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Integrated Habitat Assessment of a Protected Fish Species in the Upper Yangtze River, China: Connectivity and Suitability

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ABSTRACT: In the context of anthropogenic climate change, dam construction, and other human activities, the biodiversity of freshwater fish is rapidly declining. The Upper Yangtze River Basin (UYRB) is a hotspot for hydropower development and is home to numerous endemic and rare freshwater fish species, most of which are on the brink of extinction. *Schizothorax chongi* is an endangered and protected fish species endemic to the UYRB, with significant economic and ecological value. However, the potential habitat of its wild population has not been reported, which hampers conservation efforts for this valuable species. This study utilized the Dendritic Connection Index (DCI) and Species Distribution Models (SDMs) to assess habitat connectivity in the UYRB and habitat suitability for *S. chongi* during the periods 1970–2000 and 2001–2020, respectively. The results show that *S. chongi* habitats underwent significant reduction during the 2001–2020 period, with the total length of medium and high suitability habitats decreasing by 51.7%. However, high suitability habitats in the southern section of the middle and lower Jinsha River, which is located in the upper and middle part of the UYRB, did not experience a noticeable reduction. Despite the relatively high habitat suitability maintained in the southern section of the middle and lower Jinsha River, connectivity has significantly declined. Restoring connectivity reduced by dam construction in this region is critically urgent. This study is the first to conduct a watershed-scale assessment of fish habitat integrating habitat suitability and connectivity providing valuable insights for local governments to develop specific conservation measures and plans. It can offer a valuable reference for researchers in the field of freshwater fish conservation.

Keywords: River connectivity; Ensemble modeling; Climate change; Dam construction; *Schizothorax chongi*

1. Introduction

Freshwater fish are a vital component of freshwater ecosystems [1], hold significant economic value [2], and provide unique cultural value for residents [3]. Unfortunately, due to climate change, dam construction, and other human activities, the habitat distribution, biological characteristics, and community composition of freshwater fish have been forced to change [4–7], with many species now on the brink of extinction. It is essential to conduct research on these species and implement conservation efforts to prevent their extinction. To address these challenges, integrating species distribution models with river network connectivity is a novel approach for habitat assessment of endangered species, which not only helps identify critical habitats but also provides insights into the impacts of human activities on freshwater ecosystems.

Schizothorax chongi (Fang, 1936; *S. chongi*), belonging to the family Cyprinidae and the subfamily Schizothoracinae [8], is an endemic fish species of the Upper Yangtze River Basin (UYRB). Due to overfishing, environmental degradation, and dam construction, the population of *S. chongi* has been continuously declining [9,10]. Its wild population was officially listed as a National Class II protected species in China in 2021. *S. chongi* is also an important economic fish species in its distribution area, known for its tender flesh, delicious flavor, and high market price [9]. Therefore, conducting research and implementing conservation measures for *S. chongi* is of paramount significance. Currently, research on *S. chongi* primarily focuses on developmental and growth aspects [7,11,12], the influence of environmental factors on swimming and spawning [11–15], aquaculture techniques and disease

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management [16–18], population dynamics and ecology [19,20], genetics and nutrition [9,21,22], as well as anesthesia effect experimentation on juvenile fish [23]. However, there is a lack of assessments regarding its potential habitat distribution and connectivity.

Species Distribution Models (SDMs) are useful tools for identifying potential habitat distributions for species [24] and are increasingly applied in freshwater ecosystems [25–27] as well as for freshwater fish [28]. Biologists and managers can utilize SDMs to identify critical habitats, prioritize the locations of protected areas, and appropriately relocate endangered species [24]. Therefore, it is feasible and necessary to employ SDMs to assess the potential habitat distribution of *S. chongi*. River network connectivity (RNC) is defined as the water-mediated transfer of matter, energy, and organisms along longitudinal (upstream-downstream), lateral, and vertical dimensions [29,30]. For centuries, dam construction has disrupted RNC [31,32], significantly altering hydrological conditions and material flow processes in rivers [29,33], thus threatening the dispersal and migration of freshwater fish, which are critical life history processes [34,35]. Amid the global surge in dam construction, quantifying and assessing RNC and its changes is crucial for the conservation of fluvial fish diversity. The Dendritic Connection Index (DCI) [36] is an effective tool for quantifying the impacts of dam construction on RNC, as it implicitly considers the movement and arrival probabilities of organisms within the river network. Therefore, when implementing conservation measures, in addition to considering the distribution of habitat suitability, river connectivity needs to be considered.

To address the knowledge gap of *S. chongi*, we employed SDMs and the DCI [36] to assess the potential habitat distribution and river network connectivity of *S. chongi* during the periods 1970–2000 and 2001–2020 (2000: dividing line for whether dams in the UYRB were completed on a large scale) [37]. This study can provide concrete recommendations for the restoration of *S. chongi* habitats in the current UYRB and offer valuable references for researchers in freshwater fish conservation.

2. Materials and Methods

2.1. Study Area

Upper Yangtze River Basin (UYRB), located between 97.62°–110.30° E and 21.22°–34.55° N, covers an area of approximately 1×10^6 km^2 and extends a total length of 4511 km. This basin features significant topographical variation, with an elevation difference reaching 6790 m. The annual average temperature in the UYRB ranges from 8.6 to 16.8 °C, with the average temperature in the coldest month ranging from −16 to 15 °C. Annual precipitation ranges from 723 to 1134 mm, displaying a spatial distribution characterized by lower amounts in the west and higher amounts in the east, with uneven seasonal distribution mainly concentrated between April and October. Influenced by the East Asian monsoon, South Asian monsoon, and the topography of the Tibetan Plateau, the UYRB exhibits distinct regional climatic characteristics, primarily impacted by climate disasters such as low temperatures, droughts, and floods.

2.2. Species Occurrence

To collect as much data as we can, occurrence data for *S. chongi* was primarily obtained from two sources: (1) through literature surveys (CNKI search keyword: *Schizothorax chongi*; in Chinese) (https://www.cnki.net/; assessed on 9 June 2023) and (2) sampling conducted by the Institute of Hydrobiology, Chinese Academy of Sciences (listed in Supporting Information). All occurrence records were checked for synonyms and naming errors, and their spatial accuracy was verified before modeling [38], ensuring that all occurrence points fell within the river network of the UYRB. To eliminate the effects of spatial autocorrelation, the occurrence records were thinned [39,40], retaining only one record per grid cell at a spatial resolution of 30 arc seconds [41]. After processing, a total of 26 and 24 occurrence records for *S. chongi* were retained for modeling for the periods 1970–2000 and 2001–2020, respectively (Figure 1).

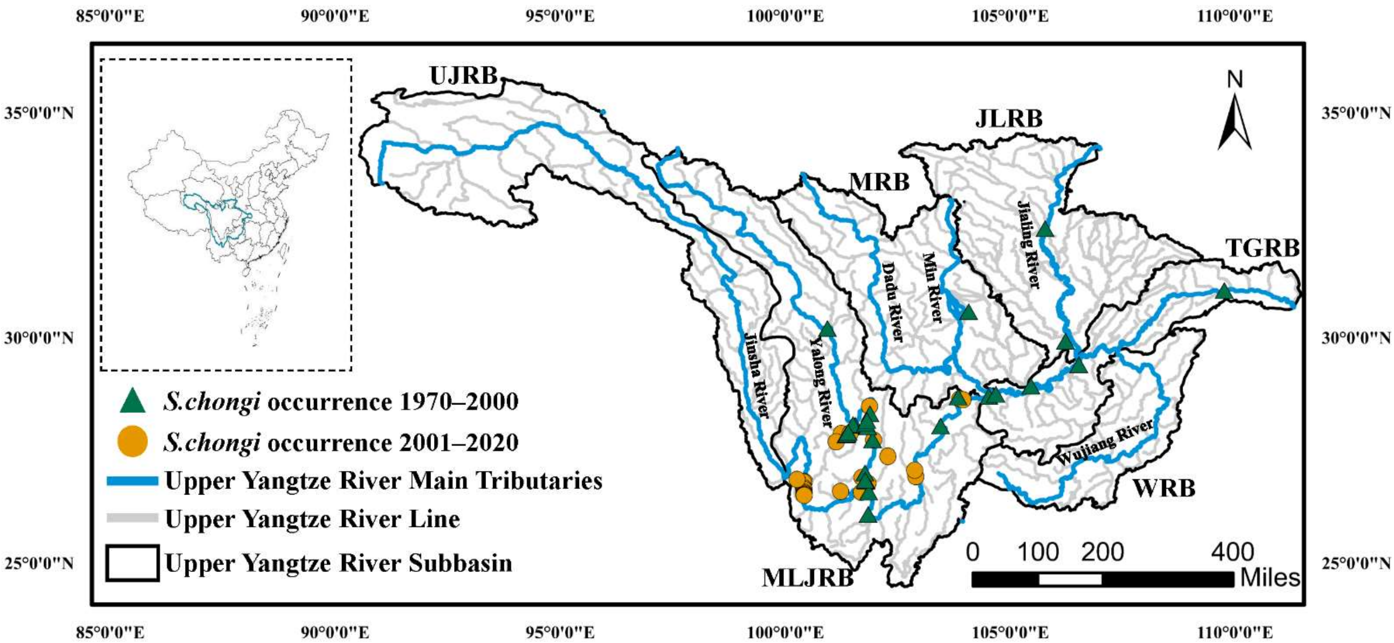

Figure 1. The location of the study area and the occurrence of *S. chongi* in the periods of 1970–2000 and 2001–2020. The Upper Yangtze River Basin is divided into five major sub-basins (Figure 1): the Upper Jinsha River Basin (UJRB), the Middle and Lower Jinsha River Basin (MLJRB), the Min River Basin (MRB), the Jialing River Basin (JLRB), and the Wu River Basin (WRB), as well as the Three Gorges Reservoir Basin (TGRB).

2.3. Modeling Variables Selection

We considered the impact of environmental factors as Zhang et al. (2020) [42] suggested and selected a total of 25 environmental variables as candidate modeling factors including 19 climate variables and six human activity-related variables (Table 1).

Table 1. Pre-selected modelling factor descriptions and sources (All the datas here were assessed on 13 March 2023).

Type	Variables	Description	Source
	BIO1	Annual Mean Temperature	https://www.worldclim.org/data/worldclim21.html
	BIO2	Mean Diurnal Range	https://www.worldclim.org/data/worldclim21.html
	BIO3	Isothermality	https://www.worldclim.org/data/worldclim21.html
	BIO4	Temperature Seasonality	https://www.worldclim.org/data/worldclim21.html
	BIO5	Max Temperature of Warmest Month	https://www.worldclim.org/data/worldclim21.html
	BIO6	Min Temperature of Coldest Month	https://www.worldclim.org/data/worldclim21.html
	BIO7	Temperature Annual Range	https://www.worldclim.org/data/worldclim21.html
	BIO8	Mean Temperature of Wettest Quarter	https://www.worldclim.org/data/worldclim21.html
	BIO9	Mean Temperature of Driest Quarter	https://www.worldclim.org/data/worldclim21.html
Climate	BIO10	Mean Temperature of Warmest Quarter	https://www.worldclim.org/data/worldclim21.html
	BIO11	Mean Temperature of Coldest Quarter	https://www.worldclim.org/data/worldclim21.html
	BIO12	Annual Precipitation	https://www.worldclim.org/data/worldclim21.html
	BIO13	Precipitation of Wettest Month	https://www.worldclim.org/data/worldclim21.html
	BIO14	Precipitation of Driest Month	https://www.worldclim.org/data/worldclim21.html
	BIO15	Precipitation Seasonality	https://www.worldclim.org/data/worldclim21.html
	BIO16	Precipitation of Wettest Quarter	https://www.worldclim.org/data/worldclim21.html
	BIO17	Precipitation of Driest Quarter	https://www.worldclim.org/data/worldclim21.html
	BIO18	Precipitation of Warmest Quarter	https://www.worldclim.org/data/worldclim21.html
	BIO19	Precipitation of Coldest Quarter	https://www.worldclim.org/data/worldclim21.html
	CLA	Crop Land Area	https://sedac.ciesin.columbia.edu/data/set/aglands-croplands-2000
	DPI	Development Pressure Index	https://sedac.ciesin.columbia.edu/data/set/lulc-development-threat-index
Human	HIP	The Human Impervious Area Percentage	https://sedac.ciesin.columbia.edu/data/set/ulandsat-hbase-v1
Activity	POPC	Population Count	https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-rev11

POPD	Population Density	http://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-density
HII	The Human Influence Index	http://sedac.ciesin.columbia.edu/data/set/wildareas-v2-human-influence-index-geographic

The climate variables were derived from the WorldClim database (http://www.worldclim.org/; assessed on 13 March 2023), which provides commonly used bioclimatic variables for ecological niche modeling (BIO1–BIO19) [43]. These data were downscaled from CRU-TS-4.06 [44] by the Climate Research Unit at the University of East Anglia and bias-corrected using WorldClim 2.1 [45]. The resolution of the climate variables is 30 arc seconds, and all six human activity-related factors (specific references can be found in Table A1) were resampled to the same resolution before selection.

We selected the modeling variables in two steps. First, we conducted modeling using the candidate factors, sequentially removing the climate variables related to temperature and precipitation, andthe human-related variables with low contributions, ultimately retaining two climate variables and two human activity-related variables. Next, we performed a collinearity test on the four selected variables by calculating their Variance Inflation Factor (VIF) values to ensure that all VIF values were less than 10, thus avoiding overfitting and eliminating the effects of multicollinearity [46].

2.4. Ensemble Modeling

Ensemble modeling, by integrating the strengths of multiple models, mitigates the limitations inherent in single-model approaches, thereby enhancing the accuracy, stability, and reliability of predictions [47]. In this study, we selected four algorithms to establish the base submodels required for the ensemble model (weighted by AUC; see below): Artificial Neural Networks (ANN) [48], Surface Range Envelope Models (SRE) [49], Flexible Discriminant Analysis (FDA) [50], and Maximum Entropy Models (MAXENT) [51], as these algorithms perform well and are not prone to overfitting. All algorithms were fitted using the default settings in the biomod2 package [52] within the open-source statistical software R 4.3.1. The models were evaluated on the assessment dataset (20~30% of the combined occurrence and pseudo-absence data) using the Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) [53] and the True Skill Statistic (TSS) [54]. The ROC curve illustrates the relationship between the true positive rate and the false positive rate at different thresholds. A ROC curve that bends more toward the upper left corner indicates a higher AUC value, which represents better model predictive performance. The True Skill Statistic (TSS) quantifies model performance, calculated as TSS = specificity + sensitivity − 1. A higher TSS value signifies better model predictive performance. Generally, when the AUC is greater than 0.90 and the TSS is greater than 0.75, the model performance is considered excellent [55,56]. Subsequently, this study employed repeated split-sampling and cross-validation to evaluate the models, retaining only those with an AUC of 0.75 to create an ensemble model weighted by AUC [57,58]. We randomly selected 70% of the total occurrence and pseudo-absence (randomly generated in grids without occurrence, with the same number as the occurrence) records as the training set for fitting the algorithms, while the remaining 30% were reserved for assessing algorithm performance. This process was repeated 10 times to minimize biases in dataset splitting caused by the variability of individual algorithms and to enhance the robustness of the results.

2.5. DCI Calculation

The physical RNC was evaluated using the DCI, which identifies river connectivity as a layered system operating across the entire network and considers stream segments as essential parts of a river continuum extending from its source to its mouth [36]. It assesses the extent to which river connectivity is disrupted by barriers such as dams, waterfalls, locks, and weirs by estimating the likelihood of a fish successfully crossing these obstacles to travel between two segments within a river network [36]. The DCI is determined using factors such as the number of barriers, their spatial distribution, biological passability, and river length, with scores ranging from 0 (wholly disconnected) to 100 (fully connected). It can be applied to calculate connectivity for potamodromous fish migrating within freshwater systems and diadromous fish moving between freshwater and ocean environments. On the assumption that the pass rates between dams are mutually independent, the formula for calculating the DCI for potamodromous fish is as follows:

$$DCI = \sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij}\frac{l_i}{L}\frac{l_j}{L} \times 100\% \tag{1}$$

where *n* is the total number of the sections of the river network; *i* and *j* are the river section numbers; *L* is the total length of the river network; l_i and l_j are the lengths of sections *i* and *j*, respectively; C_{ij} is passability that refers to the probability of fish being able to cross a barrier in both the upstream or downstream direction, which is calculated as

$$C_{ij} = \prod_{m=1}^{M} P_m^U P_m^D \quad (2)$$

where *M* is the number of the dams between sections *i* and *j*; P_m^U and P_m^D are the upstream and downstream passibility of the m^{th} dam, respectively, which is assumed to have equal possibility to move upstream and downstream for potamodromous fish [59].

To calculate the DCI for the UYRB, we began by verifying the geographical location of the dams to confirm their alignment with the river network. Next, all the dams within the basin were classified into three categories based on their construction or planned construction dates: pre-2000, post-2000, and those constructed between these two periods. Finally, the river networks were divided into segments according to the geographical locations of the dams in the three time periods, which were then used to calculate the DCI. The DCI was calculated using the Fish Passage Extension (FIPEX) for ArcGIS 10.4 on the ArcGIS platform [60]. To calculate the DCI, the probability *P* in Equation (2) must be determined. Passability is influenced by various factors, including physical characteristics (e.g., dam height, flow rate, and hydrodynamics), chemical conditions (e.g., pollution), and the biology of the species involved, which can vary by species, age, and other factors [36]. In this study, only the impact of dam height was considered, with a fixed pass rate assigned to dams of different heights (Table 2). For dams taller than 70 m, classified as large dams by the International Commission on Large Dams, the pass rate is set to 0. For dams exceeding 15 m in height, the passability value is set to 0.6.

Table 2. Dam height and corresponding pass rate.

Dam Height (m)	Pass Rate
<15	0.6
15–30	0.4
30–70	0.2
>70	0

3. Results

3.1. Model Performance and Predominant Predictors

The habitat models for *S. chongi* during the two periods (1970–2000 and 2001–2020) were successfully established, demonstrating excellent model performance. The ensemble model for the 1970–2000 period achieved an AUC of 0.943 and a TSS of 0.777, while the habitat model for the 2001–2020 period achieved an AUC of 0.989 and a TSS of 0.942 (Figure 2). Both AUC and TSS values exceed 0.85 and 0.75, respectively, indicating that our models are accurate and reliable.

After the selection process, the four retained modeling factors in this study were BIO7 (temperature annual range), BIO11 (mean temperature of coldest quarter), CLA (crop land area), and POPD (population density). The modeling factors for both the 1970–2000 and 2001–2020 periods underwent collinearity testing, and their model contributions and VIF values are presented in Table 3.

Table 3. Relative contribution (RC) and Variance inflation factor (VIF) of modelling factor in 1970–2000 and 2001–2020.

Modelling Periods	Variables	RC	VIF
1970–2000	BIO7	18.7%	6.405106
	BIO11	54.0%	7.871423
	CLA	12.9%	2.479721
	POPD	14.4%	2.275276
2001–2020	BIO7	35.2%	6.165412
	BIO11	33.8%	7.818387
	CLA	12.9%	2.364912
	POPD	18.1%	1.953089

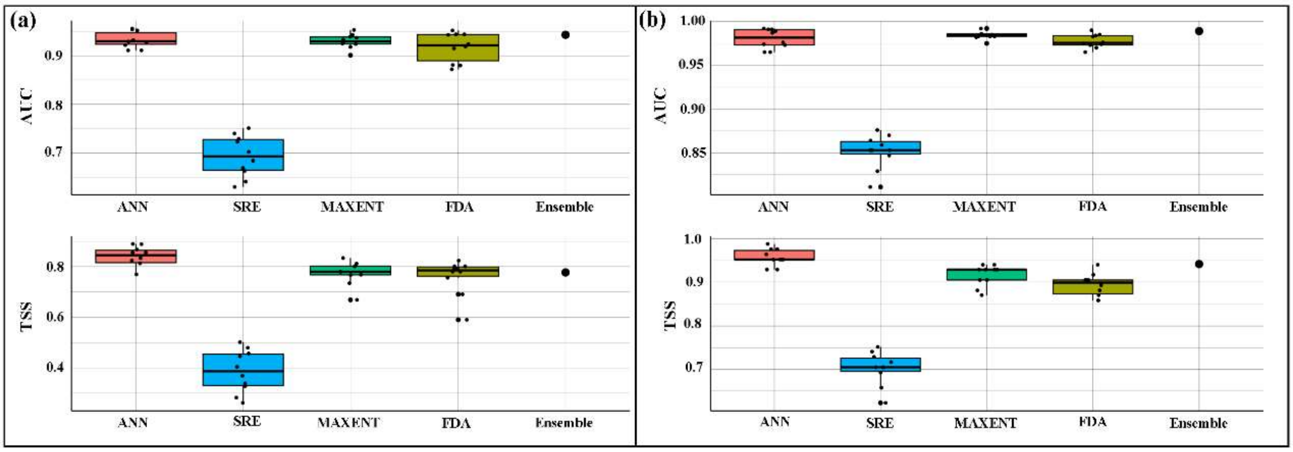

Figure 2. Model performance of sub-models and ensemble model (AUC and TSS) for *S. chongi* in (**a**) 1970–2000 and (**b**) 2001–2020; AUC means Area Under the Curve and TSS means True Skill Statistic.

3.2. Potential Habitat Distribution Change

The simulated potential habitat distribution of *S. chongi* for the periods 1970–2000 and 2001–2020 is shown in Figure 3. *S. chongi* experienced a significant reduction in habitat, with the lengths of medium and high suitability habitats decreasing from 10,213.76 km in the 1970–2000 period to 4932.04 km in the 2001–2020 period, representing a decline of 51.7%. The predominant type of habitat reduction was medium suitability, which decreased by 4711.78 km, primarily occurring outside the Jinsha River basin. Notably, there was no significant reduction in high suitability habitats in the middle and lower reaches of the Jinsha River between the two periods (Figure 3).

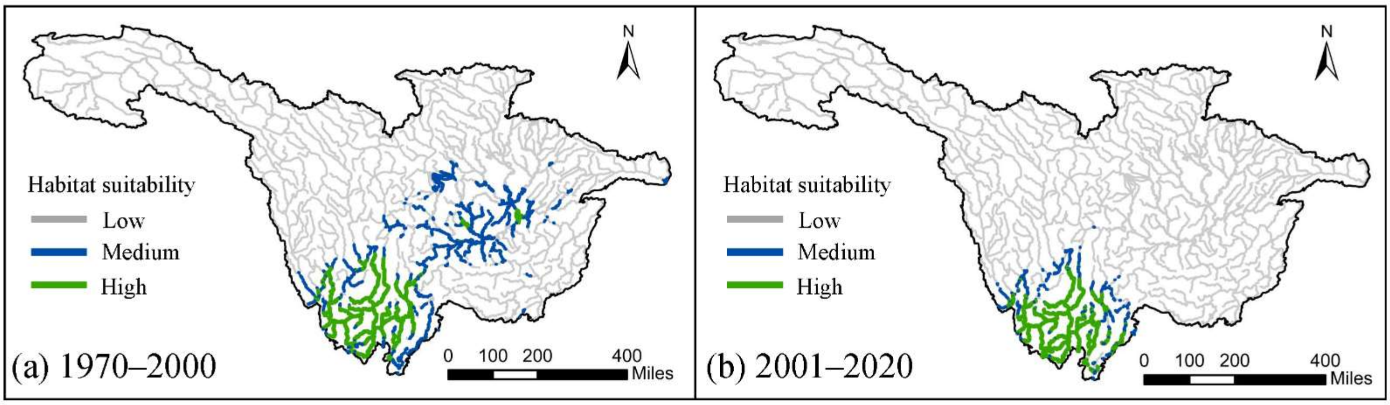

Figure 3. Habitat suitability distribution for *S. chongi* in 1970–2000 and 2001–2020. It was categorized into three levels: Low (habitat suitability < 0.4), Medium (habitat suitability 0.4–0.7), and High (habitat suitability 0.7–1).

3.3. River Network Connectivity Variation under Dam Construction

Comparisons of DCI distribution in different periods show that the RNC experienced a drastic reduction with the continuous advancement of hydropower development in the UYRB (Figure 4). Before 2000, although some dams had been constructed in the UYRB, the DCI values of the mainstream still ranged between 40 and 60. Most of the sub-basins had DCI values above 10, with the exception of the northern part of the Jialing River, where the DCI was below 10. After 2000, the national government began to heavily develop the hydropower resources of the UYRB, resulting in a significant decline in the DCI values across the entire basin, with some parts of the mainstream in the MLJRB having DCI values below 1. Additionally, the DCI in the MRB and WRB also saw substantial declines, with more than 50% of these areas having DCI values below 1. Only the headwaters of UJRB, TGRB, and their surrounding areas maintained relatively high DCI values (greater than 10).

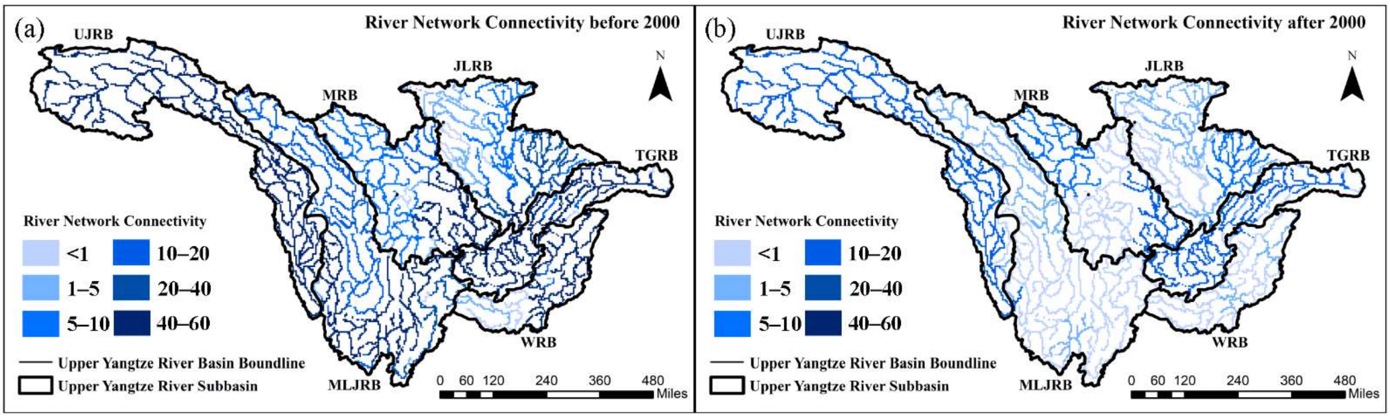

Figure 4. The distribution of river network connectivity of the Upper Yangtze River Basin (**a**) before and (**b**) after 2000.

3.4. Regional Conservation Focus

The bivariate map of the Habitat Suitability Index (HSI) and the Dendritic Connectivity Index (DCI) for *S. chongi* during the periods 1970–2000 and 2001–2020 are illustrated in Figure 5. In the 1970–2000 period, the southern region of the Middle and Lower Jinsha River Basin (MLJRB) exhibited both high connectivity and high suitability, while a region at the junction of the Min River, Jialing River, and Three Gorges Basin showed high connectivity and medium suitability. However, in the 2001–2020 period, connectivity and habitat suitability in the junction area of the Min River, Jialing River, and Three Gorges Basin declined simultaneously, resulting in a complete loss of colonization potential in this area. Furthermore, although the southern region of the MLJRB maintained relatively high habitat suitability, its connectivity decreased.

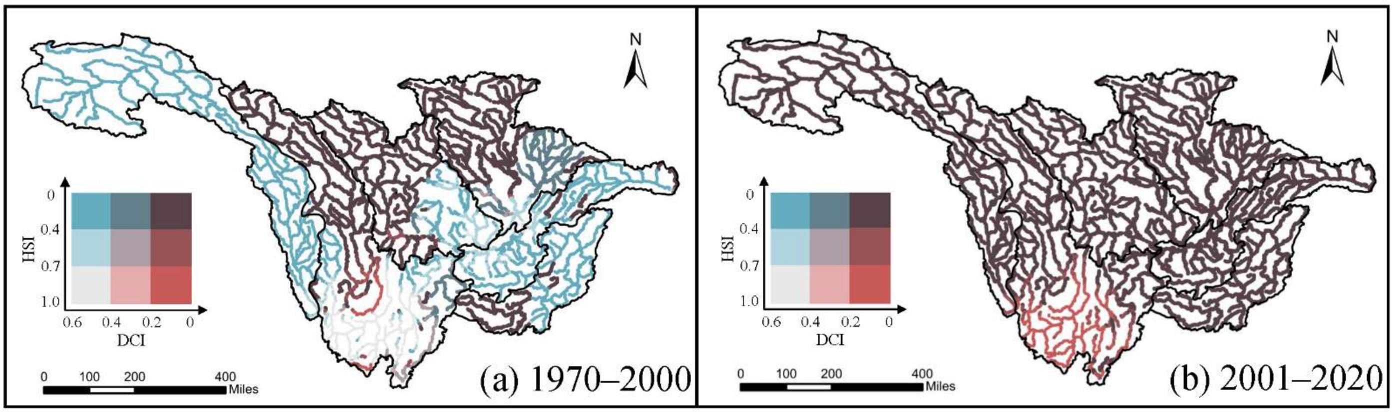

Figure 5. Bivariate distribution of Dendritic Connectivity Index (DCI) and Habitat Suitability Index (HSI) in periods (**a**) 1970–2000 and (**b**) 2001–2020 for *S. chongi*.

4. Discussion

Our study assessed the suitability and connectivity of *S. chongi* habitat for 1970–2000 and 2001–2020 from two critical perspectives. The results reveal a significant decline in both river network connectivity in the Upper Yangtze River Basin (UYRB) and habitat suitability for *S. chongi*, serving as a further warning for the conservation of the wild population of this valuable economic fish species. This research is the first to provide a basin-scale assessment of the potential habitat distribution and connectivity of *S. chongi*, which can assist local governments in formulating specific conservation measures and plans.

Overall, the modeling results for 1970–2000 and 2001–2020 indicate that BIO7 (temperature annual range) and BIO11 (mean temperature of coldest quarter) are the most significant contributing factors in the models (Table 3). BIO7 and BIO11 are temperature-related climate factors, and air temperature is often highly correlated with water temperature [61]. As a cold-water species [13], *S. chongi* is reasonably sensitive to changes in water temperature. CLA (crop land area) and POPD (population density) are the human activity-related factors selected. CLA has been shown to negatively impact the survival of freshwater fish [62], and high levels of POPD can exacerbate the pressures faced by freshwater fish populations [63], such as pollution of the aquatic environment, night time light pollution, the construction of more barriers, and fishing activities [64].

During the period from 2001 to 2020, only the habitat of *S. chongi* in the southern region of the Middle and Lower Jinsha River Basin (MLJRB) was preserved (Figure 3), which is consistent with the distribution of occurrence points (Figure 1). Furthermore, the connectivity of the entire Upper Yangtze River Basin (UYRB) has declined, posing a threat to the remaining habitat of *S. chongi* in MLJRB (Figure 4). Fortunately, since dam construction plans often start from the downstream of tributaries, the headwaters of UJRB, TGRB, and their surrounding areas maintained relatively high connectivity with only a slight decrease. These results provide strong evidence supporting Han et al. (2009) and Duan et al. (2010) [9,10], indicating a deterioration in the survival conditions of *S. chongi* and a continuous decline in its resource availability.

Conserving biodiversity requires the formulation of appropriate strategies [65], particularly in the Upper Yangtze River Basin (UYRB), where the diversity of freshwater fish and the number of related conservation areas are extremely unbalanced [66]. This study simultaneously assesses river network connectivity and habitat suitability (ecological factors), which aids in effective river conservation [67,68]. For *S. chongi*, the most urgent task is to restore river connectivity in the southern Middle and Lower Jinsha River Basin (MLJRB), as habitat suitability here is still high, to protect the last remaining habitats of its wild population. For instance, fish passages specifically designed for *S. chongi* can be constructed to facilitate their upstream migration in the MLJRB. Additionally, other measures can be implemented. On one hand, artificial breeding and release programs upstream of dams can be employed to enhance the population size of wild individuals. On the other hand, optimizing dam operations with greater consideration for ecological benefits is also essential.

In the calculation of Dendritic Connectivity Index (DCI), due to the lack of measured data for specific fish species, we assumed a fixed pass rate for the fish [69], which might lead to an incorrect assessment of the fish's migratory ability. Additionally, this study assumes that the ability of fish to pass a particular dam is independent of their ability to pass other dams, which may not hold true in many cases [69]. Further research is needed to address the issue of biological passability from both physical (flow regulation) and biological (species physiology) perspectives [36]. Therefore, the DCI calculated in this study may deviate from the actual situation of the fish. At smaller spatial scales, the distribution of species may be shaped by both abiotic factors (such as flow dynamics and hydrological conditions) and biotic factors (including interspecies relationships and resource availability) [70]. While our models focus on broad-scale patterns and project potential habitats, these simulations may not fully align with local-scale habitat suitability [37]. Further research could enhance accuracy by incorporating fine-scale environmental variables, such as river morphology, water chemistry, and ecological interactions, to better reflect actual habitat distributions.

5. Conclusions

This study utilized the Dendritic Connectivity Index (DCI) and Species Distribution Models (SDMs) to assess the habitat connectivity and suitability of *S. chongi* during the periods of 1970–2000 and 2001–2020. The results indicate that from 2001 to 2020, there was a substantial reduction in the habitat of *S. chongi*, with a total length of medium and high suitability habitats decreasing by 51.7%. The high suitability habitat in the southern section of the Middle and Lower Jinsha River Basin (MLJRB) did not experience a significant reduction. Although this region maintained relatively high habitat suitability during 2001–2020, the connectivity has significantly declined, making the restoration of connectivity in this area extremely urgent. Implementing fish stocking upstream of the dam and constructing fish passages in the MLJRB are effective restoration measures. The findings provide effective recommendations for conserving both the current and future wild populations of *S. chongi*.

Appendix A

Table A1. Sources of human activity related variables.

Variables	Description
CLA	Crop Land Area [71,72]
DPI	Development Pressure Index [73,74]
HIP	The Human Impervious Area Percentage [75]
POPC	Population Count [76]
POPD	Population Density [77]
HII	The Human Influence Index [78]

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Author Contributions

Conceptualization, P.Z.; Methodology, P.Z.; Software, X.B.; Data Curation, X.B., Y.Y., M.X. and L.Q.; Writing–Original Draft Preparation, X.B.; Writing–Review & Editing, X.B. and P.Z.; Visualization, X.B. and Z.N.; Supervision, P.Z.

Ethics Statement

This study does not involve human or animal subjects.

Informed Consent Statement

Not applicable.

Data Availability Statement

Original data and code are available from the corresponding author upon reasonable request.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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