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Distribution Characteristics of *Trichiurus japonicus* and Its Relationship with Environmental Factors in Central and Southern East China Sea and Yellow Sea

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Abstract: *Trichiurus japonicus* is the most productive fish caught in our country. In order to understand the seasonal distribution of *Trichiurus japonicus* in the central and southern parts of the East China Sea and Yellow Sea, three species distribution models were adopted, namely Random Forest Model, K-nearest neighbor algorithm and gradient ascending decision Tree model, based on the data of trawling surveys in the central and southern parts of the East China Sea and Yellow Sea from 2008 to 2009. Combined with variance inflation factor and cross-check, the distribution model of *Trichiurus japonicus* was screened and constructed to analyze the influence of environmental factors on the distribution of *Trichiurus japonicus* in the central and southern parts of the East China Sea and the Yellow Sea. The results showed that the random forest model had the advantages of fitting effect and prediction ability among the three models. The analysis of this model showed that the water depth, bottom water temperature and surface salinity had a great influence on the habitat distribution of *Trichiurus japonicus*. The relative resources of *Trichiurus japonicus* increased with the increase of bottom water temperature and reached the maximum at 23.8℃, and first increased and then decreased with the increase of water depth and surface salinity, reaching the maximum at 72 m and 31.2‰, respectively. The random forest model was used to predict the spatial distribution of *Trichiurus japonicus* in the East China Sea and the central and southern Yellow Sea during 2008-2009,

and the results showed that the predicted results were close to the actual situation. The research results can provide reference for the exploitation and protection of *Trichiurus japonicus* resources in the East China Sea and the central and southern Yellow Sea.

Keywords: East China Sea; south central Yellow Sea; *Trichiurus japonicus*; Species distribution model; Spatial distribution; Environmental factor

Key Contribution: In this study, we used a random forest model to analyze the effects of environmental factors on the distribution of *Trichiurus japonicus* in the East China Sea and the south-central Yellow Sea and made distribution predictions. The results of this study can help to comprehensively understand the distribution of *Trichiurus japonicus* fisheries in the East China Sea and the south-central Yellow Sea, and provide valuable theoretical support for their rational development and utilization

1. Introduction

Trichiurus japonicus belongs to the order Perciformes, family Trichiuridae, and genus Trichiurus. It is a warm-temperate species that typically forms schools near the seafloor. The single-species catch exceeded 1 million tons in 1995[1], making it one of the few marine species in China with over one million tons in landing. Currently, the main fishing methods in the East Yellow Sea include bottom

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trawling and seine netting. *Trichiurus japonicus* resources in the East China Sea have been exploited since the 1950s, with catches often ranking first among various species since the late 1950s. Consequently, *Trichiurus japonicus* is a key species in domestic fisheries research and management. Many resource management systems in the East China Sea, including fishing bans and protected areas, are based on research findings related to *Trichiurus japonicus* resources, primarily focusing on conserving traditional economic fish species, with *Trichiurus japonicus* being the primary target [2].

One of the hot topics in fishery ecology is the spatial distribution characteristics of species and their relationships with environmental factors[3]. The spatial distribution of fish populations is influenced by a variety of control factors, both external and internal, of which the external control, also known as environmental control, includes hydrological conditions, substrate types, etc., and is generally considered to be the main factor affecting the spatial distribution of fish populations[4]. On the other hand, population size, age structure, fish condition, diversity, and behavior, etc., internal control factors can also regulate the spatial distribution of fish populations through density-dependent, age-dependent habitat preference, migration ability differences, etc.[5]. The adaptability and limitation of fish to marine environment are one of the key factors determining their migration, distribution, and movement, and the study of the influence of environmental factors on the spatial distribution of fish populations is of great reference value for fishery analysis, fishing ground exploration, and rational use of fishery resources[6]. Species distribution model (SDM) is a mathematical model that uses environmental data to predict the spatial distribution of species according to their survival conditions, and has become one of the important methods in the application of conservation biology and ecology[7]. Widely used species distribution models in fisheries include generalized additive models and generalized linear models[8,9], with relatively fewer applications of machine learning methods. As automation and intelligence advance, machine learning algorithms increasingly predict fish abundance and distribution[10], identify populations[11], standardize catch per unit effort (CPUE)[12], and explore relationships between fishery resources and environmental factors[13,14], showing distinct advantages. For instance, Chen[15]developed a forecasting model for Indian Ocean yellowfin tuna fisheries using a random forest model, enhancing the forecasting capabilities of distant offshore fisheries. Hou[16] researched the modeling and forecasting of South Pacific yellowfin tuna fisheries using six ensemble learning models, improving the accuracy of their predictions. Gao[17] constructed a forecasting model for mackerel in the East and Yellow Seas employing gradient boosting decision trees, playing a crucial role in managing and protecting mackerel resources. Song built a forecasting model for bigeye tuna in the Atlantic tropical waters using K-nearest neighbors and gradient boosting decision trees, enhancing the accuracy of their model predictions. Currently, research utilizing species distribution models to examine the habitat distribution of ribbonfish remains scarce.

Based on the trawl survey data in the central and southern waters of the East China Sea and the Yellow Sea from 2008 to 2009, this study used random forest model, K-proximity algorithm and gradient lifting decision tree to analyze the distribution characteristics of *Trichiurus japonicus* and their relationship with environmental factors, and then compared and analyzed the fitting effect and prediction ability of the models. The habitat index was used to predict the distribution of *Trichiurus japonicus* in the East China Sea and the south of the Yellow Sea, so as to provide a basis for the rational utilization and scientific conservation of its resources, and provide a reference for fishery policy management.

2. Materials and Methods

2.1. Data Sources

The samples of belt fish in this study were collected from the fixed bottom trawl survey of the national science and technology support program "Investigation and Assessment of important fishery Resources in the Main fishing grounds of the East China Sea" conducted in May (spring), August (summer) and December (autumn) of 2008 and February (winter) of 2009 in the central and southern waters of the East China Sea and the Yellow Sea. The sea area covered 121°~126.5°E and 26°~35°N(Figure 1), with 119 stations. The survey ship uses a 6 m×80 target net, the width of the network port is 48 m, the mesh size of the bag net is 30 mm, the towing speed of the survey ship is 2.0 kn, and the towing time of each station is 1 h. The relative catch Y(g/h) was obtained by using trawling time of 1 h and trawling speed of 2 kn.

Sample processing and environmental factor measurements adhered to the "Ocean Survey Standards" [19]. Environmental data were collected using a shipborne synchronized CTD instrument, which measured Sea Water Depth (SWD), Sea Surface Temperature(SST), Sea Bottom Temperature(SBT), Sea Surface Salinity(SSS), and Sea Bottom Salinity(SBS).

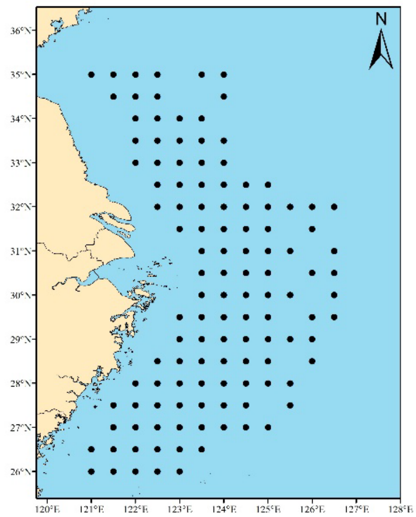

Figure 1. Survey stations.

1.2. Model Construction

Random Forest (RF), proposed by Breiman[20], is an ensemble learning method based on the classification and regression tree algorithm. This approach improves the predictive performance of models by combining multiple decision trees. Specifically, Random Forest achieves this through several steps: first, it randomly extracts multiple samples from the original dataset, known as bootstrap samples; next, it models decision trees for each bootstrap sample; finally, it aggregates the predictions from each decision tree, arriving at the final prediction through voting or averaging. This method exhibits high tolerance to noise and outliers, achieves high classification accuracy and predictive precision, shows a lower probability of overfitting, and possesses strong generalization capabilities[21,22].

The K-Nearest Neighbor (KNN) algorithm serves as a widely adopted classification method. The steps for classification are straightforward: First, compute the distance between an object, whose category is unknown, and every sample in the training set. Next, select the K most similar (nearest) samples within the feature space. Then, determine which category most of these K samples belong to. Finally, if the majority of samples fall into a specific category, classify the object into that category as well[23]. The fundamental concept behind the KNN algorithm is clear: if most of the K nearest samples reside in a particular category, the sample should be assigned to that category too[24]. KNN can facilitate both regression and classification by evaluating distances between various feature values. For any N-dimensional input vector, which correlates to a point in the feature space, the outcome is the category label or predicted value associated with that feature vector. While the concept remains simple and intuitive, the algorithm boasts significant maturity and stability[25–27].

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Gradient Boosting Decision Tree (GBDT) is an enhanced ensemble learning model based on Classification and Regression Trees (CART) algorithm [28]. It is one of the important algorithms in the field of machine learning. This model combines multiple weak classifiers into strong classifiers by iterating continuously. In each iteration, based on the previous iteration, the loss function is calculated to obtain the pseudo-residual, and the iteration is obtained, and then a new decision tree is constructed. Then, all the generated decision trees are weighted and fused according to the weight of the decision tree through gradient descent [29]. The model can deal with nonlinear relations effectively, has good generalization performance and accuracy in many prediction studies, and can identify and correct errors in the modeling process. However, GBDT is sensitive to outliers, and in multiple iterations, GBDT models will try to fit outliers, which may lead to overfitting. Therefore, when applying this model, hyperparameter tuning should be performed on the imported data to obtain the optimal solution of parameters and reduce the risk of overfitting [30].

1.3. Factor Screening and Model Fitting

ln(Y+1) was obtained by natural logarithm conversion of the relative resource amount (Y) of ribbon fish as the response variable, and SWD, SST, SBT, SSS and SBS were selected as the explanatory variables. A significant correlation between two or more explanatory variables in a multicollinearity representation model can negatively affect the final result. In order to avoid such influence, variance inflation factor (VIF)[31] is used in this study to test the multicollinearity of the above five factors and screen out the factors that can be added to the model. In general, $\sqrt{VIF}$ <2 indicates that there is no multicollinearity, and explanatory variables that exceed the threshold need to be removed.

1.4. Evaluation of Model Prediction Ability

1.5. Mapping Habitat Distribution Prediction

2. Results and Analysis

2.1. Impact Factor Screening

2.2. Model Performance Evaluation

As can be seen from Table 1, after model fitting, MSE of random forest model is 0.348, which is smaller than KNN and GBDT models, and R^2 is 0.919, higher than KNN and GBDT and closer to 1. Therefore, this model has the best fitting effect. The mean values of MSE and R^2 of 100 model predictions and observations were obtained by cross-validation. The results show that the MSE of random forest is 2.566±1.734, smaller than KNN and GBDT, and its R^2 is 0.373±0.563, higher than KNN and GBDT. The difference between the prediction results of random forest model and the observed values is smaller, so the prediction ability is the best. Therefore, the random forest model is superior to KNN and GBDT in all aspects, so the random forest model is adopted for follow-up research.

Table 1. Cross-validation comparison between three models.

Inspection method	**Statistical parameters**	**RF**	**KNN**	GBDT
Model fitting	**MSE**	**0.348**	**2.120**	2.445
	R^2	0.919	0.506	0.431

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Cross validation	MSE	2.566±1.734	3.295±2.161	3.004±1.264
	R^2	0.373±0.563	0.203±0.385	0.275±0.255

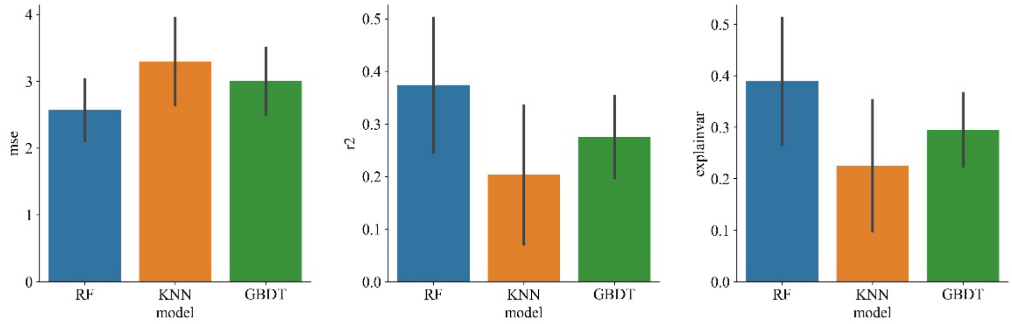

Figure 2. Performance comparison of three machine learning methods.

2.3. Importance Ranking of Impact Factors

In RF, the contribution rate of a feature is usually calculated based on the number of node splits of the feature in the decision tree and the information gain obtained by splitting. The random forest model was constructed, and the input variables were SWD, SST, SBT, SSS, SBS, and the output variables were resource density. The results show that in the random forest model, the contribution rates of each impact factor to resource density in different months are shown in Figure 3.

The results show that SWD is the most important in May (spring), followed by SSS, SBT, SBS and SST ; . SWD is the most important in August (summer), followed by SBT, SST, SSS and SBS ; . SWD is the most important in November (autumn), followed by SSS, SBT, SST and SBS ; . February (winter) SST is the most important, followed by SBT, SSS, SWD and SBS. It can be seen that among the five factors, SWD, SBT and SSS are relatively important.

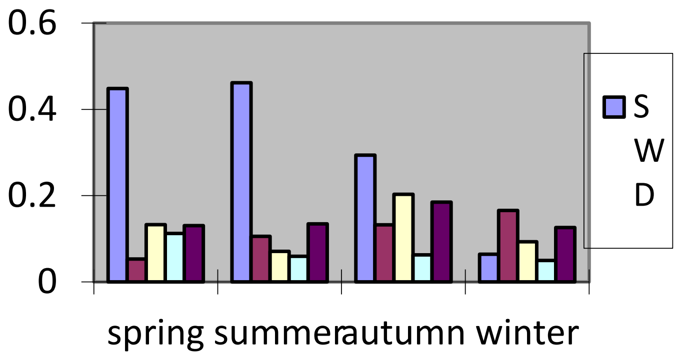

Figure 3. Importance ranking of factors affecting the density distribution of *Trichiurus japonicus.*

2.4. Relationship between Trichiurus japonicus Distribution and Explanatory Variables

The influences of various factors on the relative resources of *Trichiurus japonicus* are shown in Figure 4. The relative resources of belt fish increased slowly when SST was less than 24.8°C, fluctuated after 24.8°C, and became stable after 27°C. The relative resources of *Trichiurus japonicus* increased slowly when the SBT was less than 22.2°C, and the increase rate increased after 22.2°C and reached the maximum at 23.8°C, showing an overall increasing trend. The relative resources of *Trichiurus japonicus* increased when the SSS was less than 31.2‰, reached the maximum at 31.2‰, and decreased when the SSS was more than 31.2‰. The relative resource amount of *Trichiurus japonicus* showed a higher level when SBS was less than 33.3‰, and a lower level when SBS was more than 33.3‰, showing a decreasing trend in general. The relative resources of belt fish increased when SWD was less than 72 m, reached the maximum at 72 m, and decreased after 72 m.

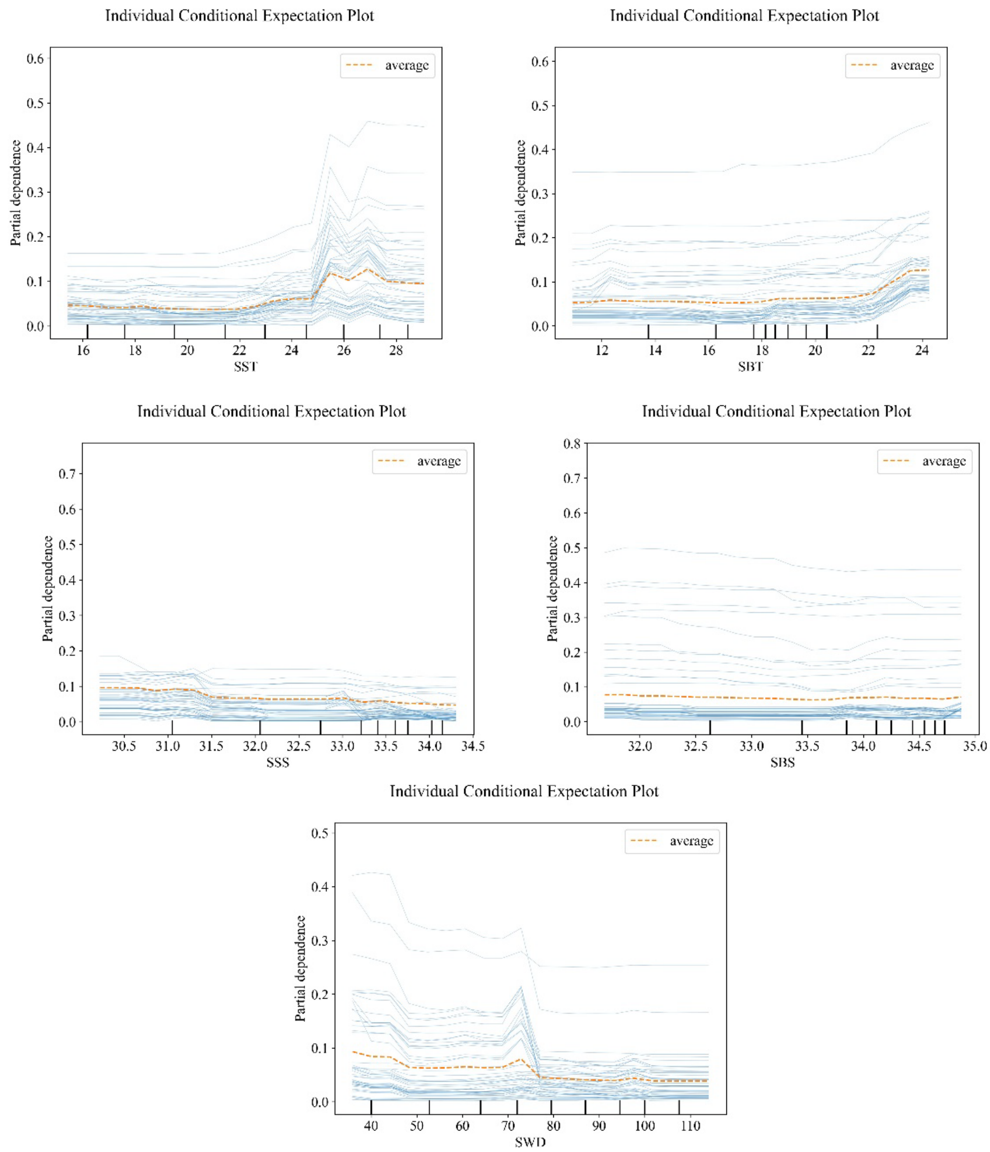

Figure 4. Impact of environmental factors on the relative resource of *Trichiurus japonicus.*

2.5. Prediction of Habitat Distribution of Trichiurus japonicus in Central and Southern East China Sea and Yellow Sea

The prediction performance of the three models is compared, and it is found that the RF has the best prediction performance. The environmental data simulated by HSI is added to the random forest model for prediction, and the spatial distribution map is drawn. It is found that the abundance distribution of *Trichiurus japonicus* in May is high in the southwest and low in the northeast, mainly distributed in the sea areas of 25.5° ~31.5° N and 119.5° ~124° E; In August, the abundance of *Trichiurus japonicus* is mainly concentrated in the northwest waters, mainly distributed in the waters of 30.5° ~33° N and 121° ~125° E; In November, *Trichiurus japonicus* resources were mainly concentrated in the middle of the sea area, mainly distributed in the sea areas of 29 ~ 33 N and 122° ~126° E; In February, the distribution of *Trichiurus japonicus* abundance showed the characteristics of high in the southwest sea area and low in the northeast sea area, mainly distributed in the sea areas of 27 ~ 30 N and 121° ~124.5° E (Figure 5), which is consistent with the characteristics that *Trichiurus japonicus* likes to cluster in the warm environment near the bottom. In Figure 5, the predicted results are compared with the actual results, and it is found that the predicted results are close to the actual results, which shows that the predicted results have certain accuracy.

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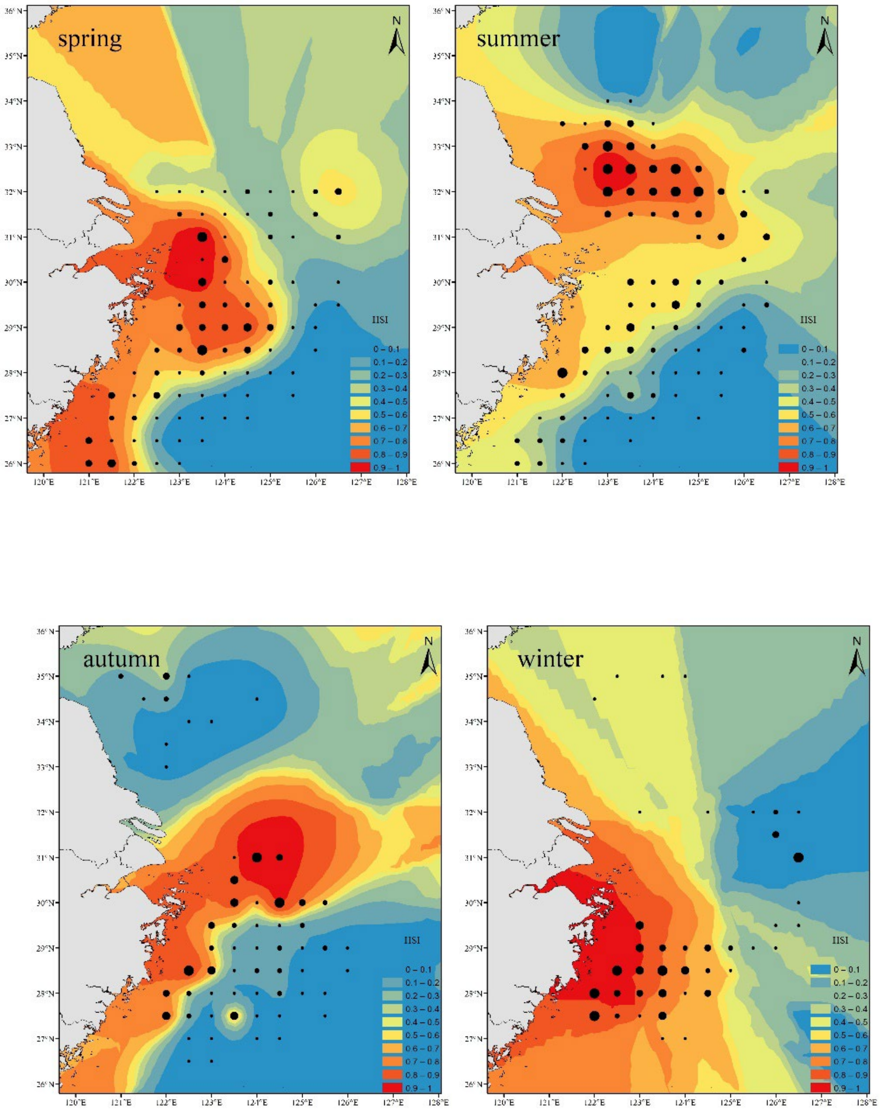

Figure 5. Simulated habitat and actual survey site of *Trichiurus japonicus* in different seasons.

3. Discussion

3.1. Model Analysis

3.2. The Influence of Environmental Factors on the Distribution of Trichiurus japonicus

3.3. Habitat Distribution Characteristics of Trichiurus japonicus

4. Conclusions

By comparing three kinds of machine learning models, this study analyzed the habitat distribution characteristics of *Trichiurus japonicus* in the East China Sea and the central and southern Yellow Sea and its relationship with environmental factors. The following findings were found: (1) Random forest had better fitting effect and prediction ability in the three kinds of machine learning models; (2) Among the five environmental factors, SWD, SBT and SSS had a great impact on the habitat distribution of belt fish. The relative resources of belt fish increased with the increase of SBT, and increased first and then decreased with the increase of SWD and SSS. (3) Habitat index was used

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to predict the habitat of *Trichiurus japonicus* in the central and southern parts of the East China Sea and the Yellow Sea, and the predicted results were similar to the actual survey results. The study of the habitat distribution characteristics of *Trichiurus japonicus* in the East China Sea and the south Yellow Sea and its relationship with environmental factors can provide some reference for the sustainable utilization and scientific management of *Trichiurus japonicus* resources. In future studies, comparative statistical methods and machine learning methods can be tried to help explore models and methods that are more suitable for this species; In addition, this study only considered 5 environmental factors, namely SWD, SST, SBT, SSS and SBS, and did not involve other factors, such as dissolved oxygen, chlorophyll, pH, flow rate and mixed layer depth, which may affect the distribution of belt fish. More environmental factors and their effects on the habitat distribution of belt fish should be comprehensively analyzed. In order to understand the relationship between the habitat distribution characteristics and environmental factors of *Trichiurus japonicus* in the East China Sea and the Yellow Sea, and to provide reference for the protection and rational utilization of *Trichiurus japonicus* resources in the East China Sea and the Yellow Sea.

Author Contributions: Conceptualization, X.S. and W.Z.; methodology, W.Z.; writing—original draft preparation, X.S.; writing—review and editing, J.L. ,X.G and Z.K.; supervision, W.Z. and Z.W.; project administration, W.Z. and Z.L. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare that they have no competing interests.

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