiality, presence and absence models are more reliable and functional indicators of streams condition and can predict the natural distribution of species with more certainty (Palialexis et al. 2011) and can be used well for aquatic organisms including fishes. According to the published literature there is limited information about the habitat preference of most aquatic species in streams of Iran (Abdoli & Naderi 2009). This study was carried out to evaluate habitat requirements of riverine stone loach focusing on six non-correlated variables. The Hircanian stone loach, *P. hircanica* was mostly observed in middle to downstream regions of the Zarin-Gol River. This distribution pattern may be attributed to hydrological, physical and chemical properties of the stream as suggested for other stone loaches (Porter et al. 1999; Patimar et al. 2009; Olson 2012). It was observed that the stone loach density increased as size and diversity of habitat descriptors such as surface width, depth, velocity and substrate structure increase from up to downstream

Stream depth, width and velocity are complementary measures of stream volume, which was one of the most efficient descriptors of species richness (MacArthur & Wilson 1967). Therefore, streams with larger volumes (width and depth) have more resources available and consequently support higher species diversity (Gorman & Karr 1978). Similarly, Infante et al. (2006) showed that streams in Michigan's Lower Peninsula with decreased depth at low flow and increased incision had reduced fish species richness and biomass.

Habitat physical properties such as surface width, depth, flow discharge and substrate significantly affected richness and combination of the species under study (see Dias & Tejerina-Garro 2010). River surface width indicates river size and habitat diversity at local scales (Li et al. 2016). The obtained results showed that river surface width had significant negative effect on the presence of *P. hircanica.* This is in congruence with another study on Kordan River (with average width of 4.24m) reporting the significant negative effect of river surface width on the presence of *P. hircanica* at surface width greater than 15m (Tabatabaei et al. 2015). Also, study of *Oncorhynchus kisutch* in British Columbia (Rosenfeld et al. 2000) showed the highest density of the species in rivers with surface width lower than 5m. This emphasizes the importance of conservation of small rivers for long-term conservation and management programs.

Another factor that affect aquatic organisms diversity, abundance and assemblage is water current. It has a direct effect on survival of aquatic animals inhabiting flowing streams and also can indirectly affect the distribution of food (Ahmadi-Nedushan et al. 2006; Hoghoghi et al. 2015). Powerful water discharge may have negative effect on the population of fishes living in flowing streams. Obtained results showed that water current, turbidity and human activity (agriculture, Fish culture and rural wastewater) at different stations in the Zarin-Gol River had significant effect on the presence and distribution of *P. hircanica* by changes in physical habitat and chemical factors.

This research provides an overview of existing methods and compare the relative advantages and drawbacks of statistical methods used in aquatic habitat modelling using a native stone loach. We show that statistical models are significant tools in the prediction of species distributions and abundance based on relevant environmental parameters. A variety of statistical methods are already in use to model the aquatic species-environment relationship. It was found that most of the statistical models reported in the literatures are based on logistic regression which have been used for analysis of aquatic species density (mostly fish) as well as presence-absence. Our model indicated habitat variables could predict the appropriate distribution of habitats. Habitat variables are good predictors of distribution, and our estimates were good approximations for the actual distribution of *P. hircanica*. The presence of an individual does not prove the habitat is suitable for breeding based on our analysis of presence-absence data. The model we developed indicated high probability of species occurrence and validation indicated the model was effectively functional within the study area.

Based on the obtained results, different land use could effect on distribution of *P. hircanica.* Agricultural and rural areas revealed poor habitat quality, low river bank stability and high levels of sediments on stream substrate (Roa-Fuentes & Casatti 2017). Wang et al. (2003) compared a variety of measures of urbanization, such as commercial land, urban land and highway and street, to identify which one(s) had the strongest relation with fish habitat quality, fish assemblage structure and biotic integrity in 47 small south-eastern Wisconsin, USA. Hence, in future research, it is very necessary to refine and optimize the catchment-scale environmental data for assessing the influence of land use/cover on fish assemblages in the headwater of the Zarin-Gol River basin.

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مقاله پژوهشی

مدل‌سازی نیازهای زیستگاهی لوچ ماهی جویباری هیرکانی (*Paracobitis hircanica*) در رودخانه زرین گل، ایران

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چکیده: چکیده: برای بهره‌برداری پایدار و حفظ تنوع زیستی اکوسیستم‌های رودخانه‌ای که در اثر فعالیت‌های انسانی دستخوش تغییرات شده‌اند شناخت نیازهای زیستگاهی گونه‌ها ضروری است. رودخانهٔ زرین‌گل از ارتفاعات شمالی البرز شرقی، استان گلستان سرچشمه می‌گیرد و یکی از زیستگاه‌های ماهی بومی *Paracobitis hircanica* است. این رودخانه تحت تأثیر فعالیت‌های انسانی از قبیل کشاورزی، خروجی پساب پرورش ماهی و طبیعت گردی قرار گرفته است. نیازهای زیستگاهی این ماهی و تأثیرات فعالیت‌های انسانی، در ۱۷ ایستگاه در طول رودخانه بررسی شد. رگرسیون لجستیک برای توسعه توزیع مدل از *P. hircanica* با متغیرهای زیستگاه انجام گرفت. بر پایهٔ بهترین مدل انتخاب شده، با توجه به معیار اطلاعاتی آکایکه (AIC)، متغیرهای عرض رودخانه، عمق، پوشش گیاهی، ارتفاع و دبی عوامل تعیین کننده‌ای در حضور این گونه بودند. همچنین، سایر مدل‌هایی که بر پایهٔ معیار اطلاعاتی آکایکه، به منزلهٔ مدل‌های مناسب، تعیین شدند نشان دادند که دو متغیر عرض و عمق رودخانه مهم ترین متغیرهای مستقل مؤثر در حضور این گونه اند. بنابراین، با توجه به نتایج تحقیق حاضر، فعالیت‌های انسانی که در این رودخانهٔ در حال انجام است و سبب تغییر در ویژگی های محیطی مانند عرض، عمق، بستر و سرعت جریان رودخانه می شود، احتمالاً می‌تواند حضور و پراکنش سگ ماهی جویباری را در این رودخانه تحت تأثیر قرار دهد.

کلمات‌کلیدی: حضور و عدم حضور، رگرسیون لجستیک، معیار اطلاعاتی آکایکه، فعالیت‌های انسانی، لوچ ماهی.