

Article

Unravelling the Characteristics of Microhabitat Alterations in Floodplain Inundated Areas Based on High-Resolution UAV Imagery and Remote Sensing: A Case Study in Jingjiang, Yangtze River

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Abstract: The floodplain of a large river plays a crucial role in the river's ecosystem and serves as an essential microhabitat for river fish to complete their life history events. Over the past four decades, the floodplain represented by the Jingjiang section in the middle reaches of the Yangtze River has experienced a significant reduction in area, complexity, and diversity of fish microhabitats. This study quantitatively analyzed the dynamic changes and geomorphological structure of the floodplain in the Jingjiang reach (JJR) of the Yangtze River using satellite remote sensing images and high-resolution unmanned aerial vehicle (UAV) optical images. We built an enhanced U-Net model incorporating both the CBAM and SE parallel attention mechanisms to classify these images and identify environmental structural units. The accuracy of the enhanced model was 16.39% higher compared to original U-Net model. At the same time, the improved normalized difference water index (mNDWI), enhanced vegetation index (EVI), and normalized difference vegetation index (NDVI) were utilized to extract the flood frequency of the floodplain and analyze the area changes of the floodplain in the JJR. The trend of the flood area in the JJR during the flood season was consistent with the overall trend of flood areas in the flood season, which generally exhibits a downward tendency. In 2022, the floodplain of the JJR underwent substantial anthropogenic disturbances, with 40% of its area comprising anthropogenic environmental units. Compared to historical periods, the impervious surface within the floodplain has increased annually, while ecological units such as riparian forests and trees have gradually diminished or even disappeared, leading to a simplification of structural complexity. These findings provide a critical background and robust data foundation for the protection and restoration of fish habitats and the formulation of strategies for fish population reconstruction in the Yangtze River.

Keywords: floodplain; inundated area; microhabitat; UAV; deep learning; U-Net



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1. Introduction

The floodplain serves as a crucial transitional zone facilitating the exchange of material, energy, and information between rivers and terrestrial ecosystems, boasting a distinctive ecosystem structure and service functions [1]. It is defined as the stretch of land between the highest flood level and lowest low level of the river bed, encompassing both intermittently submerged river beds and adjacent new or residual floodplains that can extend laterally to the foothills [2]. As an intermediary zone between water and land, it experiences

alternating phases of inundation and exposure, resulting in complex geomorphological structures comprising various seasonal shallow water lakes, freshwater marshes, meadows, bushes, and other wetland environments [3]. Due to micro-terrain fluctuations and periodic floods, this seasonally flooded region exhibits a spatio-temporal pattern of diversified biological habitats [4–8]. Consequently, the floodplain ecosystem showcases exceptionally high biodiversity along with spatially heterogeneous species distribution over time; its rich landform unit composition serves as the foundation for diverse floodplain biological habitats [9]. Moreover, floodplains serve as vital habitats, supporting highly productive aquatic organisms and frequently utilized as feeding grounds for fish within rivers, while simultaneously serving as breeding areas for numerous aquatic organisms during their early life stages [10–13]. The biotic and abiotic conditions that support the specific life history stages of species are referred to as a microhabitat [14].

However, due to dense populations, floodplain areas have long been subjected to extensive resource development and utilization [15,16]. In particular, the floodplain inundated area of large rivers has slowly evolved from a large floodplain in ancient times to a river bank inundation area with a water level variation of less than a few meters. Urbanization is progressively encroaching upon the ecological space of floodplain inundation areas, while the construction of artificial embankments and diverse riparian infrastructure markedly restricts the extent of seasonal flooding [17–19]. Human interventions, including shoreline development and surface hardening, have altered the natural geomorphological structure of these floodplains. Consequently, the microhabitats essential for riverine aquatic life have been both degraded and diminished.

Attention to the dynamic changes in the submerged areas and environmental structures within river floodplains can directly reflect the impact of human activities on the microhabitats of riverine aquatic organisms. The intricate geomorphological units present in floodplain submerged zones serve as a critical factor for fish to accomplish key life history events, providing diverse geomorphological environments essential for fish reproduction and refuge [20,21]. Studies have demonstrated that the grain size and chemical composition of sediments play a significant role in the establishment and survival of macrophytes [22], as well as providing optimal spawning conditions for large benthic invertebrates and lithophilous fish. Sophanna et al. conducted an investigation into the biomass and habitat conditions of 74 migratory fish species in the floodplain of the Lower Mekong River, revealing a strong negative correlation between the total area of flooded forests in the floodplain and the biomass of pelagic fish species, thus underscoring the importance of microhabitat management in the floodplain for the conservation of migratory fish species [13]. The quality of habitats for fish growth is influenced by multiple environmental factors, including water temperature, water depth, bank slope, flow velocity, riverbed material, environmental structural complexity, habitat diversity, ecological connectivity, and food resource availability [21,23–25]. Thus, the extent of the floodplain inundation area and alterations in environmental structures have significant implications for the habitat and survival of riverine aquatic organisms.

For an extended period, human activities such as dam construction and river regulation have significantly altered the hydrological conditions of rivers [26]. Moreover, artificial modifications to river shorelines, including embankment construction and port development, have disrupted the natural microhabitats of aquatic organisms in floodplain inundation zones, leading to mismatches with their life histories [7]. To elucidate the long-term changes and structural integrity of these microhabitats, this study integrates remote sensing imagery and hydrological data to quantitatively analyze the spatial extent of floodplain inundation over time. Furthermore, a classification system for microhabitats within the floodplain inundation area is constructed using high-resolution UAV images, enabling

the categorization and quantification of various environmental structural units [27–30]. This research effectively clarifies the impact of human activities on the natural environmental structure of floodplain inundation areas. Building on this foundation, by considering the life history requirements of aquatic organisms, the ecological effects of changes in floodplain inundation can be quantified, and constructive suggestions for ecological management can be proposed. To achieve this objective, we analyzed and extracted the inundation state of the floodplain in the Jingjiang section of the middle reaches of the Yangtze River over a 20-year period. Using a UAV equipped with a 1.5 cm-resolution mapping lens, aerial images of the flooded area on the left bank of the Jingjiang section were collected, followed by image segmentation and classification analysis to quantify the dynamics of extent and structural integrity changes in the floodplain inundation area under long-term anthropogenic influences.

2. Study Area

The study area targeted the floodplain inundated zone in the Jingjiang reach (JJR), which is located in the middle reaches of the Yangtze River (the largest river in China) (Figure 1). The JJR starts from Zhicheng (ZC), and ends at Chenglingji (CLJ), with a total length of 347.2 km, divided into the Upper Jingjiang and the Lower Jingjiang, and bounded by the mouth of the Ouchi River. Due to the construction of the upper Yangtze River terrace water conservancy project and the storage of the Three Gorges Reservoir in recent years, the water level change in the JJR has significantly weakened compared with the historical period, and the extent of the floodplain inundated area has significantly reduced compared with the inundated floodplain in the historical period.

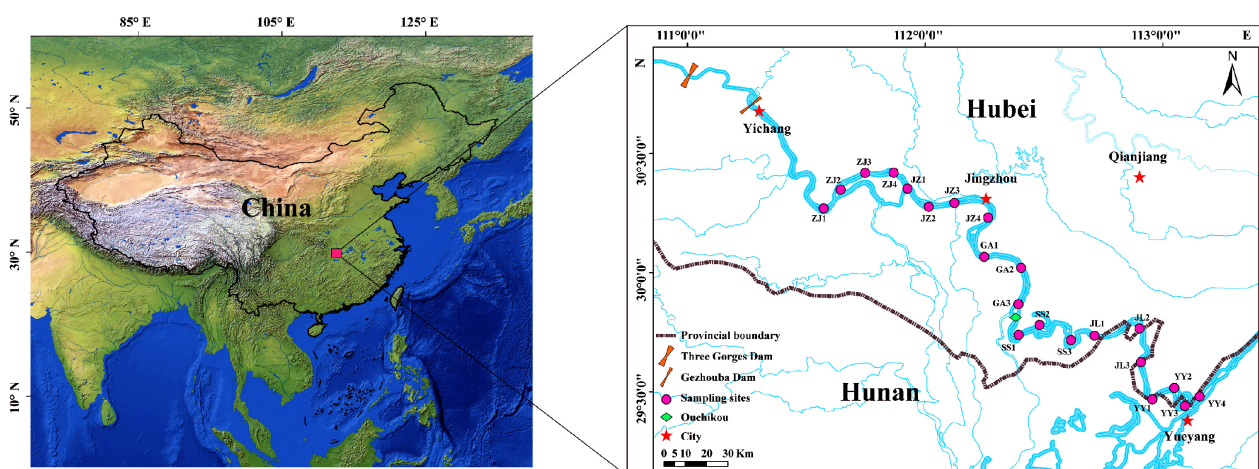


Figure 1. Study Area: Jingjiang reach of Yangtze River.

Since the 1950s, with the exception of a few flood-prone areas in the JJR, nearly all lakes, regardless of size, have been regulated by sluice gates for water resource management. This has disrupted the natural migration patterns of fish between rivers and lakes, creating barriers that impede the connectivity between feeding and breeding grounds essential to the life cycles of drifting egg fish. The construction of dams has prevented juvenile fish from accessing blocked lakes for feeding and growth, severely limiting their population. Only during periods when the sluice gates are opened do some individuals occasionally enter the lakes, but these occurrences are rare, leading to the complete disappearance of certain species. Consequently, the fish community structure in these isolated lakes has evolved to consist primarily of species capable of reproducing in still water environments, completing their entire life cycles within the lake. This shift has resulted in the degradation

of the original food web structure, inefficient utilization of prey organisms, and overall deterioration of the ecological environment.

More critically, the construction of water conservancy protection projects (such as flood control and slope protection), port development, and urban landscaping along the JJR has significantly altered the natural inundated zone of the floodplain. These changes have resulted in surface hardening of the natural floodplain and exacerbated the succession of aquatic vegetation in the riparian zone. The transition of riparian vegetation communities from *Phragmites australis*, reeds, and *Carex* in natural habitats to the degraded Canopy-verbena community has led to a substantial decrease in organic matter input and a simplification of the food web. Historically, the lakes and floodplains in the JJR served as critical habitats for juvenile fish. However, the reduced connectivity between rivers and lakes has severely impacted fish diversity and diminished juvenile fish habitats, thereby posing significant challenges to fish populations during their early life stages due to habitat reduction and microhabitat loss.

3. Method

In this study, we delineated the extent of the floodplain inundated area and analyzed its long-term dynamic changes. We employed water index and inundation frequency calculation methods to extract non-permanent water bodies within the floodplain using historical remote sensing image data from the JJR. By integrating long-term hydrological sequences of the study area, we verified the dynamic changes in the floodplain inundation area. Additionally, for the analysis of environmental structural units within the inundated floodplain, we constructed a classification model of microhabitat environmental structures based on high-resolution images collected by UAVs. This model utilizes a deep learning optimization algorithm with U-Net as the main network, incorporating an attention mechanism to enhance segmentation accuracy for large-scale, high-resolution floodplain images. Based on the results of this classification model, we extracted land cover types from low-resolution historical remote sensing images, focusing on the decline in natural environmental structure units and the increase in anthropogenic intervention units, thereby clarifying the dynamic characteristics of microhabitat structure changes in the JJR floodplain inundated area.

3.1. Data

The extent of the inundated area between the highest and lowest water levels is influenced by river hydrological data. To analyze and verify this, daily water level and flow data from four hydrological stations in the JJR (ZC, SS, JL, CLJ) were collected for the period 1996 to 2023. These data were provided by the Changjiang Basin Ecology and Environment Monitoring and Scientific Research Center, Changjiang Basin Ecology and Environment Administration. Additionally, remote sensing images of floodplain inundation were sourced from the United States Geological Survey. All Landsat Collection 1 Tier 1 image data covering the study area from 1984 to 2022 were gathered to identify open surface water bodies and lakes, with cross-calibration, geometric correction, and atmospheric correction applied across different sensors. This dataset was utilized to analyze and verify the historical dynamics of the extent and submerged area of the floodplain inundation zone in the JJR.

Furthermore, high-resolution aerial imagery of the entire left bank of the JJR was systematically acquired. A Puzhou S400 UAV equipped with a QX-6100PRO professional mapping camera was utilized to conduct the aerial photography operation (Figure 2). The relative altitude for image acquisition was set at 160 m, with a flight speed maintained at 10 m per second. The photo interval was configured at 1.9 s, achieving a ground resolution

of 1.5 cm. The heading overlap and side overlap were set at 75% and 70%, respectively. The UAV flew along the left bank of the JJR to capture orthophotos with the camera lens oriented perpendicular to the ground. The imaging period spanned from 19 January to 29 January 2022, during clear weather conditions with light winds and high visibility, typically between 9 a.m. and 4 p.m., ensuring optimal image quality. A total of 57,844 images were acquired, covering a distance of 332.9 km along the left bank of the JJR, effectively encompassing the entire section. Due to the extensive coverage area and lengthy route, strategic take-off points were pre-selected for the UAV operations.

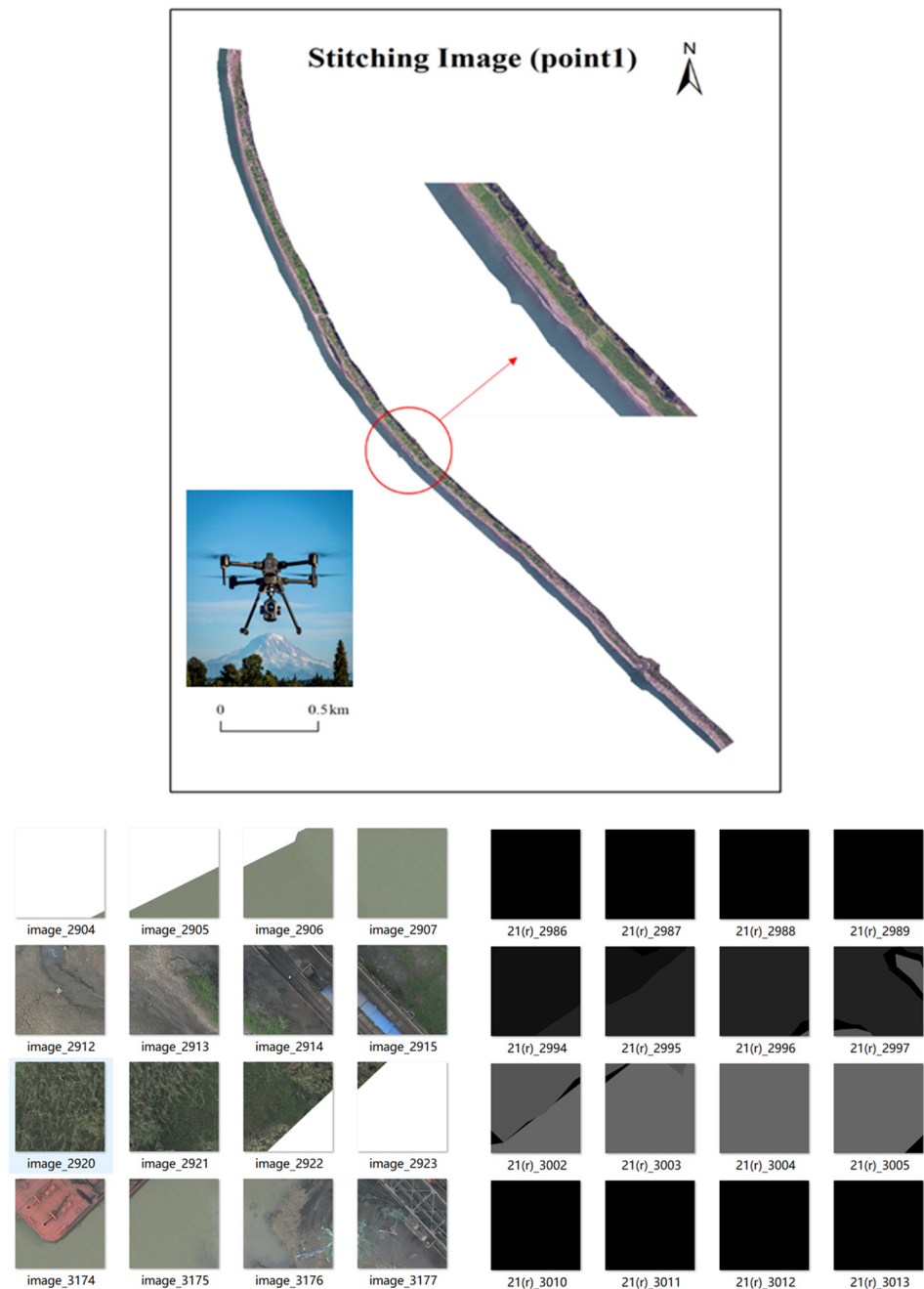


Figure 2. An example of a stitched image (point 1) and the cropped data.

Due to the overlap between the UAV images, Pix4Dmapper v4.5.6 was utilized for the stitching and rectification of aerial imagery. Consequently, 58,744 individual aerial images were processed and seamlessly stitched into 50 digital orthoimages in TIFF format based on their respective shooting point locations (Figure 2). These digital orthophotos were stored

in RGB format with a ground resolution of 1.5 cm GSD. The resulting orthophotos exhibit no visible stitching artifacts, no apparent cracks or gaps at the edges, uniform color tones, clear textures, and no noticeable misalignment or distortion of roads and buildings, thereby meeting the experimental requirements.

Actually, it was impractical to directly utilize the complete stitched images for training the semantic segmentation network. Therefore, the stitched UAV remote sensing images had to be divided into smaller patches. Based on the image resolution, ground features of the experimental area, and prior research experience, this study selected a segmentation size of 512 pixels $\times$ 512 pixels. A total of 41,895 small-size images and 387,055 cropped artificial labels were generated from five stitched images using a standardized cropping method. However, these images contained a significant number of blank background images, and the original images did not correspond one-to-one with their cropped labels. To standardize the input dataset format and ensure correspondence between the original images and artificial labels, the small-size images were screened. The filtering criteria were as follows: only images with a background value ratio less than or equal to 10% were retained. One-to-one correspondence verification was conducted based on the suffix numbers in the filenames of the original images and artificial labels (which included geographical location information) to ensure accurate alignment between the original images and their labels. This operation was implemented using Python 3.8 within the Anaconda3 environment.

The pixel value range of RGB remote sensing images is typically within the interval [0, 255]. To ensure the consistency of image pixel characteristics, it is essential to normalize the data, thereby constraining the data distribution to a specific range. In this study, min-max normalization was employed for data normalization, and the specific formulation is as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

where $x_{\min}$ denotes the minimum value of the data, and $x_{\max}$ denotes the maximum value of the data. After preprocessing the aforementioned training dataset, a total of 19,671 original images of size 512 $\times$ 512 with a background value ratio less than or equal to 0.1, as well as 19,671 manually labeled samples, were obtained.

3.2. Modeling Approach

We employed the water index and inundation frequency calculation method to delineate non-permanent water bodies within the JJR floodplain, quantifying their areas to define the floodplain's boundaries. Research on water indices has significantly matured. The original Normalized Difference Water Index (NDWI), proposed by McFeeters in 1996, is a remote sensing-based method that highlights water features by calculating the normalized difference between the green band and the near-infrared (NIR) band [31]. This approach effectively suppresses land features as water bodies exhibit positive values, while land surfaces show zero or negative values. In 2005, Xu Hanqiu introduced an enhanced version of NDWI, termed modified NDWI (mNDWI), which substitutes the short-wave infrared (SWIR-1) band for the NIR band, thereby improving water body extraction accuracy. The Leaf Water Index (LSWI), developed by Gao in 1996 [32], integrates NIR and SWIR bands to estimate land surface moisture content. Building on these advancements, Feyisa et al. introduced the Automatic Water Extraction Index (AWEIsh) in 2014, which enhances water extraction accuracy in noisy environments and provides a stable threshold, particularly effective for water classification in shadowed and dark surface areas. Given that mNDWI can still misclassify water and vegetation in floodplain wetlands, leading to errors in surface water delineation, Zhou et al. demonstrated that combining mNDWI with the Normalized

Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) yields more accurate and stable results in water delineation. The formula is as follows:

$$mNDWI = \frac{\rho_{green} - \rho_{SWIR1}}{\rho_{green} + \rho_{SWIR1}} \quad (2)$$

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (3)$$

$$EVI = 2.5 \times \frac{\rho_{NIR} - \rho_{red}}{1.0 + \rho_{NIR} + 6.0\rho_{red} + 7.5\rho_{blue}} \quad (4)$$

Here, p_1 , p_2 , p_3 , p_4 , and p_5 denote the surface reflectance values for the blue (0.45–0.52 μm), green (0.52–0.60 μm), red (0.63–0.69 μm), near-infrared (NIR) (0.77–0.90 μm), and short-wave infrared-1 (SWIR1) (1.55–1.75 μm) bands, respectively. To identify pixels with a stronger water signal than vegetation signal, the criteria $mNDWI > EVI$ or $mNDWI > NDVI$ were employed. An EVI threshold of less than 0.1 was set to ensure that pixels representing vegetation or mixed water–vegetation pixels were excluded [33]. Consequently, only pixel points satisfying $[(mNDWI > EVI \text{ or } mNDWI > NDVI) \text{ and } (EVI < 0.1)]$ were classified as water body pixels, while all other pixels were categorized as non-water body pixels. For each Landsat pixel within the study area, Formula (4) was utilized to calculate the annual water frequency.

$$F(y) = \frac{1}{N_y} \sum_{i=1}^{N_y} w_{y,i} \times 100\% \quad (5)$$

where F denotes the water body frequency of a pixel, y denotes the designated year, N_y denotes the total number of Landsat observations in that year, and $w_{y,i}$ indicates whether the pixel is classified as water (1) or non-water (0) in a given observation. The annual water frequency map for the JJR was generated by aggregating the water frequencies of all Landsat pixels. By applying a specific threshold, the water area can be delineated from the annual water frequency map, with variations depending on different threshold settings. Based on previous studies and the characteristics of the JJR, a threshold of 0.75 was selected. Pixels meeting an annual frequency threshold of ≥ 0.75 were classified as permanent water bodies.

The present study employs high-resolution UAV imagery to investigate the floodplain classification of the JJR. The technical methodology includes four primary components: acquisition of floodplain UAV images, data preprocessing, development and application of a deep learning model, and optimization evaluation. Data acquisition and preprocessing procedures are detailed in previous sections. During the model development phase, an advanced remote sensing image semantic segmentation algorithm based on an enhanced U-Net architecture was established, achieving superior classification accuracy compared to the original U-Net network. Finally, to optimize the model's application stage, a novel edge prediction algorithm for large remote sensing images using a windowing approach was developed to address memory overflow issues caused by directly inputting large, high-resolution remote sensing images into the network model. This algorithm successfully processed and predicted the 332.9 km stretch of floodplain UAV images within the JJR of the study area.

3.3. Model Structure

Based on the classic U-Net network model, this study proposes a CBAM-SEU-Net semantic segmentation model that integrates the CBAM and SE parallel attention mechanisms [34,35]. Additionally, optimization techniques such as joint batch normalization

layers and spatial dropout layers are introduced. The overall architecture of this proposed model retains the U-Net structure, comprising an encoder, skip connections, and a decoder. The left-side encoder is constructed using convolutional layers and downsampling layers, uniformly employing 3×3 convolution kernels with zero-padding for boundary processing and a stride of 1. The encoder comprises four fundamental blocks, each performing two convolutions, followed by two batch normalization processes and with the ReLU activation function applied immediately after each convolution. As the depth increases, the number of feature map channels doubles while the spatial dimensions are halved. To enhance feature representation adaptively, the CBAM-SE parallel attention mechanism is embedded after each batch normalization stage [36,37]. Furthermore, a Dropout layer is strategically introduced before the final downsampling operation and prior to the first upsampling step, serving as a regularization strategy to mitigate overfitting risks by randomly dropping neuron connections during training.

The decoder module integrates convolution operations, upsampling techniques, and skip connection strategies. The convolutional architecture and activation functions mirror those of the encoder to ensure symmetric information processing. The decoder consists of four building blocks, each employing upsampling to double the size of the feature map while halving its channel count. Additionally, through the skip connection mechanism, the upsampled feature map is concatenated with the corresponding encoder stage's feature map (which has been appropriately trimmed to match dimensions), thereby restoring and enhancing the channel number of the feature map to align with the pre-convolution state in the encoder. To further enhance the model's capability to fuse multi-scale information, a CBAM-SE parallel attention module is embedded after each convolution operation (including batch normalization) to achieve multi-scale fusion of feature maps, thereby improving segmentation accuracy. Throughout the decoding process, convolution and deconvolution operations are accompanied by ReLU activation functions to enhance non-linear mapping capabilities. For multi-classification tasks, the decoder ultimately utilizes a 1×1 convolutional layer to predict categories and converts the multi-channel output into a probability distribution via the Softmax activation function, yielding a feature map with multi-classification characteristics. The skip connection strategy effectively promotes information integration at each stage of the encoder, enabling multi-level fusion of deep and shallow features during upsampling, and significantly enhancing the model's feature extraction and representation abilities. Figure 3a illustrates the improved semantic segmentation model developed in this study. The structural process of the combined CBAM-SE attention mechanism is illustrated in Figure 3b. Unlike the sequential combination of Channel and Spatial Attention Modules in CBAM, we adopt a parallel structure to integrate these modules with the SE module. A sequential arrangement would cause the computation of the spatial attention module to interfere with that of the channel attention module. Therefore, a parallel architecture ensures comprehensive consideration of outputs from both branches.

The channel attention of SE may be more refined as a result of the nonlinear interaction within the fully connected layer, while the spatial attention of CBAM is capable of capturing local structures. This study innovatively incorporates the CBAM and SE attention mechanisms in parallel into the model network, thereby combining the strengths of both attention mechanisms. This approach enhances the model's ability to capture complex features through complementary multi-path attention. It is particularly well-suited for tasks that require simultaneous capture of channel relationships and spatial details, demonstrating superior effectiveness in fine-grained classification and segmentation.

To identify the most suitable model for high-resolution UAV image classification in the study area, it is imperative to rigorously evaluate and validate the accuracy of the models.

We have established a comprehensive set of evaluation criteria based on widely accepted metrics. These metrics encompass precision, recall, overall accuracy, and intersection over union (IoU), among others [38–40].

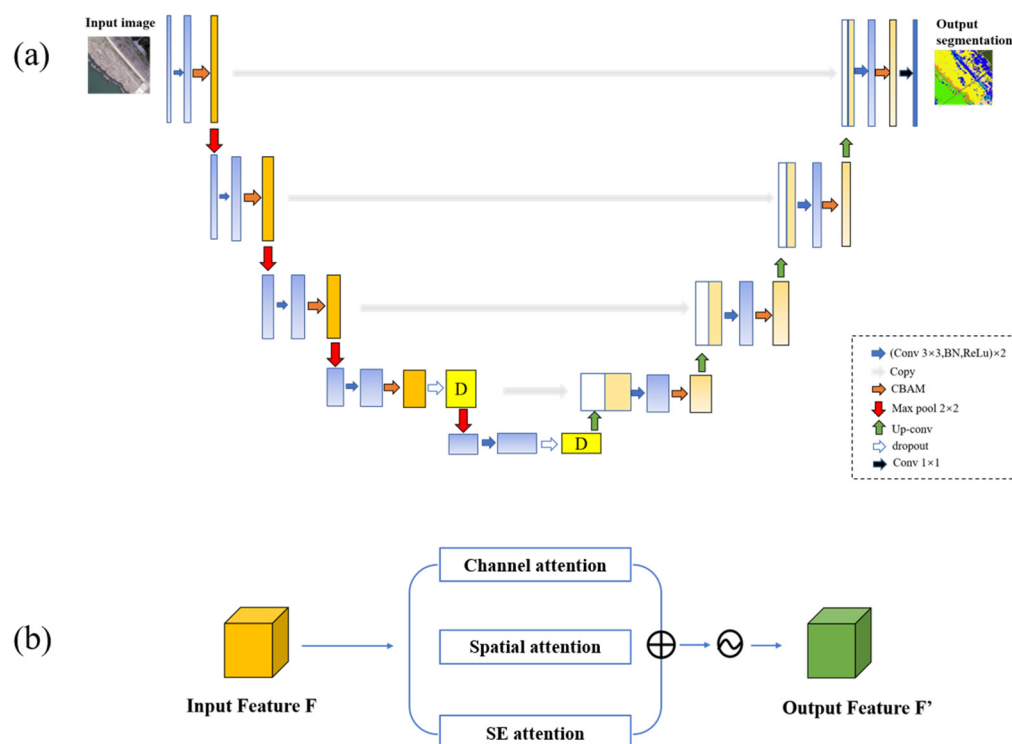


Figure 3. The model structure: (a) overall network structure; (b) attention network structure.

4. Results

4.1. Inherent Hydrological Characteristics

The extent of the floodplain inundated area is primarily determined by water level and discharge parameters. This study analyzes the water level and discharge data of the JJR collected from 1996 to 2022. The monitoring data from the ZC and CLJ hydrological stations, which mark the upstream starting point and downstream endpoint of the JJR, respectively, provide a comprehensive reflection of changes in the river's hydrological regime. On a temporal scale, the runoff at the ZC of the JJR exhibited a declining trend from 1996 to 2022. The peak runoff occurred in August 1998, reaching $54,867 \text{ m}^3/\text{s}$, while the lowest runoff was recorded in February 2003 at $3581 \text{ m}^3/\text{s}$. Annual runoff has stabilized, with fewer occurrences of extreme flood or drought events. Between 1996 and 2022, the water level at the ZC Station exhibited an overall downward trend. The impounding of the Three Gorges Reservoir has a significant impact on water level changes in the Jingjiang section. Prior to 2002, the annual average water levels at the ZC station and CLJ station were notably higher compared to those after the reservoir's impoundment. Following the impoundment of the Three Gorges Reservoir, due to adjustments in reservoir operations, the fluctuation amplitude of the water level at the ZC station became more stable than before the impoundment. Conversely, the water level variation at the CLJ station exhibited greater volatility as a result of the influence from Dongting Lake. The highest annual average water level was recorded in 1998 at 45.48 m (Figure 4a), while the lowest was observed in 2022 at 37.78 m (Figure 4b). Since 2003, the annual average water level of the Three Gorges Reservoir has stabilized; however, the overall water level post-reservoir construction is notably lower than pre-construction levels. Over this period, the difference between the annual maximum and minimum water levels at ZC station

followed an “S-shaped” downward trend. Specifically, the difference in water levels after the impoundment of the Three Gorges Reservoir was significantly lower compared to pre-impoundment levels, but the fluctuation range became more stable post-impoundment. This trend suggests a decreasing inundation range of the floodplain along the JJR since 1996. Notably, after the Three Gorges Reservoir began operation in 2003, the extent of floodplain inundation decreased and its interannual variation became more consistent (Figure 4b). The trend in the change in runoff and water level at CLJ station is largely consistent with that observed at ZC station. However, the annual difference between the maximum and minimum water levels at CLJ section exhibits a trend of initially decreasing and subsequently increasing. This phenomenon can be attributed to the fact that CLJ section is connected to Dongting Lake, with its water levels being influenced by both Dongting Lake and the main stem of the Yangtze River. Dongting Lake exerts a regulatory effect on river runoff, resulting in less pronounced fluctuations in water level differences compared to the main stem.

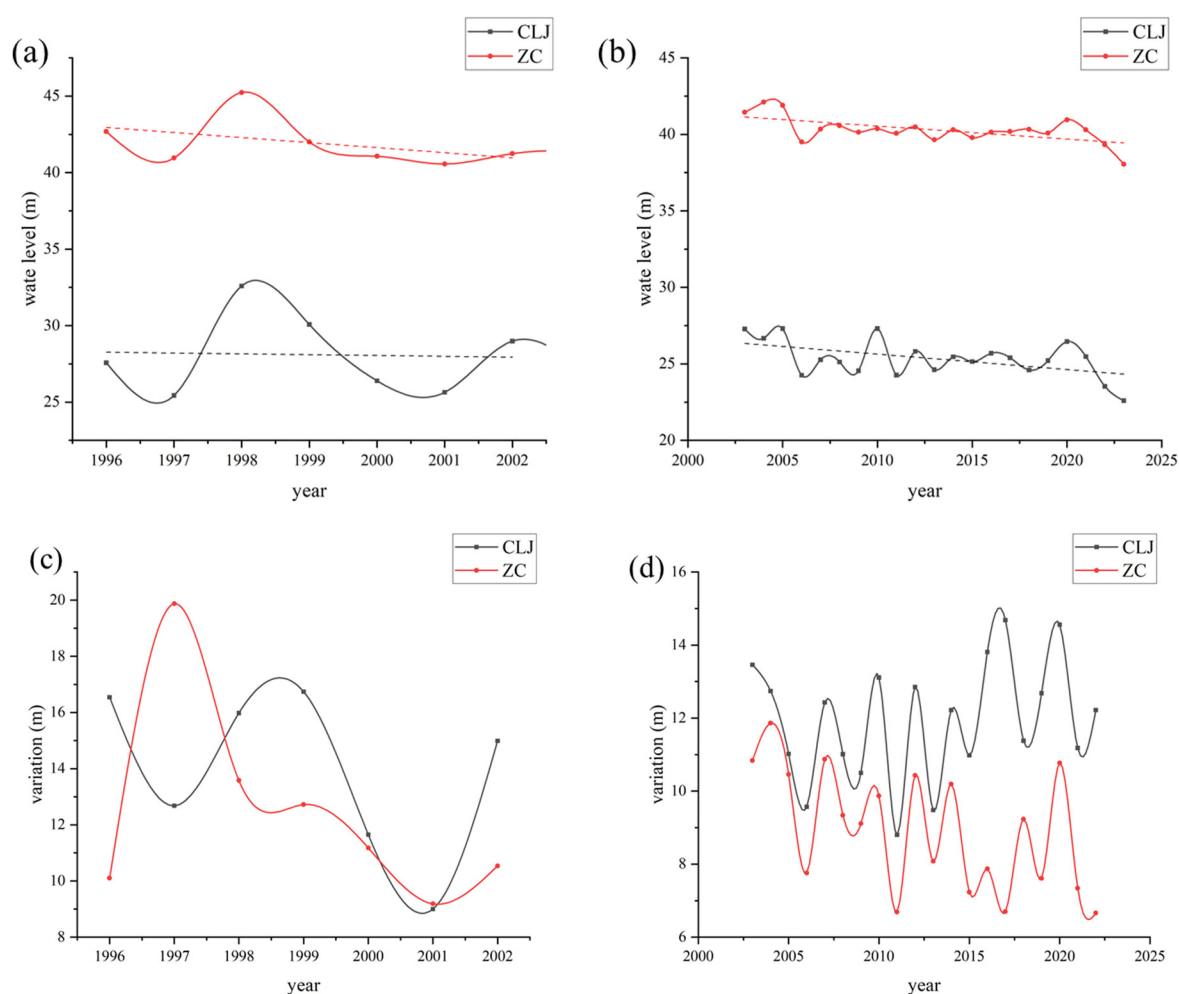


Figure 4. (a) 1996–2002 annual water level range; (b) 2003–2022 annual water level range; (c) 1996–2002 annual variation of water level; (d) 2003–2022 annual variation of water level.

From spatial scale analysis, CLJ station is situated downstream of ZC station. As a result, its water level and discharge are lower than those at ZC. However, the annual maximum and minimum water level differences at CLJ are also smaller compared to ZC (Figure 4c). Specifically, from 1996 to 2022, the annual maximum and minimum water level differences at ZC ranged from 7.06 m to 20.11 m, whereas, at CLJ, these values ranged from 8.36 m to 17.32 m (Figure 4d). This indicates that the floodplain inundated area in the lower

reaches of the JJR is smaller than in the upper reaches, yet the annual inundation variations are more stable in the lower reaches.

4.2. Inundated Range and Area

The hydrological conditions of the JJR generally reflect the inundation status of the floodplain. However, the precise extent of floodplain inundation is influenced by multiple factors including water level fluctuations, environmental geomorphological units, riverbank slope, artificial embankments, and other elements along the riverbanks. Therefore, it is essential to accurately delineate the boundaries of the floodplain and quantitatively assess changes in its flooded area using remote sensing imagery.

Through the water extraction method based on water index and flooding frequency calculations, all Landsat 5/7/8 surface reflectance data from the GEE platform covering the JJR from 1984 to 2022 were selected. The Fmask function was applied to mask the collected images, thereby eliminating low-quality pixels caused by clouds, snow, and shadows. Ten representative Landsat remote sensing images corresponding to distinct water level segments were chosen, and EVI, NDVI, and MNDWI indices were calculated on a pixel-by-pixel basis. Surface water was identified using the criteria ($MNDWI > NDVI$ and $EVI < 0.1$) or ($MNDWI > EVI$ and $EVI < 0.1$). Pixels meeting these conditions were classified as surface water and assigned a value of 1; otherwise, they were classified as non-water and assigned a value of 0. Water frequency analysis was conducted to determine the floodplain inundation extent of the Jingjiang section. The floodplain inundation ranges for 1990, 2000, 2010, and 2020 were compared, as illustrated in Figure 5. Furthermore, the area of the water body frequency map from 1984 to 2022 was quantified. To achieve this, images from February and August of each year were selected to represent the lowest and highest water levels, respectively.

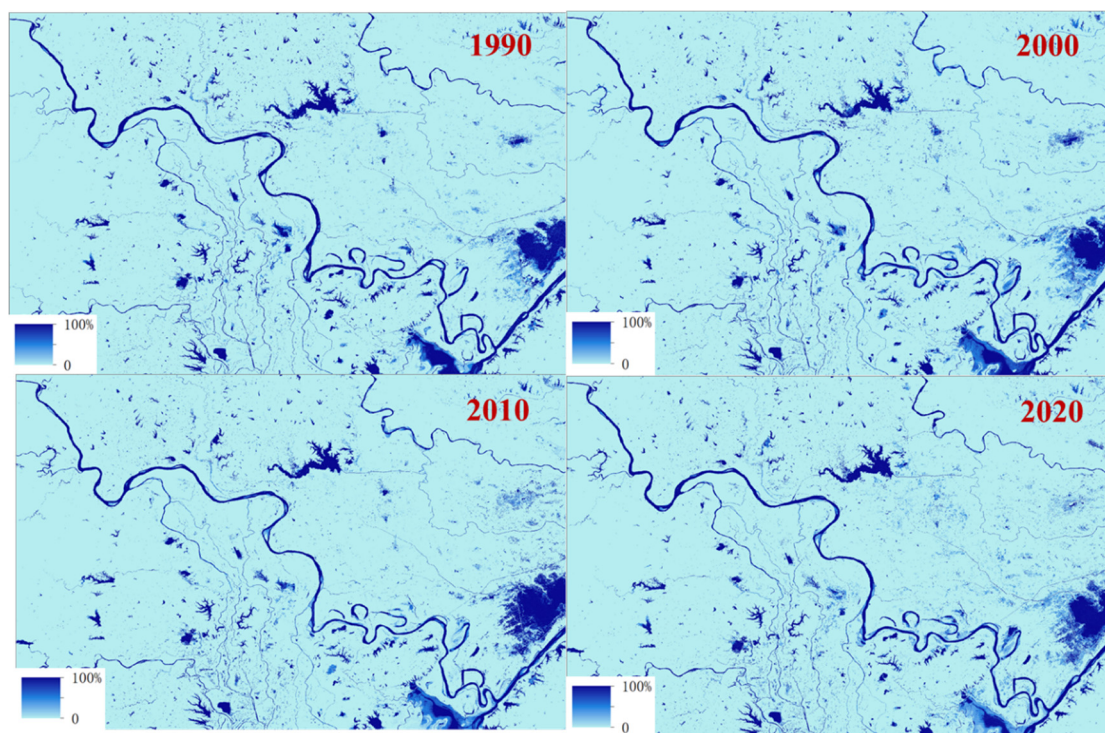


Figure 5. The floodplain inundation ranges in 1990, 2000, 2010, and 2020.

According to Figure 6 and Table 1, the water area of the JJR during the dry season from 1986 to 2022 has remained relatively stable within the range of 310 to 350 km². This

stability in the dry season water area reflects the permanent water coverage of the JJR. In contrast, the wet season submerged area generally exhibits a downward trend, with a peak of 516.7 km² observed in 1998, coinciding with the extreme flooding event of that year. The change in floodplain inundation extent mirrors the trend of the wet season submerged area, also showing a general decline and reaching its maximum of 187.6 km² in 1998. As illustrated in Figure 7, the flooded area of the floodplain in the JJR is highly correlated with the annual difference between the highest and lowest water levels, and the interannual variation trend is downward. Figure 5 intuitively demonstrates that, compared to 1990, the inundation range in both 2010 and 2020 has remained relatively stable.

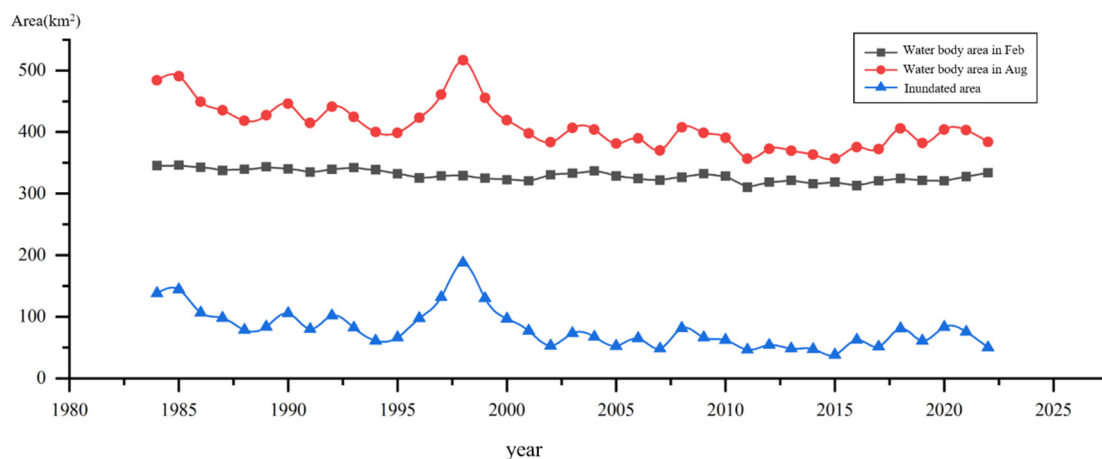


Figure 6. The water body and inundated area of the JJR.

Table 1. 1984–2022 water body and inundated area of the JJR.

Year	Water Body Area in February (km ²)	Water Body Area in August (km ²)	Inundated Area (km ²)
1984	345.6	483.8	138.2
1985	346.3	490.7	144.4
1986	342.8	449.3	106.5
1987	337.5	435.5	98
1988	339.6	418.2	78.6
1989	343.5	427.2	83.7
1990	340.1	445.8	105.7
1991	334.8	414.7	79.9
1992	339.3	441.1	101.8
1993	342.3	424.5	82.2
1994	338.9	399.9	61
1995	332.1	398.5	66.4
1996	325.5	423.2	97.7
1997	328.9	460.6	131.7
1998	329.1	516.7	187.6
1999	325.3	455.4	130.1
2000	322.5	419.3	96.8
2001	320.9	397.9	77
2002	330.6	383.5	52.9
2003	333.4	406.7	73.3
2004	336.8	404.2	67.4
2005	328.6	381.2	52.6
2006	324.6	389.5	64.9
2007	321.9	370.2	48.3

Table 1. *Cont.*

Year	Water Body Area in February (km ²)	Water Body Area in August (km ²)	Inundated Area (km ²)
2008	326.3	407.8	81.5
2009	332.4	398.8	66.4
2010	328.3	390.7	62.4
2011	310.2	356.7	46.5
2012	318.6	372.7	54.1
2013	321.5	369.7	48.2
2014	315.9	363.3	47.4
2015	318.6	356.8	38.2
2016	312.9	375.5	62.6
2017	320.9	372.2	51.3
2018	324.7	405.8	81.1
2019	321.3	382.3	61
2020	320.8	404.2	83.4
2021	327.8	403.2	75.4
2022	333.8	383.8	50

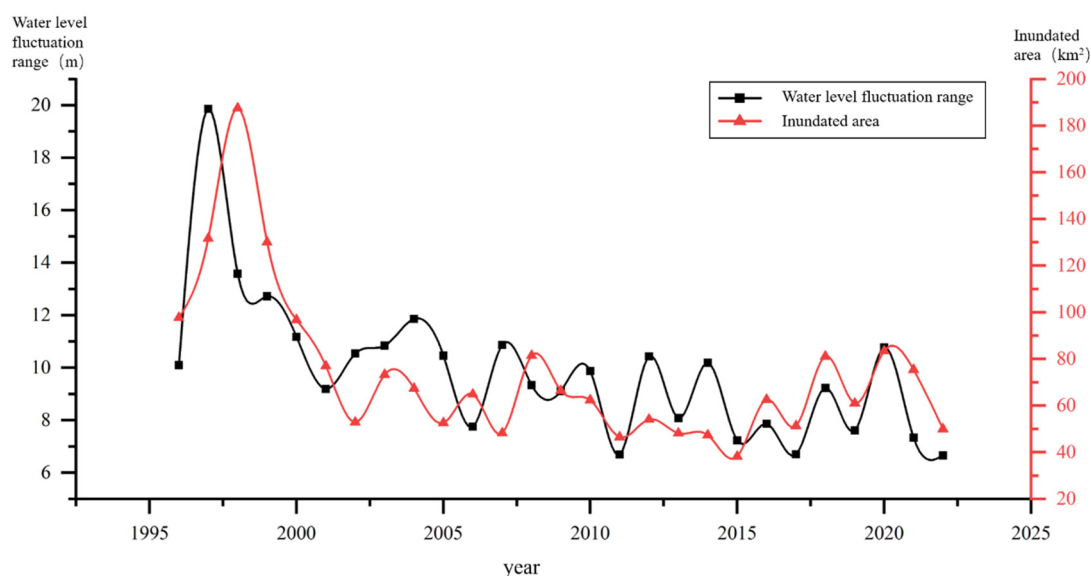


Figure 7. The water level fluctuation range of the JJR.

In conclusion, analysis of the hydrological data reveals that the inundation characteristics and dynamic changes of the floodplain in the JJR are largely consistent with the quantitative assessments derived from satellite remote sensing imagery. From 1986 to 2022, the extent of inundation in this region has generally exhibited a declining trend, with its area showing a strong correlation to the annual difference between peak and lowest water levels. Following the impoundment of the Three Gorges Reservoir, the interannual variability in inundation extent has stabilized, indicating that the hydrological conditions significantly influence the inundation dynamics of the floodplain in the middle reaches of the Yangtze River.

4.3. Categorization of Microhabitat Environmental Units in Inundated Zones

Due to the overlap between the UAV images, Pix4D mapper v4.5.6 was utilized for the stitching and rectification of the aerial imagery. Ultimately, 58,744 aerial images were processed and stitched into 50 digital orthoimages, which were stored in TIFF format based on the acquisition point locations. The digital orthophotos were stored in RGB format with

a ground resolution of 1.5 cm GSD. The resulting orthophotos exhibit no visible stitching artifacts, no apparent image cracks or gaps at the edges, homogeneous color tones, clear textures, and no noticeable misalignment or distortion of roads and buildings, thereby meeting the experimental requirements.

The subsequent phase involved the systematic identification and classification of the stitched river river images. Prior to initiating the classification process, it is essential to conduct pre-processing of the image data. The initial step entails defining the classification categories and labels. This study primarily focuses on assessing the types and degrees of anthropogenic disturbances in the inundated zone. After a comprehensive review of all images, nine feature categories were identified: water, soil/sand, gravel, grass, shrubs/trees, roads, ports/jetties, hard embankments, and other structures (Figure 8). These nine feature classes comprehensively encompass the feature types present in the study area. Five spliced images were selected as the training dataset, which were subsequently labeled and mapped using ArcMap to generate the feature label samples.

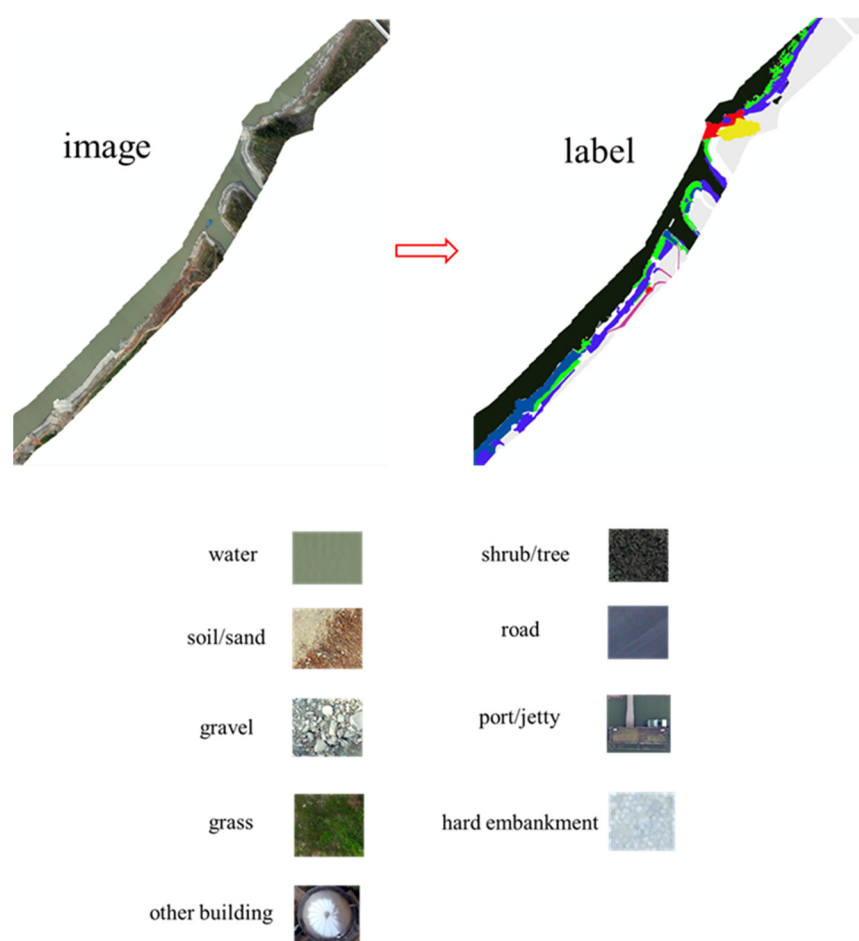


Figure 8. Stitched image and label with nine feature classes.

The quality and quantity of deep learning samples are critical factors that influence the classification accuracy of the model, directly impacting both its performance and the reliability of its results. Due to limitations in computer memory, it is impractical to input an entire mosaic image directly into the training process. Instead, the mosaic UAV images were divided into smaller segments through cropping. Consequently, this study selected five mosaic images encompassing all terrain categories as training samples. These images and their corresponding labels were cropped into 512×512 sample blocks using a standardized clipping method. To ensure a one-to-one correspondence between images and labels,

sample blocks with a background blank ratio exceeding 0.9 were excluded. Ultimately, we obtained a dataset comprising 19,671 images with dimensions of 512×512 along with their respective labels for deep learning purposes. This dataset was subsequently divided according to an 8:1:1 ratio for the training set, validation set, and test set, respectively, resulting in 15,737 training samples, 1967 validation samples, and 1967 test samples.

Given the substantial volume of classification data and high-resolution images, this study opted for an offline server to conduct preliminary processing of deep learning datasets. Following this initial processing, the data were uploaded to a cloud server for subsequent model training, testing, and prediction. The experimental training network utilized the aforementioned enhanced U-Net model. For the learning rate of model training, a cosine annealing decay strategy was employed, with an initial learning rate set to 0.0001. The restart cycle was established at 20 epochs, and the cycle multiplication factor was set to 2. Each iteration processed a batch size of six samples, and the total number of training epochs was set to 50. To further enhance the robustness of our model training process, we implemented the Early Stopping strategy and integrated weight decay regularization into the model's weight parameters. These measures were designed to constrain model complexity and reduce the risk of overfitting. Moreover, Cross Entropy Loss was adopted as the loss function to rigorously evaluate the efficacy of network training.

At the outset of the experiment, we initiated the model training process utilizing the training and validation datasets, with the number of iterations set to 50 epochs. To mitigate the risk of overfitting, we implemented an Early Stopping mechanism, which halts training if there is no improvement in validation accuracy for 10 consecutive epochs. Consequently, the model ceased training after 44 epochs, with a total training duration of 462.4 min. The trends in accuracy and loss during both training and validation are illustrated in Figures 9a and 9b, respectively. In the process of model training, as the number of input batches increases, the training and validation losses, as well as accuracies, gradually converge in an oscillatory manner. After 40 epochs of training, both the training and validation losses and accuracies progressively stabilize, demonstrating that the model training is effective under this parameter configuration. The optimal validation accuracy achieved was 87.50%, while the corresponding training accuracy stood at 85.71%, both occurring at the 19th epoch. Upon applying the trained model to the test set, an overall classification accuracy of 81.85% was obtained, indicating that the model exhibits satisfactory generalization performance.

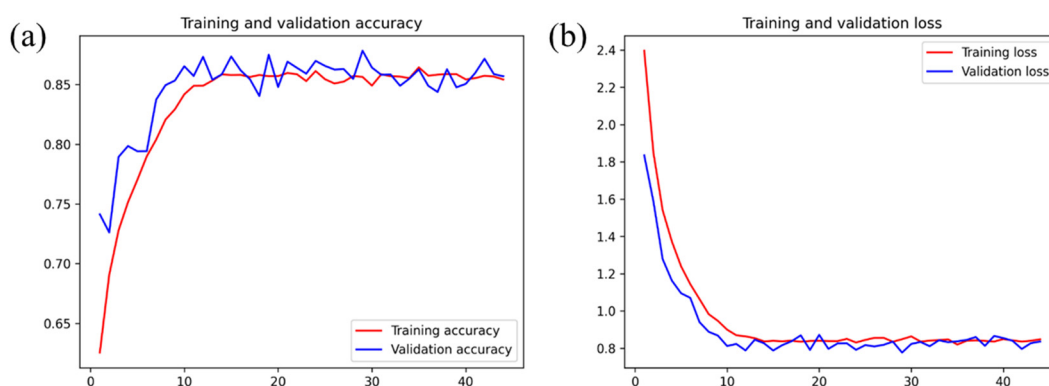


Figure 9. Accuracy and loss in training and validation of CBAM-SEU-Net model. (a) Training and validation accuracy. (b) Training and validation loss.

Figure 10a illustrates the model's prediction for a representative stitched image, while Figure 10b presents the corresponding real image. The test images encompass all predefined terrain classes. A visual analysis of the classification results reveals that, despite achieving over 80% accuracy in both training and testing phases for high-resolution UAV images,

numerous misclassifications persist. For instance, water is incorrectly classified as grassland in the upper left corner, and certain areas confuse hard banks with gravel sand. This issue primarily arises from the high pixel density in high-resolution images and the complexity of elements within the floodplain region. Specifically, insufficient training samples for large-area floodplain images lead to inadequate feature extraction and learning by the model. Consequently, when dealing with diverse features, inter-feature correlations can negatively impact each other, thereby reducing the model's accuracy and generalization capability. According to the model's classification results, the accuracy for distinguishing between floodplain water and land is relatively high, with higher precision observed in water–land junction areas compared to land alone. Additionally, the recognition accuracy for port terminals or ships along the coast is notably higher, whereas the differentiation between hard banks and bare soil/sand remains low. Overall, the proposed model demonstrates effective identification of artificial features and natural vegetation within the microhabitat of the floodplain, making it suitable for classifying artificial structures and vegetation in such environments.

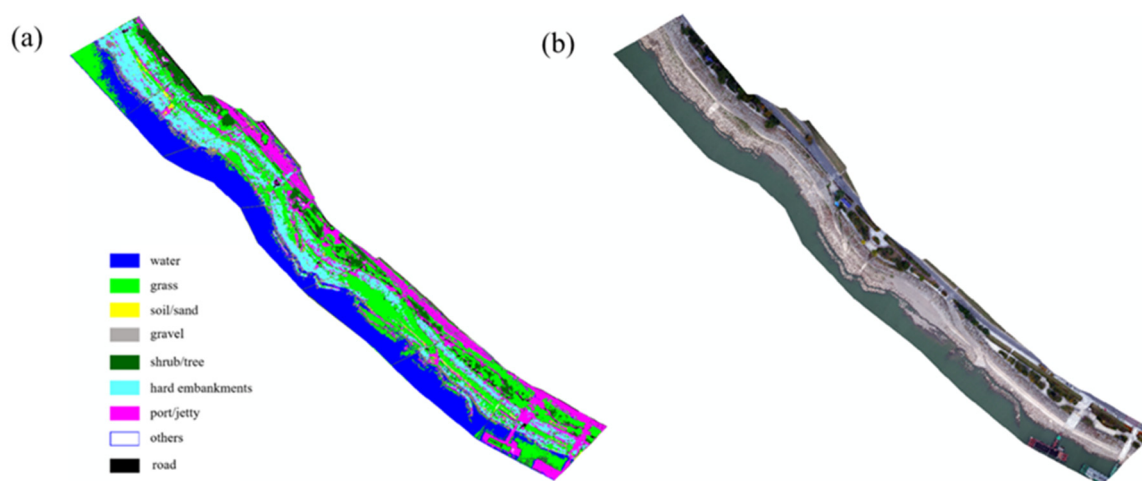


Figure 10. Prediction for a representative stitched image and the corresponding real image. (a) Predicted image. (b) Real image.

To validate the effectiveness of the enhanced U-Net floodplain microhabitat classification model, the experiment utilized the same dataset to train both the original U-Net model and the CBAM-SEU-Net model. The training accuracy and loss are illustrated in Figure 11. For the high-resolution floodplain image dataset, the U-Net model achieved a training accuracy of 73.19% and a validation accuracy of 69.05%. The performance of the CBAM-SEU-Net model and the original U-Net model was evaluated using the same test set, with results presented in Tables 2 and 3. The CBAM-SEU-Net model demonstrated significantly higher accuracy on high-resolution floodplain images, achieving an overall accuracy that is 16.39% higher than that of the U-Net model. This indicates that the parallel attention mechanism effectively enhances feature extraction for complex images, fully utilizing multi-scale feature information and significantly optimizing the model network.

Table 2. Model accuracy evaluation.

Model	OA	mIoU	FWIoU
CBAM-SEU-Net	81.85%	54.56%	70.79%
U-Net	65.46%	41.83%	51.39%

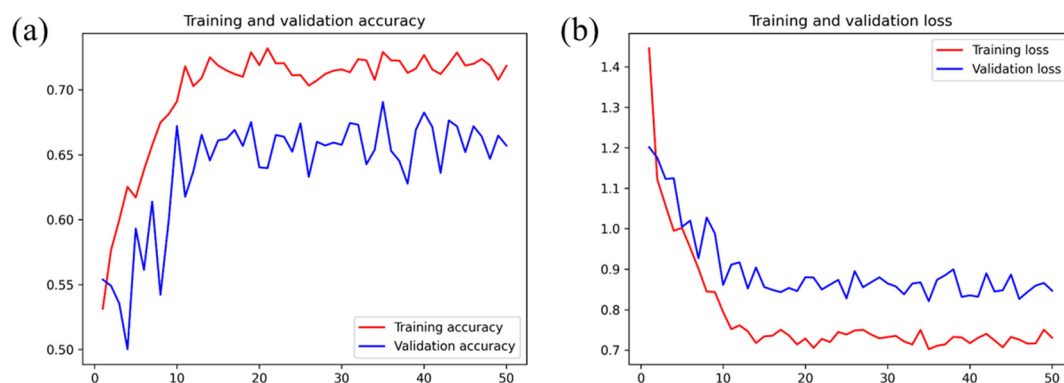


Figure 11. Accuracy and loss in training and validation of U-Net model. (a) Training and validation accuracy. (b) Training and validation loss.

Table 3. Category accuracy evaluation.

Categories	Water		Soil/Sand		Gravel	
	CBAM-SEU-Net	U-Net	CBAM-SEU-Net	U-Net	CBAM-SEU-Net	U-Net
Recall	96.68%	93.32%	71.61%	80.79%	74.04%	80.31%
Accuracy	96.13%	63.55%	72.31%	43.13%	79.12%	82.99%
F1-Score	96.41%	75.62%	71.96%	56.23%	76.49%	81.62%
IoU	93.06%	60.79%	56.21%	39.11%	61.94%	68.95%
grass			shrub/tree		road	
	CBAM-SEU-Net	U-Net	CBAM-SEU-Net	U-Net	CBAM-SEU-Net	U-Net
Recall	80.23%	69.76%	75.69%	39.43%	47.82%	56.46%
Accuracy	90.07%	94.52%	73.39%	54.66%	31.68%	37.71%
F1-Score	84.86%	55.65%	74.53%	61.29%	38.11%	45.21%
IoU	73.71%	38.55%	59.41%	44.19%	23.54%	29.21%
port/jetty			embankment		others	
	CBAM-SEU-Net	U-Net	CBAM-SEU-Net	U-Net	CBAM-SEU-Net	U-Net
Recall	78.65%	75.37%	80.33%	89.45%	44.09%	20.67%
Accuracy	79.99%	61.37%	87.81%	75.68%	12.04%	4.11%
F1-Score	79.31%	67.65%	83.91%	81.99%	18.91%	6.86%
IoU	65.72%	51.12%	72.27%	69.48%	10.44%	3.55%

Regarding the classification accuracy of various object categories, the enhanced CBAM-SEU-Net model demonstrates superior performance compared to the U-Net model in classifying most ground objects (Figure 12). However, for gravel and road classifications, the U-Net model outperforms the enhanced U-Net model. This indicates that the enhanced U-Net model excels over the standard U-Net model in extracting finer-scale features. For instance, the enhanced U-Net model significantly surpasses the U-Net model in classifying two ground objects with similar characteristics: grass and shrub/tree. In summary, from an evaluation perspective of model accuracy, the CBAM-SEU-Net model can be effectively utilized for the classification of microhabitat features in the JJR.

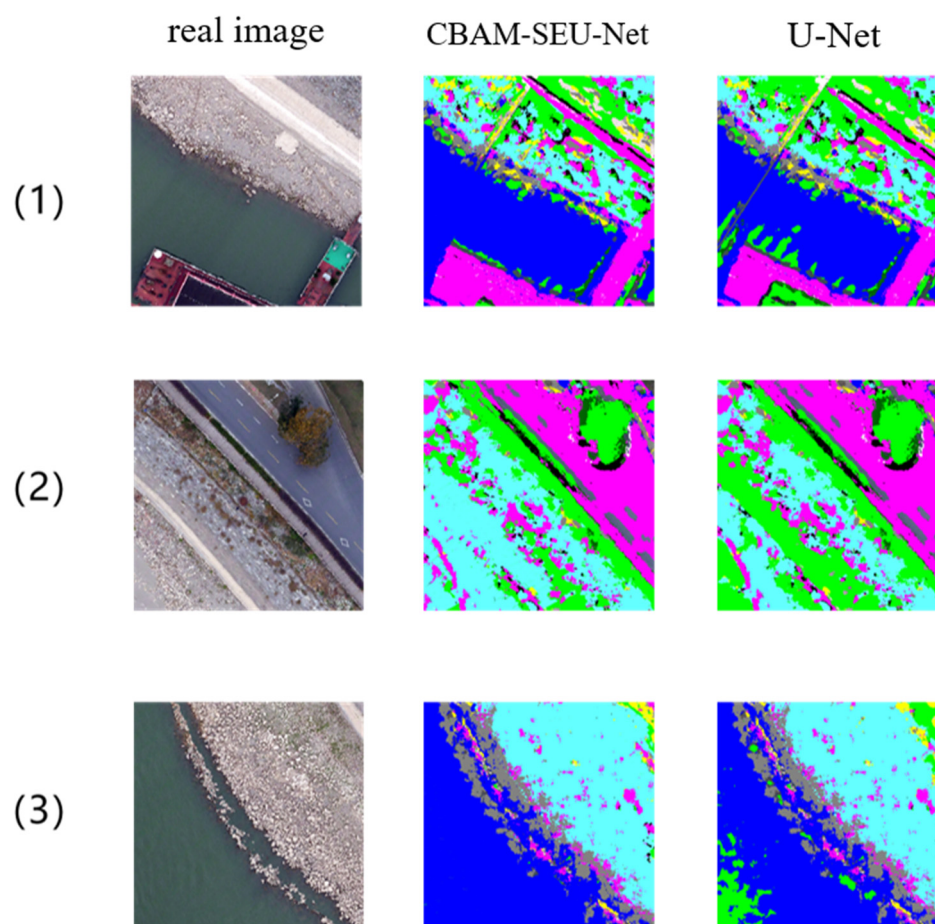


Figure 12. Predictions of CBAM-SEU-Net and U-Net model.

In the accuracy evaluation of the model, while the overall classification accuracy of the improved U-Net model is higher than that of the original U-Net model, the classification accuracy for certain categories has decreased. This reduction is particularly evident in categories with prominent edges and textures, such as roads and gravel. The potential reason may lie in the fact that the skip connections in the original U-Net model directly transmit low-level features like edges and textures. However, the introduction of attention mechanisms might suppress these critical features. Specifically, the spatial attention mechanism in CBAM could excessively smooth out low-level features. Moreover, for small target categories such as gravel, the channel weights can be easily diluted by the global pooling operation in SE, leading to feature loss. These factors may contribute to the decline in classification accuracy for some categories. In subsequent research, strategies such as optimizing the global average pooling within the attention structure or modifying the loss function could be employed to balance the impact of the attention mechanism on low-level features, thereby enhancing the model's classification accuracy.

The ignored edge prediction algorithm was employed to classify UAV images of microhabitats in the floodplain of the JJR. The classification results were then quantitatively analyzed in ArcGIS to determine the area of each microhabitat category in the floodplain and the number of environmental geology units under each control section. The microhabitat of the floodplain in the JJR has experienced significant human-induced disturbance. Although most natural ecological features are preserved in some river sections, the vegetation coverage within the floodplain microhabitat areas remains below 30%. Moreover, during the classification process, it was observed that a considerable proportion of the floodplain vegetation comprises anthropogenic features, such as meadows on hardened

banks or flower beds in riverside parks, which have been erroneously categorized as natural components. Figure 13 indicates that the proportion of artificial features within the JJR floodplain is less than 50% at most locations or river reaches. Notably, Sections 4 (Shashi) and 12 (Chenglingji) exhibit the highest levels of artificial features, exceeding 70%, with hard banks constituting the predominant feature in these sections. Beyond hard banks, Section 12 (Chenglingji) also serves as the control section with the largest number of ports or docks, which collectively account for over 20% of the area. Furthermore, compared to the historical period, the environmental units of the floodplain have significantly diminished. The majority of vegetation now consists of artificially planted landscapes, while natural environments such as bare soil and gravel have been largely replaced by impermeable concrete structures, leading to severe fragmentation of structural units.

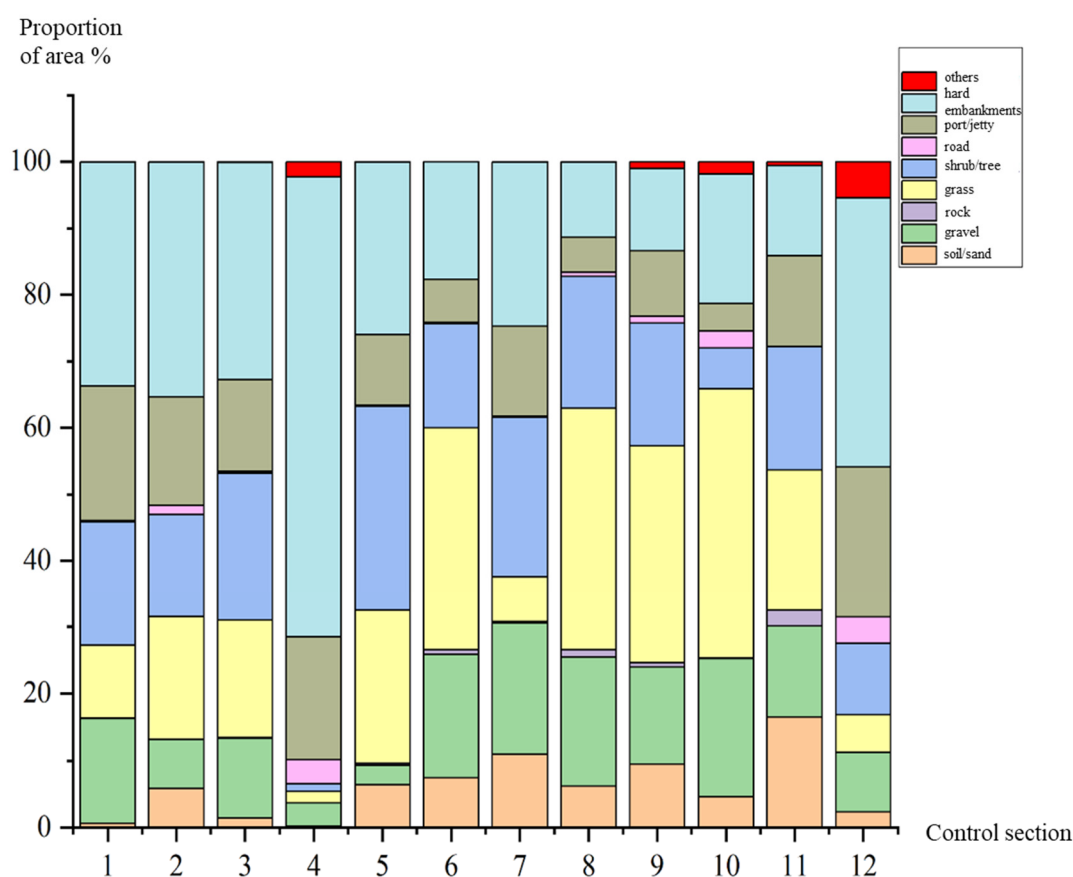


Figure 13. The proportion of different types of feature in the JJR floodplain inundated area.

5. Discussion

5.1. Key Factors Influencing the Dynamics of Floodplain Inundation Extent

Understanding the changes in floodplain inundated areas of large rivers and their impacts on river ecosystems is crucial for effective river management. This study reveals that the submerged area of the floodplain in the JJR has experienced an overall decline over the past four decades. The extent of floodplain inundation is influenced by multiple factors, including climate change and human-induced alterations to river systems. The construction of dams and water regulation projects has significantly altered natural hydrological conditions, reducing peak flood discharges and diminishing both the frequency and duration of floodplain inundation. Following the impoundment of the Three Gorges Reservoir from 2002, the floodplain inundation range in the middle and lower reaches of the Yangtze River stabilized. The reservoir's regulation and storage capacity modified the

seasonal flooding patterns of the floodplain, with the maximum flooded area decreasing by approximately 42.3% post-impoundment compared to pre-impoundment levels. Additionally, land use practices within floodplain areas represent another critical factor influencing floodplain inundation extents. Using China's 30 m annual land cover dataset from 1985 to 2020 [41], the land use types of the JJR floodplain were extracted, and the relationship between changes in land use types and floodplain area was analyzed (Figure 14). We discovered that the extent of the submerged area within the floodplain was significantly associated with land use type. In the classification of floodplain land cover at a 30 m resolution, only five categories were identified in the JJR floodplain: farmland, forest, grass, bare land, and impervious surface. Among these, grass and bare land were scarce, with their combined area not exceeding 1 km². This finding contrasts somewhat with floodplain microhabitat classifications derived from high-resolution UAV imagery, primarily due to spatial scale limitations imposed by the resolution difference. Regarding land cover distribution, farmland and impervious surfaces collectively accounted for over 90% of JJR floodplain area, with farmland comprising more than 70%. Since 1985, the proportion of farmland has decreased markedly, while the proportion of impervious surfaces has increased substantially. Additionally, the areas of forest and grassland have gradually diminished. The floodplain area exhibited a significant positive correlation with forest and bare land areas ($p < 0.01$) and a negative correlation with impervious surface area ($p < 0.01$) (Figure 15). These results suggest that human activities are increasingly encroaching upon the natural environmental components of the floodplain.

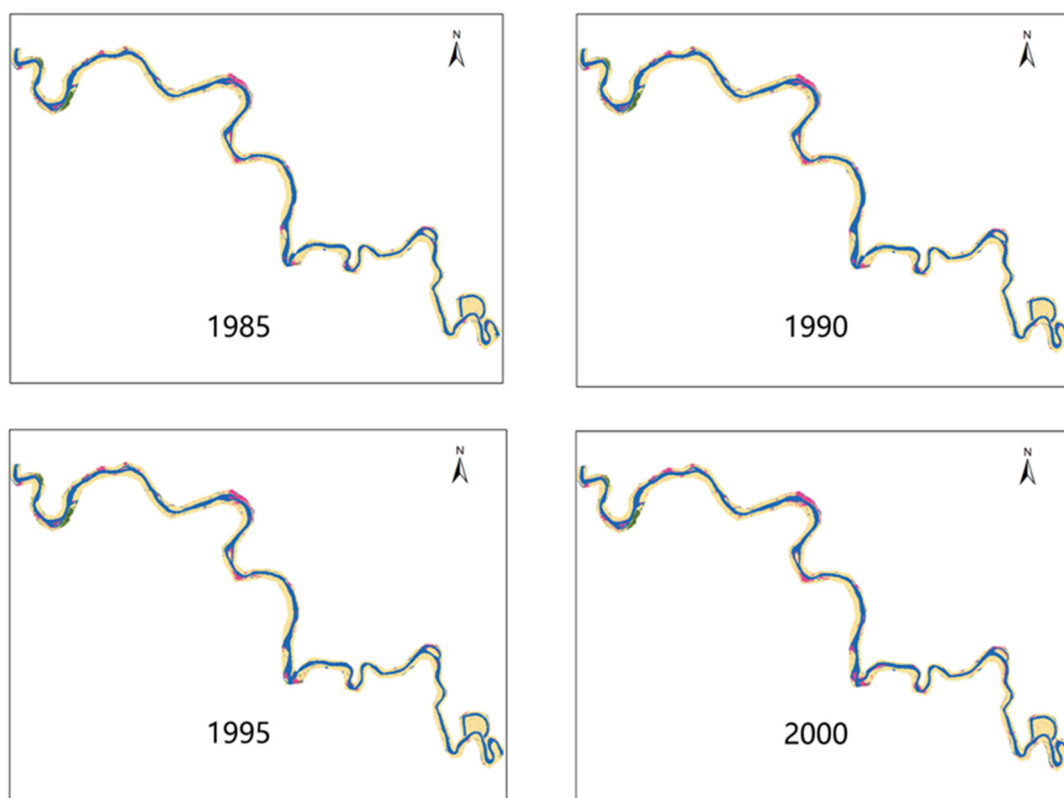


Figure 14. Cont.

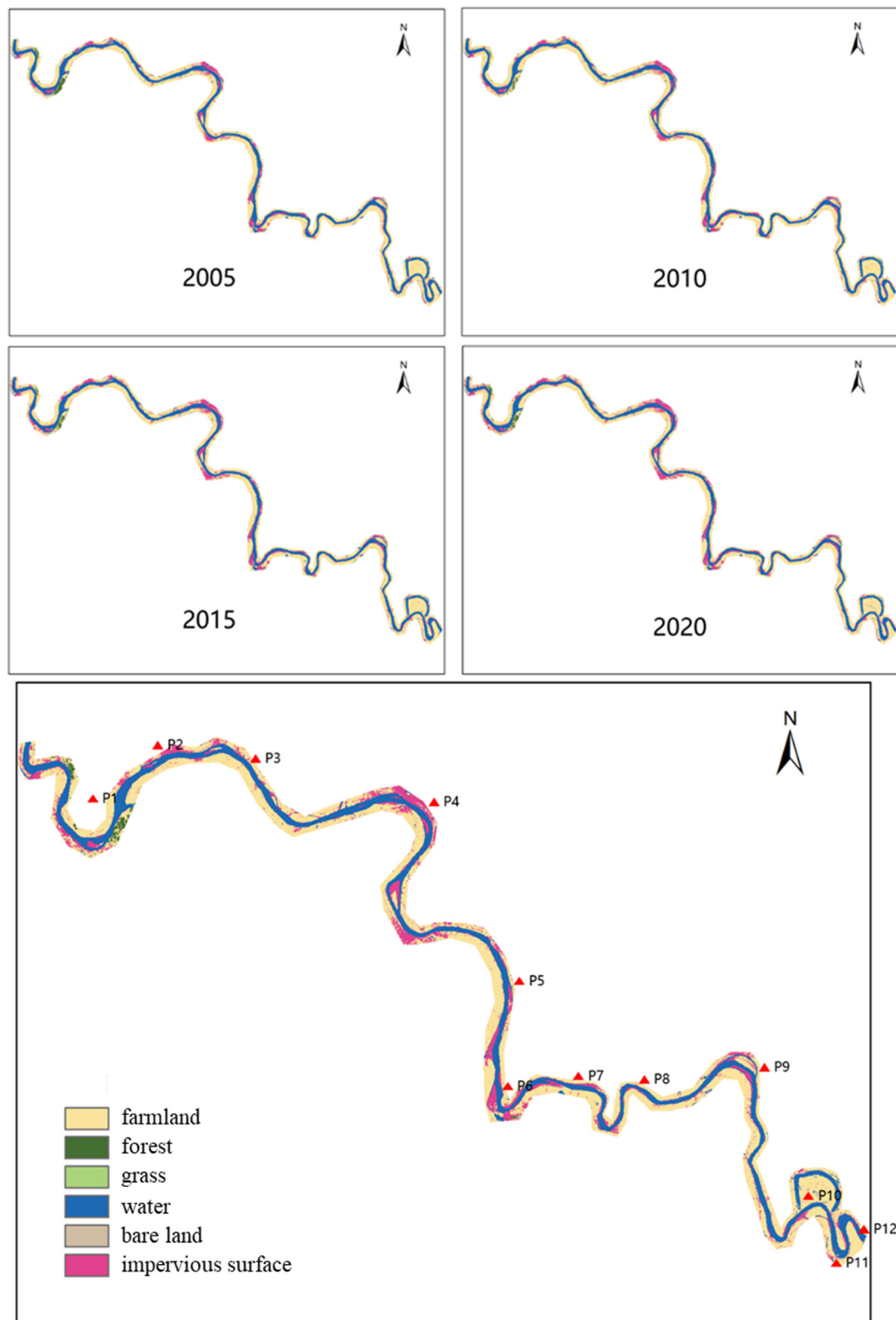


Figure 14. Land use cover of JJR floodplain from 1985 to 2022.

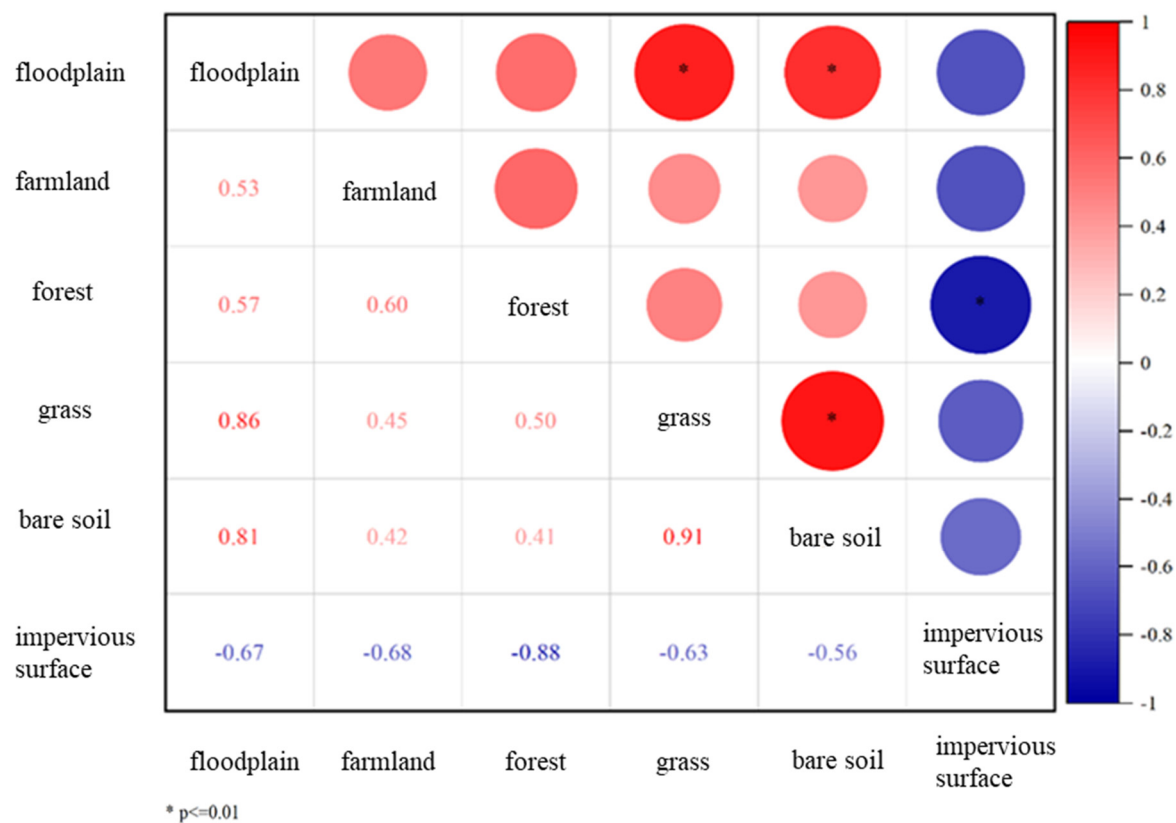


Figure 15. Correlation between floodplain area and land use type area of JJR.

5.2. Drivers of Change in Environmental Units

The variation in the submerged area of the floodplain results in continuous alterations to the micro-landforms of the floodplain. These environmental geomorphic units can consist of sediments, such as wood, vegetation, gravel, and sand, which were initially categorized based on their spatial positioning within the river course [15,16]. Classification research has primarily focused on the structure and function of geomorphic units, with the structural aspect referring more specifically to the intrinsic characteristics of these units themselves. Currently, the most comprehensive geomorphic unit classification system is derived from the EU FP7 project “Restoration of Rivers for Effective Catchment Management” (REFORM), which employs a self-designed hydrological morphological assessment procedure. Notable contributions include the Geomorphic Units Survey and Classification System (GUS) [42], as well as works by Asselman and Middelkoop [43]. Based on the high-resolution UAV images acquired, this study systematically classified the environmental geological units within the floodplain inundated area of the JJR. Nine environmental units were identified and categorized as water body, soil/sand, gravel, grass, shrub/tree, road, ports/jetty, hard embankment, and other structures. Due to the significantly lower resolution of historical remote sensing images compared to the acquired UAV images, it is challenging to discern finer-scale environmental units. Nevertheless, the analysis of land use dynamics from historical remote sensing images reveals a consistent annual increase in impervious surface areas within the floodplain inundated zone. From a classification perspective, artificial hardening units, including roads, ports/jetties, and hard embankments, account for approximately 40% of the total inundated area. The original riparian forest environment unit has largely vanished, with vegetation in the flooded region now predominantly consisting of meadows and some cultivated trees. The loss and transformation of these environmental units are intricately linked to long-term human activities. The rapid process of coastal urbanization and the development of cascade hydropower

in the upper reaches have resulted in the decline of fisheries and rice agriculture in the floodplain. The construction of flood control embankments along the Yangtze River has intensified surface hardening in the flooded areas of the floodplain, thereby encroaching upon the original natural environmental units [44]. Meanwhile, the development of the golden waterway of the Yangtze River has led to an increase in the number of ports and docks along its banks, reducing the proportion of the natural shoreline [45]. Thus, the artificial environment, characterized by hardened concrete structures, is gradually altering the structural composition of the floodplain inundation zone.

5.3. Impacts of Alterations in Floodplain Inundation Areas on Ecosystem

Floodplain microhabitats in the middle reaches of the Yangtze River serve as critical sites for fish to complete various key life history events. Notably, this region constitutes the primary spawning and nursery ground for the “four major Chinese carps” in the Yangtze River. These fish typically forage in lakes abundant with prey and spawn in rivers stimulated by suitable flow conditions [46]. After fertilization and hatching, larvae enter early growth stages, during which fry are unable to resist external disturbances and drift passively with the current. Most individuals are transported by the current to still water areas along the shore, where they feed or seek refuge. This process imposes strict requirements on both abiotic and biotic habitat conditions [47]. Floodplains play a vital role as foraging and predator-avoidance sites for juvenile fish during their early development. Young fish search for suitable prey in open areas while seeking shelter within the complex microhabitats of floodplains [48]. However, human-induced loss of microhabitats has negatively impacted their foraging and growth conditions, leading to reduced survival rates during early life stages. Consequently, this affects the resource abundance and population structure of these species [49]. Nowadays, the submerged area of the floodplain in the middle reaches of the Yangtze River has decreased significantly, resulting in the loss of natural environmental units and a gradual simplification of its ecological structure. As a consequence, the critical shelter and foraging habitats essential for the survival of important fish species have progressively disappeared, posing a severe threat to the survival and reproduction of fish populations in the Yangtze River. Therefore, this study aimed to conduct an in-depth analysis of the dynamic changes in the extent and structure of the Yangtze River floodplain, which not only quantitatively reflects the dynamic alterations of microhabitats within the Jingjiang section of the Yangtze River floodplain but also provides crucial background support for the protection and restoration of habitats for key fish species in the Yangtze River. Moreover, it holds significant implications for the development of fish habitat conservation strategies and the reconstruction of critical fish populations in the Yangtze River.

6. Conclusions

In this study, we analyzed the dynamic changes in the floodplain inundation area of the JJR River under human interference from two perspectives: the extent of floodplain submersion and the structural characteristics of the inundated region. This analysis was conducted using satellite remote sensing images and high-resolution UAV image data. An innovative enhanced U-Net network model integrating both CBAM and SE parallel attention mechanisms was constructed, which significantly improved the classification accuracy for high-resolution UAV images. The overall classification accuracy of the proposed model reached 81.85%. This method demonstrates strong applicability to high-resolution UAV image datasets of the JJR floodplain. Compared with the U-Net model, it significantly enhances the recognition accuracy for features that are either spectrally or structurally similar. Additionally, a combination of modified normalized difference water index (mNDWI),

Enhanced Vegetation Index (EVI), and normalized difference vegetation index (NDVI) was employed to extract the frequency of water inundation and precisely delineate the boundaries and areas of the JJR river floodplain. The change trend of the flooded area in the JJR aligns with the variation trend during the wet season, exhibiting an overall downward trend. The maximum flooded area of the floodplain reached 187.6 km² in 1998, and the flooded area is strongly correlated with the annual maximum–minimum water level difference. In 2022, the JJR floodplain experienced significant human-induced disturbances, with 40% of the area comprising anthropogenic environmental units. Compared to historical periods, the impermeable surface of the floodplain has been increasing annually, while ecological units such as riparian forests and trees have been gradually declining or even disappearing. The flooding area of the floodplain has been extensively replaced by artificial structures, such as hardened bank embankments, leading to a gradual simplification of its structural complexity.

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