

Article

High-Precision River Network Mapping Using River Probability Learning and Adaptive Stream Burning

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Highlights

What are the main findings?

- A novel method integrating river probability learning with adaptive stream burning is proposed for high-precision river network extraction.
- Multi-dimensional feature vectors combining spectral indices and multi-scale linear geometric features enhance river identification in complex environments.

What are the implications of the main findings?

- An adaptive stream burning algorithm dynamically adjusts burning depth based on flow accumulation, channel width, and linear features, improving hydrological consistency.
- The method outperforms existing methods in positional accuracy and morphological fidelity, especially for narrow, meandering, and braided rivers.

Abstract

Accurate river network mapping is essential for hydrological modeling, flood risk assessment, and watershed environment management. However, conventional methods based on either optical imagery or digital elevation models (DEMs) often suffer from river network discontinuity and poor representation of morphologically complex rivers. To overcome this limitation, this study proposes a novel method integrating the river-oriented Gradient Boosting Tree model (RGBT) and adaptive stream burning algorithm for high-precision and topologically consistent river network extraction. Water-oriented multispectral indices and multi-scale linear geometric features are first fused and input for a river-oriented Gradient Boosting Tree model to generate river probability maps. A direction-constrained region growing strategy is then applied to derive spatially coherent river vectors. These vectors are finally integrated into a spatially adaptive stream burning algorithm to construct a conditional DEM for hydrological coherent river network extraction. We select eight representative regions with diverse topographical characteristics to evaluate the performance of our method. Quantitative comparisons against reference networks and mainstream hydrographic products demonstrate that the method achieves the highest positional accuracy and network continuity, with errors mainly focused within a 0–40 m range. Significant



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improvements are primarily for narrow tributaries, highly meandering rivers, and braided channels. The experiments demonstrate that the proposed method provides a reliable solution for high-resolution river network mapping in complex environments.

Keywords: river network mapping; morphologically complex rivers; adaptive stream burning; conditional DEM

1. Introduction

Terrestrial river networks are essential for understanding hydrological processes, ecological sustainability, and water resource management [1–3]. As critical conduits for transporting water, sediments, and nutrients, they directly manage floodplain inundation dynamics and biogeochemical cycles through their longitudinal, lateral, and vertical connectivity [4,5]. For instance, based on the river network systems, the derived exchange capacity between floodplains and the main streams directly influences atmospheric emission fluxes. Therefore, accurate mapping of terrestrial river networks is a prerequisite for describing these complex processes and supporting global water resource research.

Specifically, two main data sources are employed for river network mapping: remote sensing images and digital elevation models (DEMs). Remote sensing methods detect rivers based on the spectral characteristics of the water body, providing relatively accurate locations. Recently, the application of cloud computing platforms (e.g., Google Earth Engine) has significantly advanced the efficiency of land and water resource management [6]. However, they are susceptible to obstructions from surface features (such as vegetation, buildings, and shadows) and do not incorporate topographical information, thus limiting effective river system classification [7–9]. Conversely, DEM-based methods utilize terrain analysis and flow dynamics, ensuring natural connectivity and basin topology in river extraction [10]. However, the accuracy is heavily dependent on DEM quality that may misrepresent the real networks. As the resolution of DEMs improves, extracted river networks can reveal more detailed topographies but are also susceptible to disturbances caused by micro-topography [11,12].

In recent years, these approaches combining the spectral information from remote sensing with the topographic fidelity of DEMs have become a research trend. The integration of both data sources ensures that the river network is not only geometrically accurate but also hydrologically consistent. For instance, the MERIT Hydro dataset employs a multi-source data fusion strategy. By integrating remote sensing information, MERIT Hydro locally corrects the river topography of the DEM and generates a river network with true spatial locations [13]. Wang et al. integrated remote sensing images with topographic data through a stream burning algorithm to refine DEM; this method generates a river network with topological structures [14]. Nevertheless, existing methods still exhibit significant shortcomings in addressing morphologically complex rivers.

To address these challenges, we propose a novel framework for the high-precision extraction of hydrologically consistent river networks. By integrating multispectral indices and the multi-scale geometric features of rivers, we construct a River-oriented Gradient Boosting Tree model to generate river probability values. A region growing algorithm that incorporates river probability values and directional constraints is then employed to extract river vectors. Furthermore, spatially adaptive stream burning is developed to integrate river vectors into DEM, producing a geometrically accurate and hydrologically consistent river network. The proposed method is evaluated across diverse topographical regions, showing strong performance, especially for rivers with complex morphologies

or complex backgrounds. It effectively overcomes the omissions and positional errors commonly encountered with traditional methods.

Contributions of the Research

The main contributions are as follows:

1. Unified multi-dimensional feature vectors are constructed, integrating water-oriented spectral indices and multi-scale linear geometric features to provide a comprehensive representation for distinguishing complex morphological rivers from complex backgrounds.
2. A probabilistic and morphology-aware extraction framework is developed, combining a River-oriented Gradient Boosting Tree model with direction-constrained region growing to generate geometrically accurate river vectors.
3. We propose spatially adaptive stream burning, which dynamically adjusts burning depth using local channel characteristics to produce a hydrologically conditioned DEM, significantly enhancing the positional accuracy and network continuity.

2. Related Works

In the following section, we explore the existing literature from two perspectives: river vectors extraction based on remote sensing imagery and river network extraction methods.

2.1. River Extraction from Remote Sensing Imagery

The core in river extraction from imagery is the accurate identification of water bodies. Methods have evolved from employing simple spectral properties to adopting complex spatial information and machine learning techniques. Spectral properties-based methods exploit the unique spectral signature of water, particularly its strong absorption in the shortwave infrared (SWIR) band. Indices like the Normalized Difference Water Index (NDWI) and the Modified NDWI (MNDWI) are widely used to enhance the contrast between water and land [15–17]. To address challenges in complex environments, researchers have developed more sophisticated indices. For instance, Wu et al. [18] proposed a Two-Step Urban Water Index (TSUWI) to suppress interference from shadows and buildings. Xie et al. [19] designed a novel index for WorldView-2 imagery that integrates its distinctive coastal blue, yellow, and red-edge bands for higher precision. Despite their computational efficiency, these methods may be complicated by spectral ambiguities, such as the spectral overlap between water bodies and dark shadows [20].

Instead of depending on spectral properties, spatial information-based methods employ the geometric characteristics of rivers (such as the linearity, curvature) [21]. Li et al. [22] extracted tidal channels based on morphological indicators including topographic curvature and linear profiles. Similarly, to extract rivers, Jin et al. [23] employed adaptive multi-scale region growing based on river linear features from Sentinel-2 imagery. A key advantage of these methods is their independence from spectral confusion in optical imagery. However, a significant limitation is the potential for false positives from non-river features with similar linear shapes, such as roads and ditches.

Machine learning-based methods are particularly effective at handling complex, high-dimensional feature spaces and have been widely applied to water body classification. Early applications included Multi-Layer Perceptrons (MLP) [24,25] and Random Forest models [26–28]. These models can achieve high classification accuracy. However, a common drawback is that their outputs are typically raster-based water vectors that lack inherent topological connectivity. To bridge this gap, Xue et al. [29] developed an integrated workflow (RF-ANN) that combined a Random Forest and an Artificial Neural Network, supplemented by an automatic centerline correction algorithm (ARWE) to obtain

topological information. In recent years, deep learning methods based on convolutional neural networks (CNNs) and architectures such as U-Net have achieved breakthrough progress in water body semantic segmentation tasks, enabling extremely high pixel-level classification accuracy [30]. In summary, these methods can produce high-precision water vectors, which alone are insufficient for hydrological applications. For example, these vectors lack topographical information, limiting effective river system classification.

2.2. River Network Extraction: From Skeletons to Data Fusion

Converting water vectors into river networks requires ensuring both geometric accuracy and hydrological correctness. After obtaining the water body vectors, a common strategy for constructing river networks involves skeletonizing them into centerlines. For instance, Isikdogan et al. [31] developed a RivWidth algorithm, which extracted river centerlines and widths from water vectors via morphological skeletonization and a graph-theoretic approach to resolve the complex braiding structures in river networks. Similarly, Allen et al. [32] utilized a skeletonization method on a global surface water map to derive river centerlines, which served as the foundational geometry for their Global River Widths from Landsat (GRWL) Database. However, this purely geometric process often results in fragmented line segments that lack important hydrological attributes, making them unsuitable for further hydrological applications.

DEMs provide topographical information, enabling the extraction of continuous and topologically correct river networks through hydrological analysis (e.g., using the D8 algorithm [33]). However, the accuracy is heavily dependent on DEM quality and may be incorrect in flat terrain or areas with complex micro-topography. To overcome these limitations, fusion-based methods that integrate the precise location from imagery with the topological information from DEMs have become the state of the art. The most related fusion algorithm is stream burning [34,35], which lowers the DEM elevation along known river vectors to enforce correct drainage. Conventional methods use binary river networks as input and a fixed burn depth, often generating artificial discontinuities. Recent research has focused on improving this algorithm. Wang et al. [14] proposed the Remote Sensing Stream Burning (RSSB) method, which fuses continuous water index values as quasi-bathymetry with DEMs to generate continuous 10 m resolution networks. Lu et al. [35] combined SWO data and Sentinel-2 imagery to enhance the NASA DEM using an improved algorithm (AGRSDEM), demonstrating superior locational accuracy. Similarly, Liang et al. [36] leveraged Sentinel-2 and MERIT DEM to enhance the extraction of small rivers on the Tibetan Plateau. Pioneering global datasets exemplify this approach, such as the HydroSHEDS product [37] and MERIT Hydro dataset [13]. These products significantly improved the reliability of global river networks [38].

Despite these advances, current fusion-based methods still have limitations. Their performance is often constrained by empirical parameters (e.g., a fixed burn depth) that may not adapt well to the river systems. Therefore, a more intelligent, adaptive, and automatic method to generate a high-precision and topologically consistent river network across diverse landscapes is needed. This gap motivates our proposed framework, which employs a River-oriented Gradient Boosting Tree model to intelligently fuse multi-dimensional features for robust river extraction and introduces an adaptive stream burning algorithm that dynamically adjusts burn depth based on local river characteristics.

3. Study Area and Datasets

3.1. Study Area

This study selects eight river regions with diverse hydro-morphological characteristics as experimental sites to evaluate their performance. These regions cover diverse climatic zones and topographical environments, ranging from plains to mountains and from arid to humid. Climatic zones include tropical rainforests, deserts, delta wetlands, and coastal regions; topographical variables include plateau mountains, plains, and hilly places; river morphology includes thread-like, network-like, and braided rivers. The distribution is shown in Figure 1, enabling comprehensive evaluation of the method adaptability and robustness. Table 1 summarizes the core environmental characteristics of the test sites.

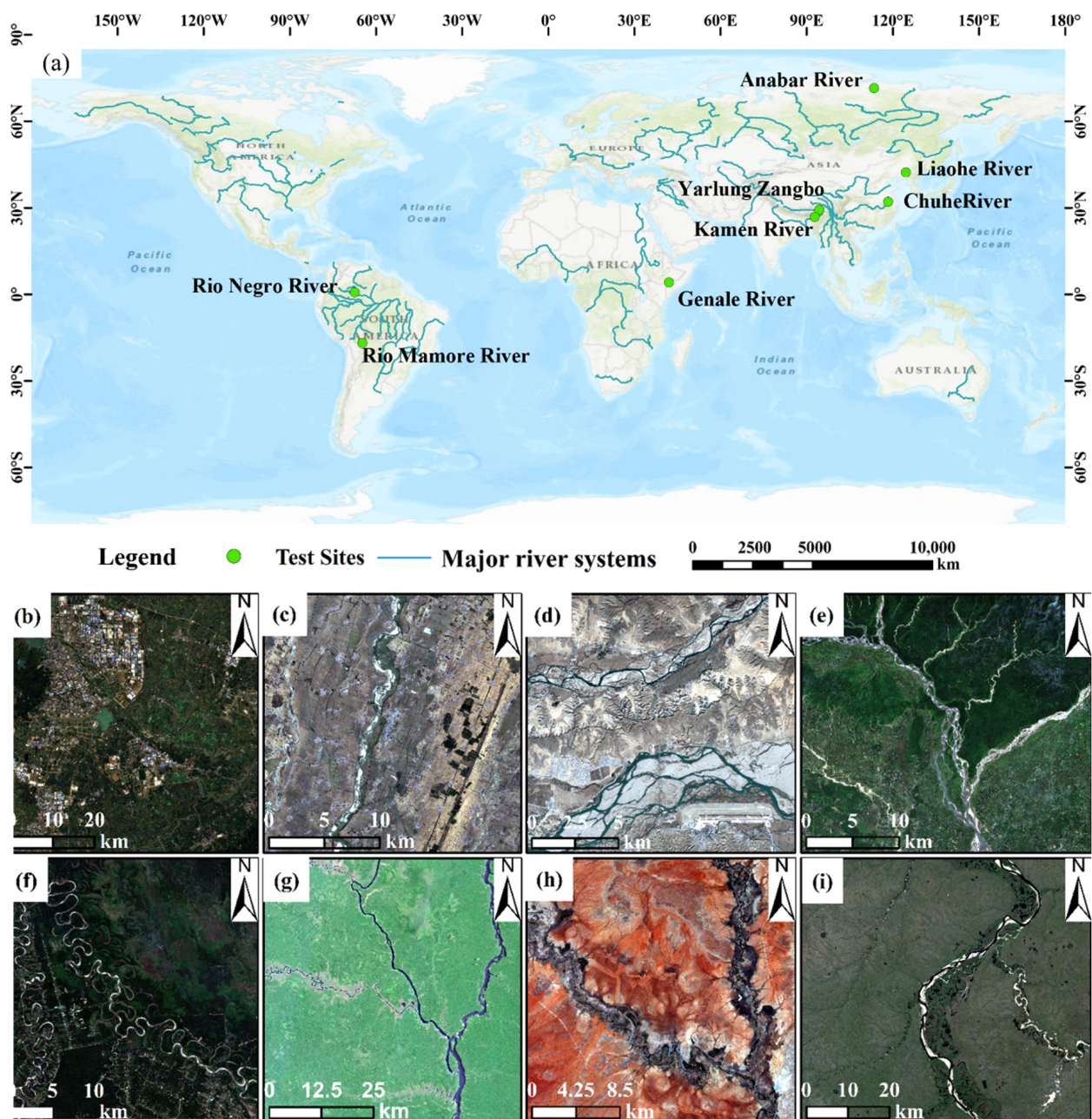


Figure 1. (a) Locations of the test sites; (b) Chuhe River in the East, China; (c) Dongliao River in the Northwest Territories, China; (d) Yarlung Zangbo river in Tibet, China; (e) Kamen River, India; (f) Rio Mamore River, Bolivia; (g) Rio Negro River in Amazonian plains; (h) Genale River, Ethiopia; (i) Anabar River in northwestern plateau, Russia.

Table 1. Specifications of the test sites.

Names	Sites	Background	River Type	Characteristics
Chuhe River	China	Plains, city	Thread	Urban interference, narrow channels
Dongliao River	China	hills	Wandering	Channel migration
Yarlung Zangbo River	China	Plateau, canyon	Braided	Topographic shadows, snow cover
Kamen River	India	Hills, plains	Wandering	Snowmelt, seasonal variations
Rio Mamore River	Bolivia	Lowland plains	Branching	Dynamic riverbed, frequent shifts
Rio Negro River	Brazil	Rainforest	Thread	Width variation, vegetation shading
Genale River	Ethiopia	Bare land	Wandering	Dense narrow channels
Anabar River	Russia	Tundra	Braided	Permafrost, freeze–thaw cycles

3.2. Satellite Imagery and DEM Data

This study employs multispectral imagery from the Copernicus Programme Sentinel-2 satellite. The imagery features 13 spectral bands, including the visible, near-infrared, and shortwave infrared spectrum (source: <https://sentiwiki.copernicus.eu/web/s2-mission> (accessed on 31 September 2025) [39]. For each study area, we select imagery data available during periods of abundant precipitation (16 June to 31 October), when the spectral contrast between river water bodies and their surrounding environments is most significant [40]. Simultaneously, we eliminate interference factors such as cloud cover, cloud shadows, and seasonal water bodies through median synthesis processing, resulting in a final image with a spatial resolution of 30 m for experiments. For each image, river areas are manually delineated through visual interpretation, marked as 1 for river sections; for non-river sections (marked as 0), we adopt a manual random sampling strategy to comprehensively capture background features, covering various non-river land cover types while maintaining a balanced river-to-non-river ratio of approximately 1:2.5. Furthermore, these samples are rigorously verified against high-resolution Google Earth imagery to ensure label purity. The vector layers are then converted into raster images to serve as ground truth vectors. Various water body indices and linear geometric features are subsequently calculated for each image. Using this approach, we completed data annotation for a total of 397 images and randomly split the dataset in a ratio of 7:1.5:1.5 for model training, validation, and testing, as illustrated in Figure 2.

The DEMs employed in this study for river network extraction are sourced from globally available datasets, consisting of four mainstream products: COP30DEM, NASADEM, AW3D30, and ASTER GDEM (details are presented in Table 2). Through comparative analysis of the river networks extracted from these DEMs, this study aims to evaluate the differential impact of varying terrain data on the structural accuracy and spatial characteristics of river networks.

Table 2. Specifications of the DEMs used in this study.

Dataset	Resolution	Vertical Accuracy (RMSE)	Data Collection Time	Data Source
COP30DEM [41]	30 m	~4 m	2010–2015	TanDEM-X mission radar observations
NASADEM [42]	30 m	~5.6 m	2000	NASA’s reprocessing of SRTM data
AW3D30 [43]	30 m	~8.6 m	2006–2011	JAXA’s ALOS PRISM-based product
ASTER [44]	30 m	~8.7 m	2000–2013	Collaborative product of NASA

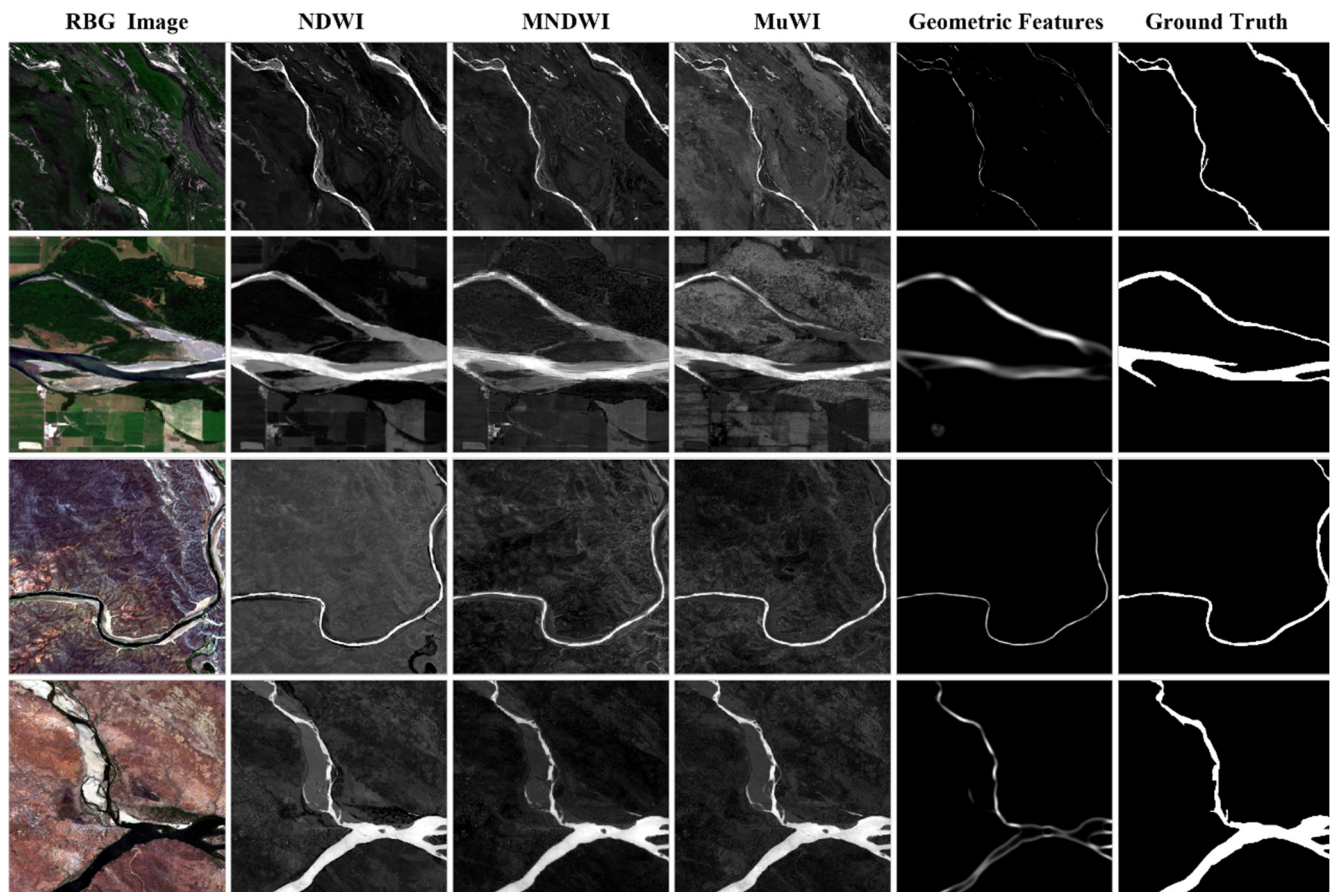


Figure 2. Partial samples of the training dataset.

4. Methods

We propose an integrated framework for high-precision river network extraction based on Sentinel-2 satellite imagery, which combines probabilistic river learning with adaptive terrain refinement. As shown in Figure 3, this method comprises three sequential stages: First, a multi-dimensional feature vector is constructed by integrating spectral indices and multi-scale linear geometric features, providing a robust foundation for river extraction. Second, we propose a River-oriented Gradient Boosting Tree model (RGBT) to generate river probability maps. Combined with directional constrained region growing, we obtain a geometrically accurate river vector. Finally, spatially adaptive stream burning adjusts the stream burning depth based on river characteristics and extracts a geometrically accurate and topologically consistent river network.

4.1. Construction of Multi-Dimensional Feature Vectors

To extract rivers from heterogeneous image backgrounds robustly, we construct a multi-dimensional feature vector integrating water-oriented multispectral indices and multi-scale geometric features, which together provide a robust representation of river characteristics across spatial scales. We employ atmospherically corrected Sentinel-2 Level-2A surface imagery from the Google Earth Engine (GEE) platform. To eliminate the impact of clouds and cloud shadows, a probabilistic cloud masking procedure was applied [45]. To ensure compatibility between multi-source data, both Sentinel-2-derived water indices and DEMs are standardized to a unified 30 m resolution grid.

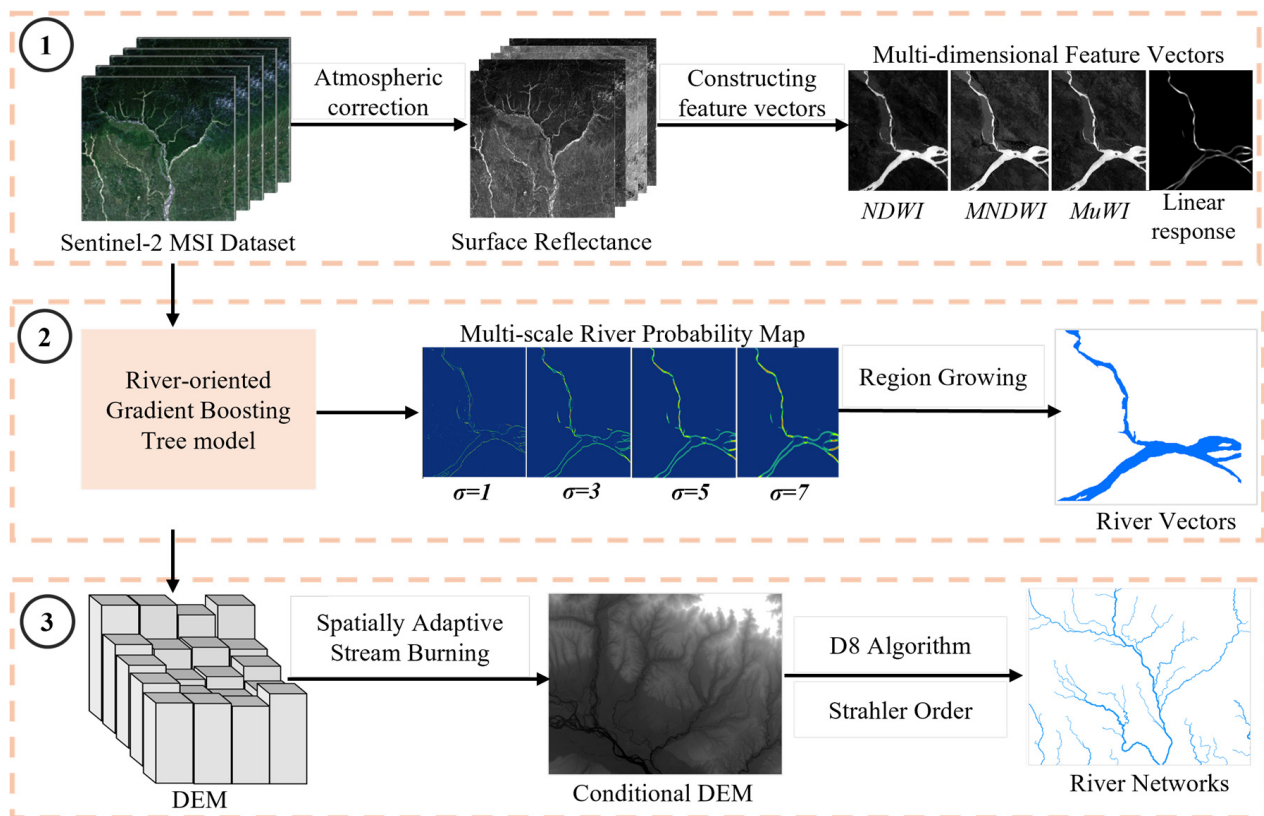


Figure 3. Flowchart of the river probabilistic learning and adaptive stream burning framework for river network extraction. (1) Construction of multi-dimensional feature vectors. (2) River vectors extraction. (3) River network generation.

Within the multi-dimensional feature vector, we compute three complementary water indices to enhance the spectral contrast between water and land covers. The Normalized Difference Water Index (*NDWI*) [46] enhances the spectral response of water bodies by combining green and near-infrared bands, providing fundamental spectral characteristics for water identification. The Modified Normalized Difference Water Index (*MNDWI*) [47] improves water detection in urban areas by incorporating shortwave infrared bands to suppress built-up noise. The Multispectral Water Index (*MuWI*) [48] employs optimized band combinations to maximize the spectral contrast between water and background features, which maintains sensitivity across diverse water quality conditions while effectively resisting environmental interference. The formulations of indices are defined as follows:

$$\begin{aligned}
 NDWI &= \frac{Green - NIR}{Green + NIR} \\
 MNDWI &= \frac{Green - SWIR1}{Green + SWIR1} \\
 MuWI &= -4ND(Blue, Green) + 2ND(Green, NIR) + 2ND(Green, SWIR2) - ND(Green, SWIR1)
 \end{aligned}
 \tag{1}$$

where $ND(i,j)$ represents the normalized difference between sentinel image bands i and j .

To address the limitations of spectral indices in complex scenes, we also incorporate multi-scale linear geometric features derived from the Hessian matrix. The *MuWI* image is first processed using a bias-corrected fuzzy C-means algorithm to improve water–land separation. The image is then convolved with Gaussian kernels to generate a scale space,

capturing the linear responses of rivers with varying widths. For each scale δ , we compute the Hessian matrix $H_\sigma(x, y)$ at pixel (x, y) as:

$$H_\sigma(x, y) = \begin{pmatrix} \frac{\partial^2 I_\sigma(x, y)}{\partial x^2} & \frac{\partial^2 I_\sigma(x, y)}{\partial y \partial x} \\ \frac{\partial^2 I_\sigma(x, y)}{\partial x \partial y} & \frac{\partial^2 I_\sigma(x, y)}{\partial y^2} \end{pmatrix} \quad (2)$$

where I_σ is the Gaussian-smoothed image at scale δ . Eigenvalue decomposition of H_σ yields eigenvalues λ_1, λ_2 ($|\lambda_1| \geq |\lambda_2|$) and corresponding eigenvectors. The linear geometric feature is defined as:

$$L_\sigma = \frac{|\lambda_2| - |\lambda_1|}{|\lambda_2| + |\lambda_1| + \varepsilon}, \quad \sigma = \{\sigma_i | i \in [1, k]\} \quad (3)$$

where ε is the stability constant. This response can capture the linear structure feature of river channels and enable the detection of river segments of various widths.

In summary, the multi-dimensional feature vector constructed for this study comprises four indicators: three water body indices (*NDWI*, *MNDWI*, *MuWI*) and one multi-scale linear geometric feature. The geometric feature is derived by integrating linear response values across four scales, forming the final four-dimensional feature vector for model training and prediction.

The integration of multispectral and geometric features forms a comprehensive multi-dimensional feature vector. This feature fusion strategy enhances the model generalization in complex environments and improves the accuracy for continuous river extraction.

4.2. River Extraction Based on Multi-Scale Probabilistic and Directional Constraints

In remote sensing imagery, rivers present linear or band-like structures. However, traditional linear response functions based on a single type of information often perform poorly in complex environments. To address this problem, we propose a River-oriented Gradient Boosting Tree Model (RGBT) to learn a probability response function. RGBT generates probability maps of rivers by using the constructed multi-dimensional feature vectors. Combined with the region growing algorithm, it significantly enhances the robustness of river extraction.

4.2.1. Construction of River-Oriented Gradient Boosting Tree Model

Advanced machine learning algorithms, due to their robustness to noise and ability to model nonlinear relationships, have been widely applied. Among them, the Gradient Boosting Tree model is well suited for complex river environments, as it effectively captures nonlinear relationships and high-order feature interactions [49]. Consequently, we construct an RGBT model for river prediction.

In the training dataset $\{(\tau_i, p_i)\}_{i=1}^N$, where τ_i denotes the formed multi-dimensional feature vector for each pixel, and $p_i \in \{1, 0\}$ represents the prediction of river or non-river. The training data include 397 images randomly selected from the eight aforementioned test sites, comprising both river and non-river pixels. The RGBT model operates as an additive ensemble of decision trees, trained through iterative minimization of the following objective function:

$$\varphi = \sum_{i=1}^N L(p_i, F(\tau_i)) + \sum_{m=1}^M \Omega(T_m) \quad (4)$$

where N denotes the number of training samples, $F(\tau) = \sum_{m=1}^M \eta T_m(\tau)$ represents the output from the model, which is transformed into a river probability by the sigmoid function:

$p_i = \frac{1}{1 + \exp(-F(\tau_i))}$, η is the learning rate controlling the contribution of each tree, and T_m denotes m -th decision tree.

To prevent overfitting in high-dimensional feature spaces, we introduce a structural regularization term into the objective function. This term ensures that the model maintains strong generalization by limiting the complexity of the tree function. The regularization term is defined as:

$$\Omega(T_m) = \gamma |T_m| + \frac{1}{2} \lambda \sum_{j=1}^{|T_m|} w_{j,m}^2 \quad (5)$$

where $|T_m|$ denotes the number of leaf nodes in m -th tree, $w_{j,m}$ is the weight of the leaf node of the tree, γ penalizes excessive model complexity (through leaf count), and λ constrains weight magnitudes. These two terms constrain the model to adopt compact but effective decision trees, effectively mitigating overfitting without compromising prediction accuracy.

The data fitting term $L(p_i, F(\tau_i))$ in the objective function is described by the log-cross-entropy loss as:

$$L(p_i, F(\tau)) = -[p_i \log p(\tau) + (1 - p_i) \log(1 - p(\tau_i))] \quad (6)$$

When the predicted probability deviates significantly from the true label, the loss function value increases markedly, thereby driving the model to optimize in the correct direction. During training, each decision tree is constructed by fitting the negative gradient (pseudo-residual) of the current model, which characterizes the direction and magnitude of prediction errors. By training a new tree to fit the pseudo-residuals and determining leaf node weights through search, the addition of the new tree minimizes the overall objective function value.

4.2.2. Region Growing by Multi-Scale Probabilistic and Directional Constraints

Obtaining the river probability maps, they should be further transformed into spatially coherent rivers. The probability maps of different scales represent complementary aspects of river morphology. For each scale σ , we obtain the probability map $p_\sigma(x, y)$, as illustrated in Figure 4. The final probability map is derived through maximum value fusion:

$$p_{final}(x, y) = \max_{\sigma} p_{\sigma}(x, y) \quad (7)$$

This operation retains the strongest linear response across scales. Beyond probabilistic responses, the eigenvectors derived from the Hessian matrix provide local directional information important for distinguishing rivers from linear non-river features. For each pixel, its linear direction is given by eigenvector e_1 associated with the largest eigenvalue.

Based on this, directionally constrained region growing is then employed to extract rivers. Seed points are selected as the top 1% highest-probability pixels (typically located at the center of the main channel). For any pair of current seed point q and its neighbor p , the growing criterion is defined as:

$$G(p, q) > \eta \cdot (1 - \Omega(p, q)) \quad (8)$$

where η is an adaptive probabilistic threshold used to regulate the extent of region growing. $\Omega(p, q)$ is a directional consistency measure, calculated as the cosine of the angle between the directions, with values ranging from $[0, 1]$.

This fusion of probabilistic responses and directional constraints effectively suppresses false positives caused by roads, shadows, and other linear non-river objects. It simultaneously ensures that extracted water bodies exhibit continuity and morphological integrity, providing high-quality river vectors for the subsequent river network extraction.

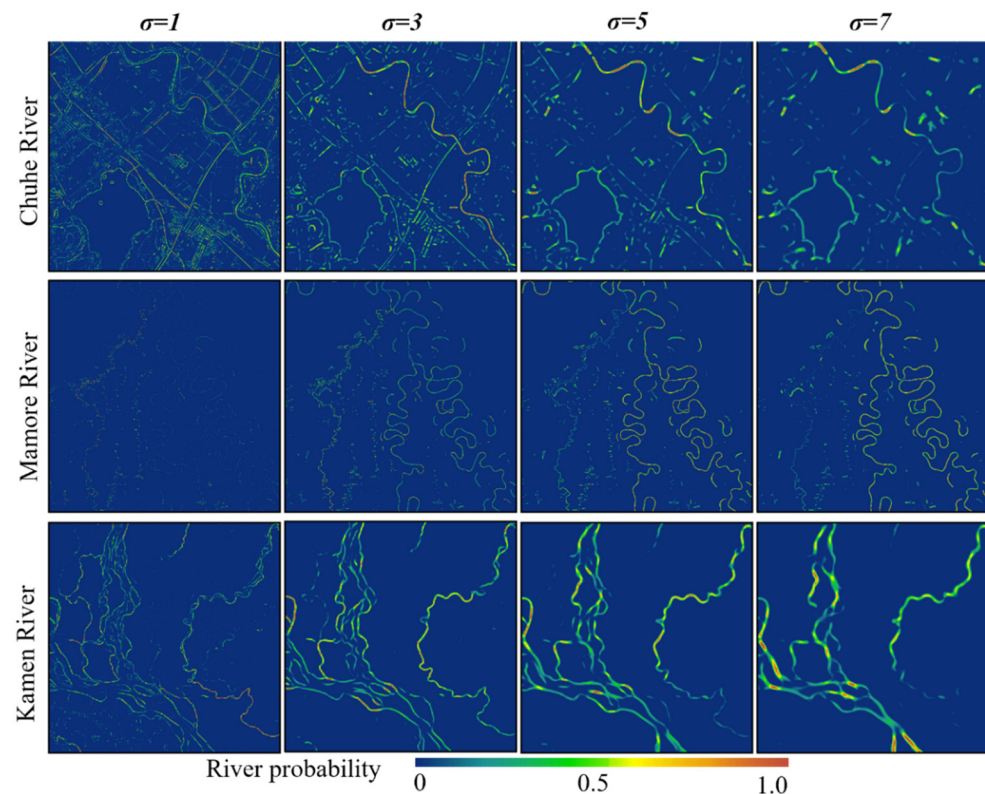


Figure 4. River probability maps of different scales ($\sigma = 1, 3, 5$, and 7).

4.3. Adaptive Stream Burning-Based River Network Classification

To further extract a hydrologically coherent river network, we perform a terrain correction integrating river constraints. Among existing methods, stream burning is one of the most widely used algorithms, in which DEM elevations are lowered along known river vectors to enforce hydrological connectivity. Conventional stream burning algorithms mainly rely on a constant burn depth, ignoring spatial heterogeneity in river morphology and failing to distinguish between main channels and tributaries. Consequently, excessive burning may distort micro-topography, and insufficient burning may be ineffective in constraining elevations in low-relief areas.

To address this problem, we propose a spatially adaptive stream burning algorithm based on the extracted river vectors, integrating the hydrological accumulation characteristics and channel geometry (Figure 5). Instead of applying a constant burn depth, we generate an adaptive burn field based on three factors: flow accumulation representing hydrological system structure, local channel width capturing morphological variation, and the linear geometric feature enhancing the narrow tributaries representation. The adaptive burn depth is computed as:

$$B_{depth(i,j)} = B_{base} \left(1 + \frac{A}{A_{\phi}} \right) (\alpha W(i,j) + \beta L_{max}) \quad (9)$$

$$MDEM_{(i,j)} = DEM_{(i,j)} - B_{depth(i,j)} \quad (10)$$

where B_{base} denotes the baseline burn depth determined by DEM resolution and regional terrain properties. A denotes the flow accumulation of the current pixel and A_{ϕ} denotes a dynamic threshold value (suggest set between 75 and 95% of the cumulative flow volume for the entire watershed). $W(i,j)$ represents the current river width. L_{max} denotes the max linear geometric feature among multi-scales, enhancing terrain correction effects for small

tributaries. α and β represent the balance factors. $MDEM_{(i,j)}$ denotes the DEM elevation after burning.

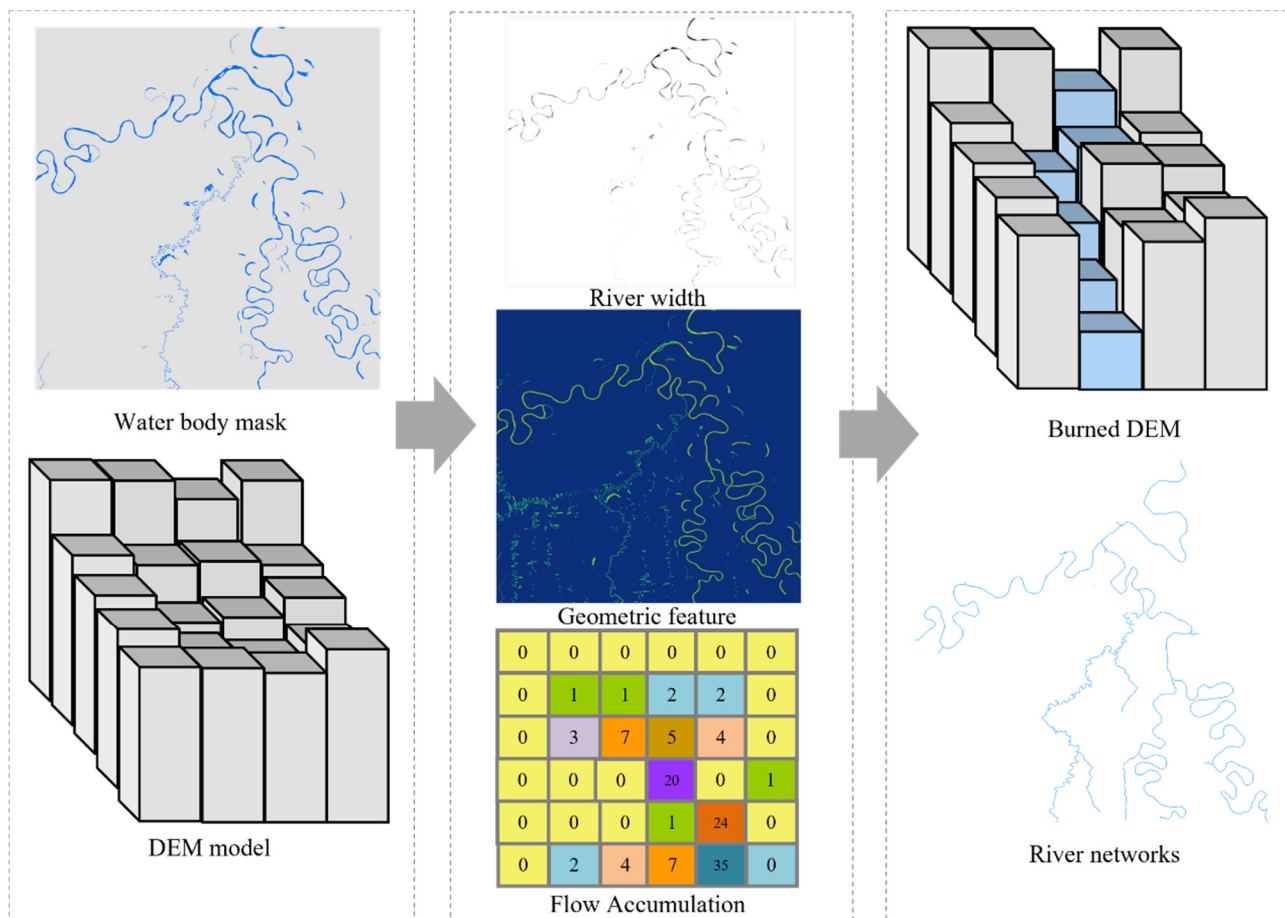


Figure 5. Framework of spatially adaptive stream burning. The colored grid cells with numbers represent the flow accumulation values used as weights and colors indicate different flow directions.

In the spatially adaptive stream burning algorithm, river widths $W(i,j)$ are systematically extracted from water vectors using the RiverWidthCloud algorithm [8], enabling dynamic adjustment of buffer zone widths. By incorporating flow accumulation-based weighting, the algorithm determines the burn depth based on the upstream catchment area, achieving more consistent erosion effects. The integration of linear geometric features ensures that burn depth increases smoothly from upstream to downstream, while narrow tributaries receive sufficient correction to maintain connectivity. This approach refines DEMs, improving morphological and hydrological fidelity compared to traditional stream burning methods.

The D8 flow-direction algorithm assumes that water flows from each DEM grid cell to one adjacent cell along the steepest slope. It is particularly effective for extracting topologically connected river networks from DEM [50]. With the refined DEM, we employ the D8 algorithm to detect river networks, enhancing positional accuracy and generating more hydrologically coherent drainage networks (as Figure 6 shows). To further evaluate the hydrological structure of generated river networks, we utilize the Strahler river classification algorithm to analyze the extracted river networks [51]. This method classifies rivers into levels based on their connectivity, quantifying the structure of the river network.

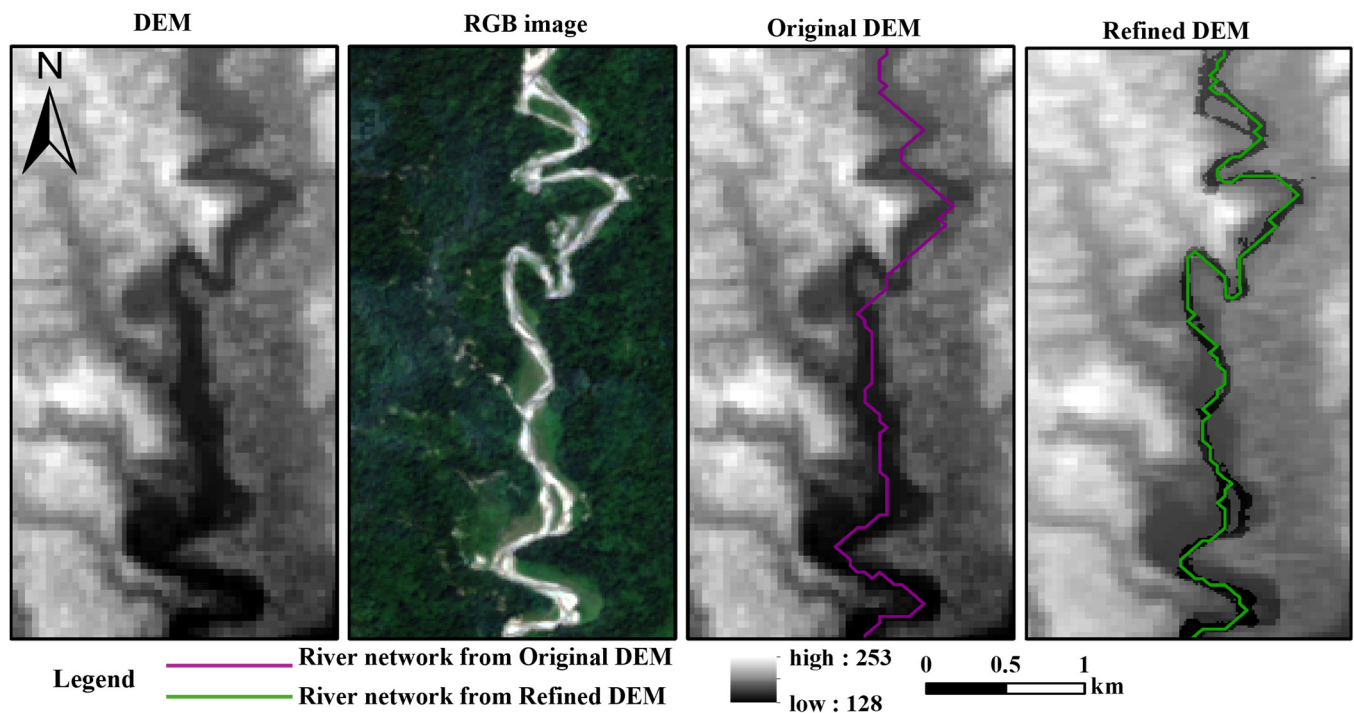


Figure 6. Extracted river networks of original and refined DEMs.

5. Results

This section presents and discusses the river network mapping performance of the proposed method, including qualitative river network results, quantitative accuracy evaluation, and comparisons with existing methods.

5.1. Evaluation Metrics

To evaluate the extraction results, manually digitized river vectors and centerlines, derived from high-resolution Google Earth imagery, serve as reference data. Three complementary metrics are adopted. Overlap Rate (OR) measures the proportion of correctly extracted river network pixels, calculated as follows:

$$OR = \frac{P_r}{P_t} \quad (11)$$

where P_r denotes the number of correctly identified river network pixels (the intersection between the extracted river networks and the reference river vectors), and P_t represents the number of extracted river network pixels. A high OR indicates that the extracted river network aligns closely with the real channels. We also use the Intersection over Union (IoU) to quantify spatial consistency between extracted networks and reference vectors, defined as:

$$IoU = \frac{\text{Intersection}(P, M)}{\text{Union}(P, M)} \quad (12)$$

where P and M denote the extracted river network pixels and the reference channel pixels, respectively. The IoU metric quantifies the spatial consistency between the extracted river networks and real river bodies. Another evaluation metric is the average offset distance between the extracted river networks and the reference river networks. Each pixel offset distance is defined as the Euclidean distance from each extracted river network pixel to the nearest reference river network pixel. Together, these metrics comprehensively evaluate both the completeness and geometric accuracy of the extracted river networks.

5.2. River Network Extraction Analysis

5.2.1. Qualitative Analysis of Experimental Results

To achieve accurate extraction of multi-scale river channels, we integrate river probabilistic responses derived from the RGBT model with a directionally constrained region growing algorithm. To systematically evaluate the adaptability of the proposed method under varying conditions, we select three representative regions for experiments. The Chuhe region represents a typical flat plain with meandering river channels. The Mamore River region exhibits distinct topographic undulations, with frequent channel migration and bifurcation characteristics. The Kamen River region exhibits composite topography with steep upper slopes and gentle lower slopes, along with strong seasonal flow variability. The extracted river channels of three representative regions are provided in Figure 7.

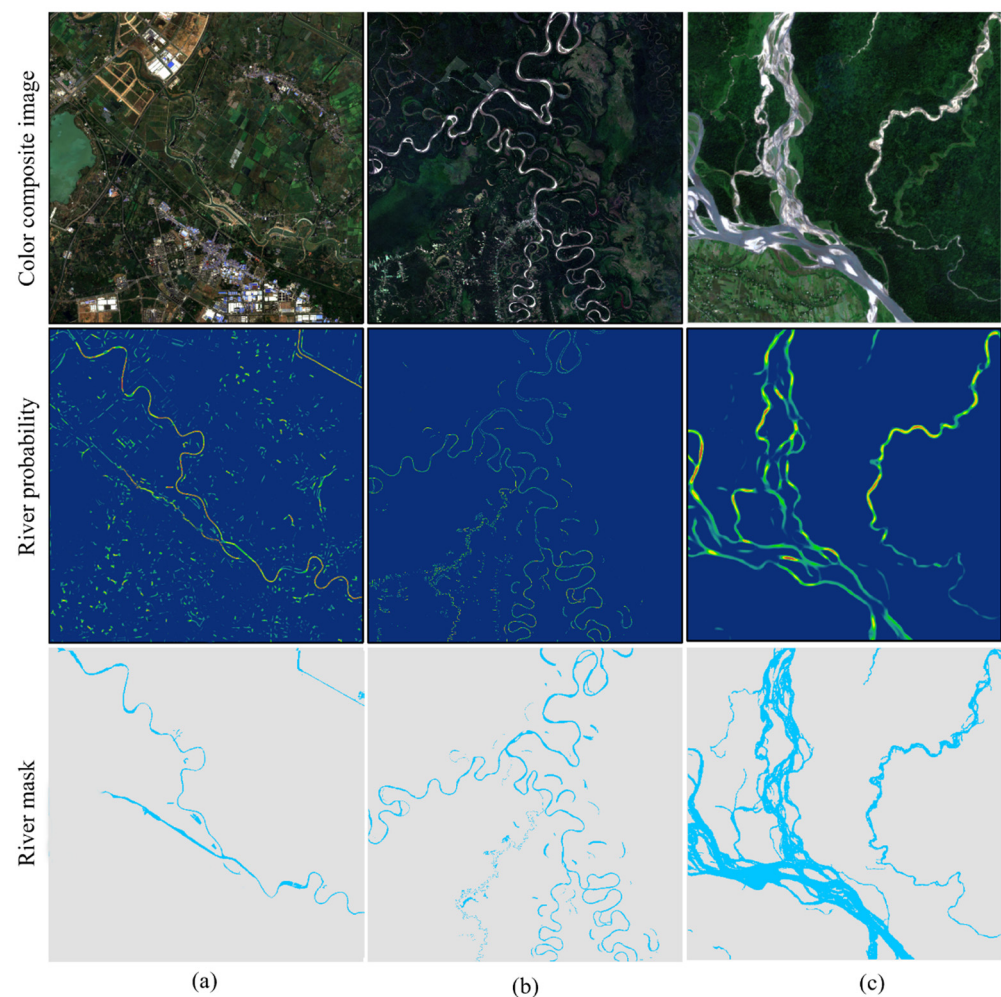


Figure 7. Extraction of river channels from three representative local regions. (a) Chuhe River region; (b) Mamore River region; (c) Kamen River region.

As shown in Figure 7, the proposed method extracts spatially continuous and topologically coherent river channel vectors. Specifically, in the Chuhe River and Mamore River regions, the extracted rivers not only fully delineate the main channels but also effectively capture the seasonal minor tributaries, notably in the Kamen River region, which is characterized by highly meandering rivers and locally linear river segments. The results preserve complex river morphology while maintaining sharp and well-defined boundaries. These indicate that the proposed RGBT–region growing framework exhibits strong adaptability to diverse river morphologies, avoiding fragmentation in narrow tributaries as well as overexpansion in wide river channels.

The high spatial continuity and geometric fidelity of the resulting river channels provide a reliable foundation for the subsequent adaptive stream burning process. Based on the extracted river channel vectors, adaptive stream burning-based river network classification is employed to extract and classify the river networks of the test regions. The final river networks are shown in Figure 8. As shown in Figure 8, the resulting river networks exhibit well-defined hierarchical structures and realistic branching patterns across all three test regions. The extracted river centerlines show strong spatial consistency with the true river channels observed in Sentinel-2 imagery, confirming that the proposed method preserves both geometric accuracy and hydrological consistency under diverse terrain conditions.

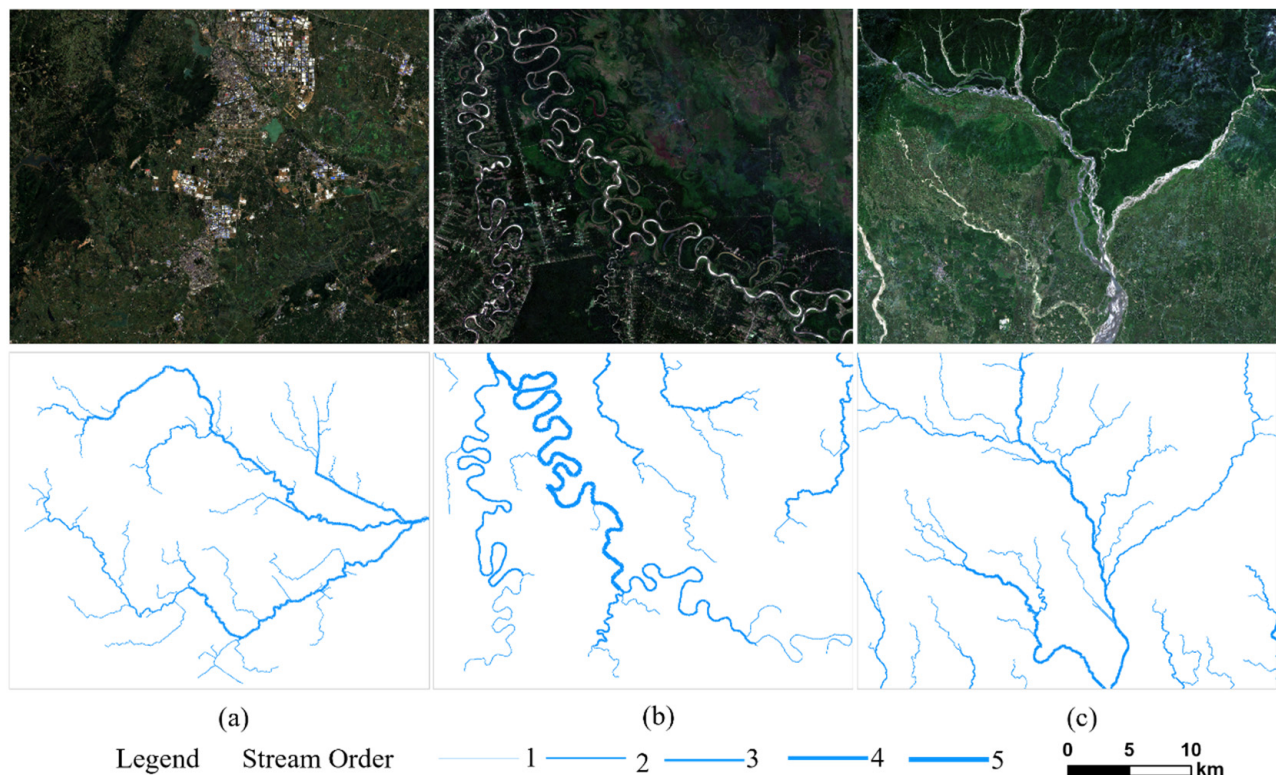


Figure 8. River network extraction and ordering of the test regions. (a) Chuhe region; (b) Mamore River region; (c) Kamen River region.

5.2.2. Quantitative Assessment of Extracted River Networks

To rigorously evaluate the accuracy and robustness of the proposed method under varying hydro-geomorphological conditions, the above three regions (Chuhe River region, Mamore River region, and Kamen River region) are selected for further experiments. For each river region, river networks generated by the proposed method are quantitatively compared with three benchmark datasets: river networks directly extracted from the raw COP30 DEM, those extracted using the AGRSDem-based improved method, and river network data from a global hydrological product—MERIT Hydro. High-precision reference river networks are also manually digitized as the reference river networks. Figure 9 presents a comparison of the results.

Figure 9 demonstrates that the river networks generated by the proposed method exhibit the highest spatial consistency with the reference river networks across all test regions. In the Chuhe region, characterized by dense artificial channels, the proposed method accurately extracts both natural and artificial river segments (as white boxes show). Compared with the river networks derived from the original DEM and other benchmark datasets, our results demonstrate the highest consistency with the reference river networks.

In the Mamore River region, where rivers exhibit significant meandering patterns, adaptive stream burning effectively corrects distorted flow paths, producing a geometrically coherent network (as white boxes show). In the Kamen River region, within the braided river network area (as white boxes show), our method generates the river network with lower displacement and more realistic morphology. Overall, Figure 9 demonstrates that the proposed method outperforms conventional DEM-based extraction and mainstream hydrographic products in terms of both spatial fidelity and topological consistency.

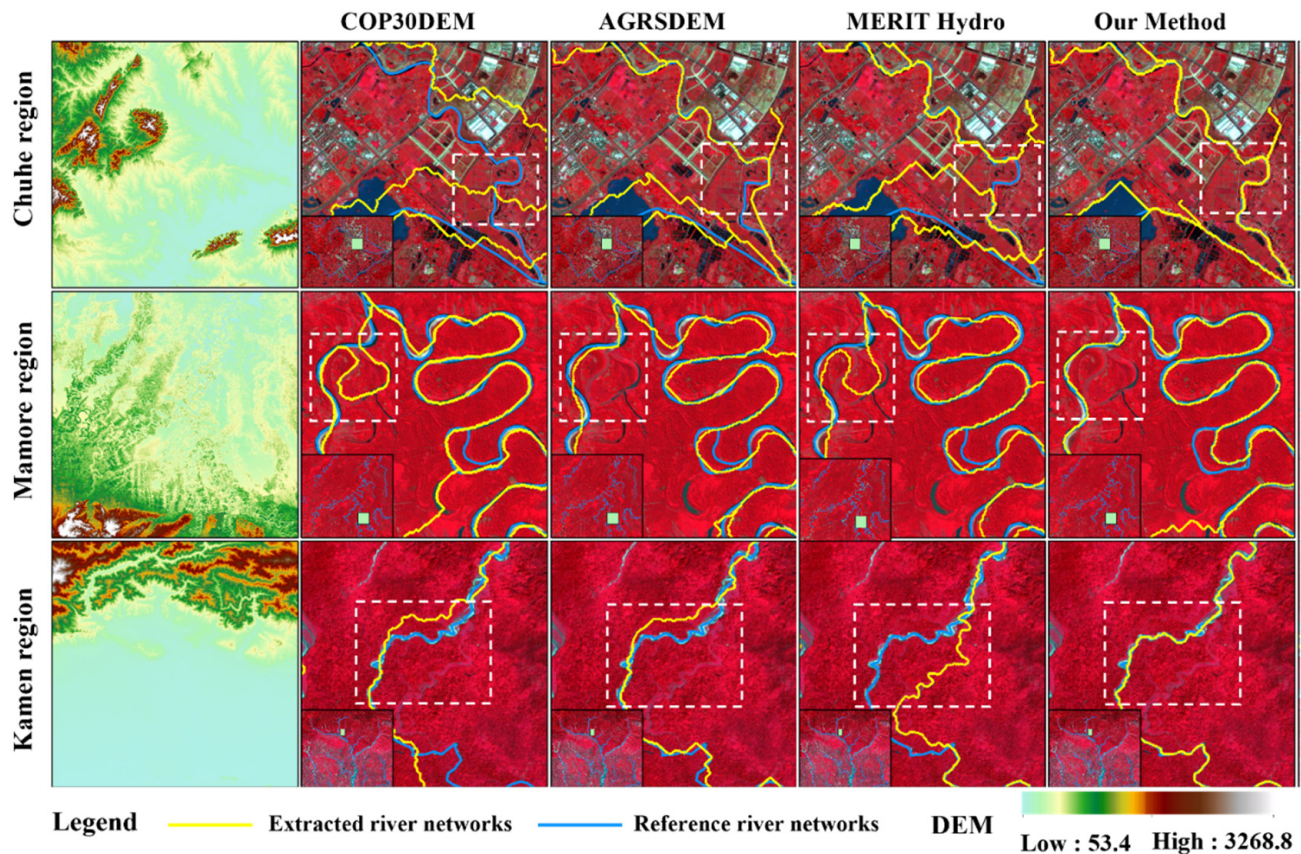


Figure 9. Comparison of river networks derived from different DEMs across three regions. The green square indicates the location of the display area, while the white dotted frame shows the specific details.

To further quantify positional errors, the minimum Euclidean offset distance between each extracted pixel and its nearest reference river network is computed. The statistical distributions of offset distances are presented in Figure 10, while the median, maximum, and mean offset distances are summarized in Table 3. Figure 10 reveals that the river networks extracted by the proposed method exhibit a significant concentration of small positional errors. Approximately 50% of pixels exhibit a displacement less than 20 m, while the proportion of pixels with displacement distances exceeding 100 m is significantly lower than other methods. The histogram exhibits obvious right-skewed characteristics, with most errors clustered within the 0–40 m range. In Table 3, across all test regions, the offset distance between the river networks extracted by our method and the reference river networks is consistently the lowest. For example, in the Chuhe region, the average offset distance of extracted river networks is 117.24 m, which is 19.58%, 8.60%, and 16.27% lower than that of COP30DEM, AGRSDEM-based improved method, and MERIT Hydro, respectively. Similar improvements are observed in the Mamore and Kamen River regions, where the proposed method achieves both the lowest average and median displacements among all datasets. These results indicate that our method achieves higher overall positional accuracy

with significantly reduced overall offset distances, particularly for narrow tributaries and complex channel sections.

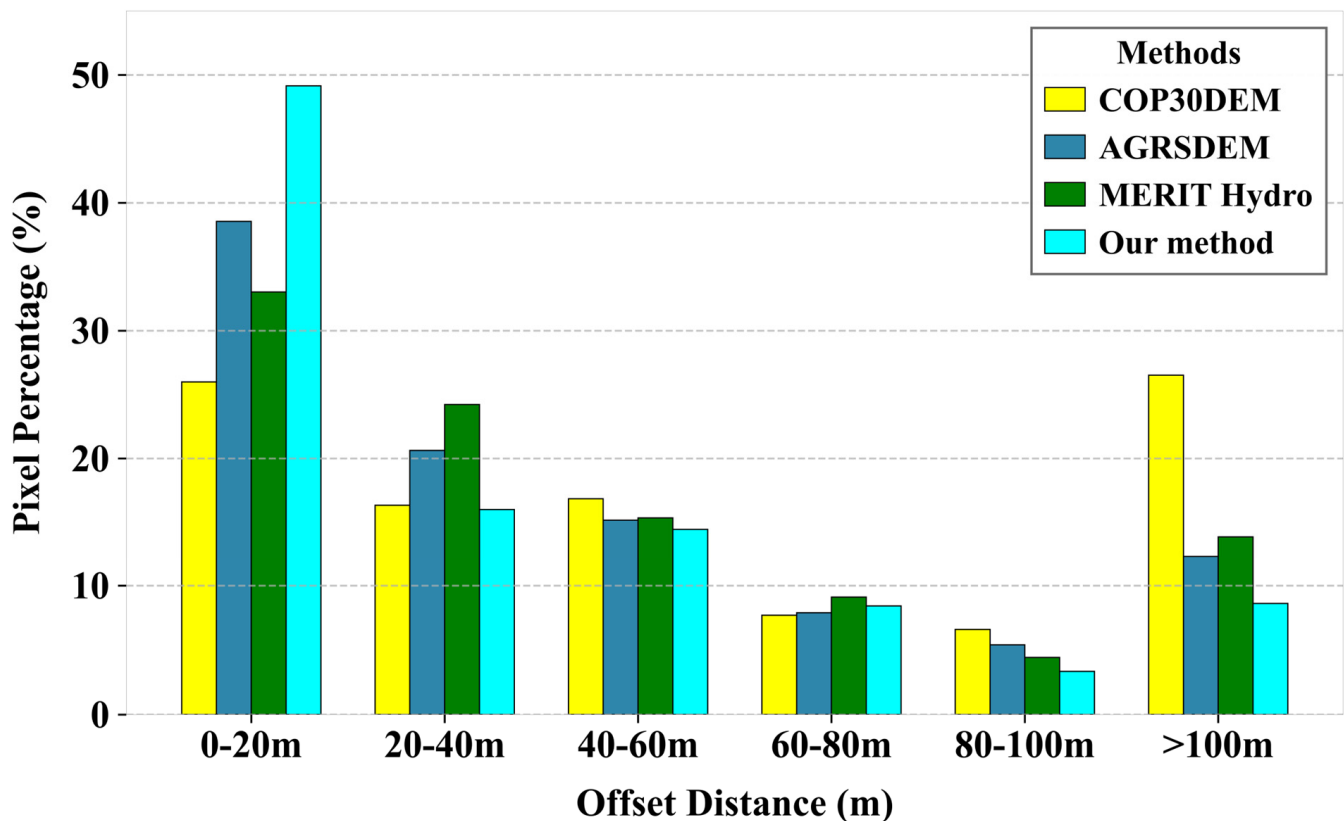


Figure 10. Distribution of offset distances for river networks extracted by different methods across the three quantitative test regions.

Table 3. Comparison of offset distances for river networks extracted by different approaches.

Test Site	Chuhe River Region			Mamore River			Kamen River		
Indicators	Median(m)	Max(m)	Mean(m)	Median(m)	Max(m)	Mean(m)	Median(m)	Max(m)	Mean(m)
COP30DEM	93.78	1053.35	145.78	26.28	422.18	67.70	6.71	718.98	36.83
AGRSDEM	35.11	1051.94	126.88	10.63	480.77	62.76	4.00	723.56	30.85
MERIT Hydro	77.28	1055.10	138.46	17.46	432.20	64.66	8.49	715.71	39.86
Our Method	23.71	1050.32	117.24	5.00	420.77	42.50	2.00	706.09	22.91

Note: Bolded numbers denote the minimum values of different columns.

5.3. Comparison with Existing River Network Products

To systematically evaluate the extraction performance, we conduct a visual comparison of the resulting river networks with three widely used hydrographic datasets: GRWL [26], MERIT Hydro [12], and HydroSHEDS [31]. Among these, GRWL provides a global 30 m resolution vector river network with width attributes, and MERIT Hydro integrates multi-source remote sensing observations with an enhanced MERIT DEM and currently represents one of the most reliable global hydrographic datasets. While HydroSHEDS is derived from SRTM data acquired around 2000 and remains one of the most extensively applied hydrographic datasets, it should be noted that in the Chuhe region, which is an urban plain area, GRWL cannot effectively provide the river network. Therefore, we only provide comparisons for the Mamore River and Kamen River regions, as shown in Figures 11 and 12.

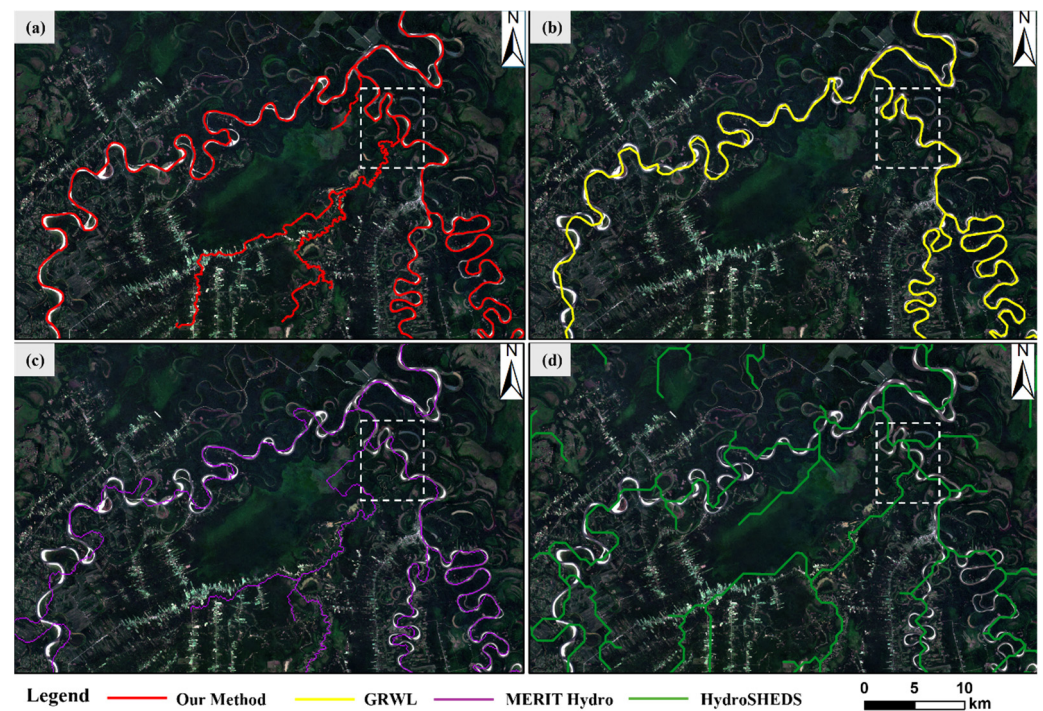


Figure 11. Comparison of river networks in the Mamore River region. (a) The river network derived by our method based on COP30DEM (red). (b) The GRWL river network (yellow). (c) The MERIT Hydro river network (purple). (d) The HydroSHEDS river network (green).

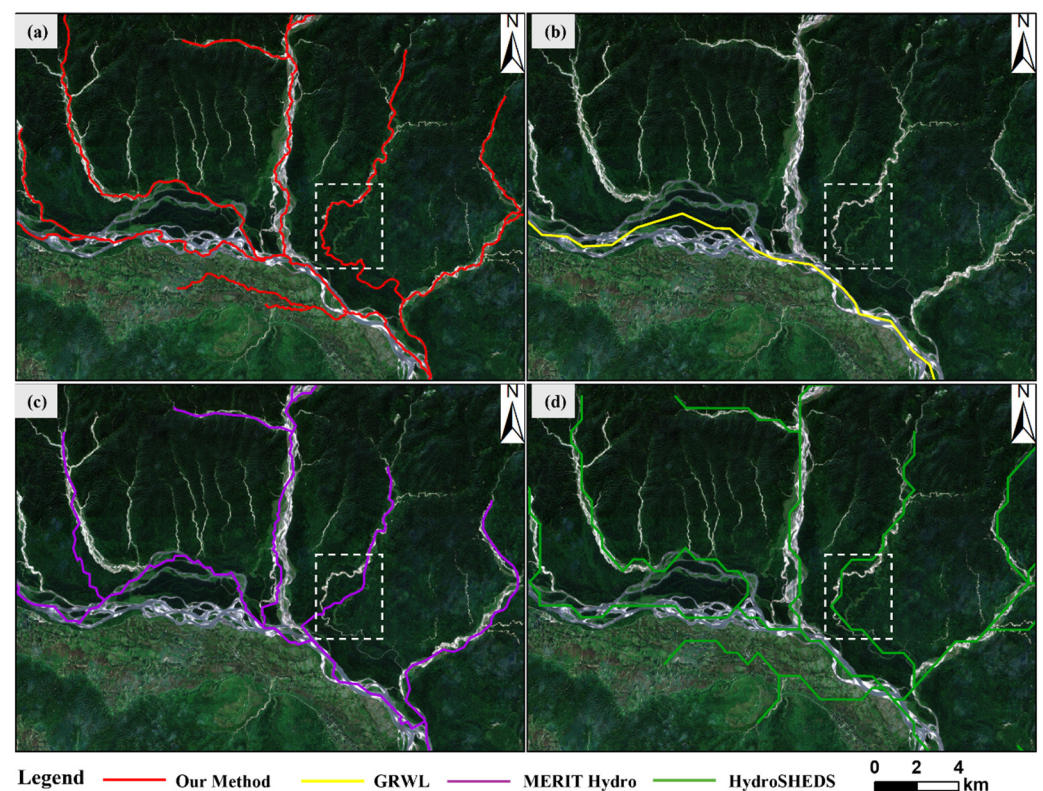


Figure 12. Comparison of river networks in the Kamen River region. (a) The river network derived by our method based on COP30DEM (red). (b) The GRWL river network (yellow). (c) The MERIT Hydro river network (purple). (d) The HydroSHEDS river network (green).

From Figures 11 and 12, we can see that the river networks extracted by the proposed method exhibit the highest spatial consistency with actual rivers observed in Sentinel-2

imagery, particularly in regions where river width varies from several meters to kilometers. In contrast, discrepancies in channel alignment and spurious channel generation are frequently observed in the existing products. In the Mamore River region, the river network extracted by the proposed method (Figure 11a) exhibits excellent geometric consistency with the reference channel, particularly in curved segments (white boxes). The GRWL river network (Figure 11b) accurately captures the main channel but fails to resolve tributaries due to its width threshold, resulting in an incomplete network. The MERIT Hydro network (Figure 11c) shows obvious displacement, while HydroSHEDS (Figure 11d) generates pseudo river channels that are inconsistent with the actual rivers.

In the highly branched and braided Kamen River region (Figure 12), the proposed method (Figure 12a) represents multi-scale channel structures and preserves the dominant flow pathways. In contrast, all three benchmark products struggle to accurately represent braided rivers. GRWL lacks performance on narrow branches, MERIT Hydro produces displaced and over-simplified channels, and HydroSHEDS generates pseudo channels from actual river channels. These comparisons indicate that the proposed method not only achieves higher positional accuracy but also preserves river morphology well. In particular, its advantages are most significant for small-scale tributaries, highly meandering rivers, and braided river channels. The proposed method effectively provides a more complete and hydrologically consistent representation of river networks.

This performance gap highlights a critical mechanism: while pure optical-based products like GRWL fail to maintain continuity when river signals become fragmented due to the mixed pixel effect at limited resolutions, our method effectively overcomes this limitation. By utilizing the discontinuous optical detections as elevation constraints in the Adaptive Stream Burning process, we enforce hydrological connectivity based on terrain gradients. This allows for the successful extraction of small rivers that appear fragmented in imagery, providing a more complete and hydrologically consistent representation of river networks.

6. Discussion

6.1. Hyperparameter Experiments

The baseline burning depth serves as the fundamental control parameter of our adaptive stream burning algorithm. It determines the reference depth imposed on the DEM along the extracted rivers without other factors (e.g., accumulation area, river width, or linear features). To quantify its influence on river network extraction, the baseline burn depth is varied from 0 to 50 m at 10 m intervals. This range adequately covers both the vertical uncertainty of DEMs and the topographic variability of rivers. The resulting OR and IoU values based on different baseline burn depths are shown in Figure 13. Based on the COP30 DEM, we also calculate OR and IoU values across eight study areas under different burning depths, shown in Figure 14.

In Figure 13, boxplot statistics demonstrate that, compared with the uncorrected condition (0 m), the adaptive stream burning algorithm leads to a significant improvement in river network extraction performance. Optimal performance occurs at approximately 30 m baseline burning depth, and the performance becomes stable over a range of 40–50 m. In Figure 14, in the urbanized and low-relief Chuhe River region, the highest performance is obtained at a baseline burn depth of 20 m, yielding an OR of approximately 0.30. In contrast, in the mountainous Kamen River region with significant topographic gradients, the optimal burn depth increases to 30 m, leading to a higher OR of 0.67. This contrast indicates that a mountainous region requires stronger hydrological enforcement to overcome elevation noise, and excessive burning in low-relief urban regions may distort channel geometry.

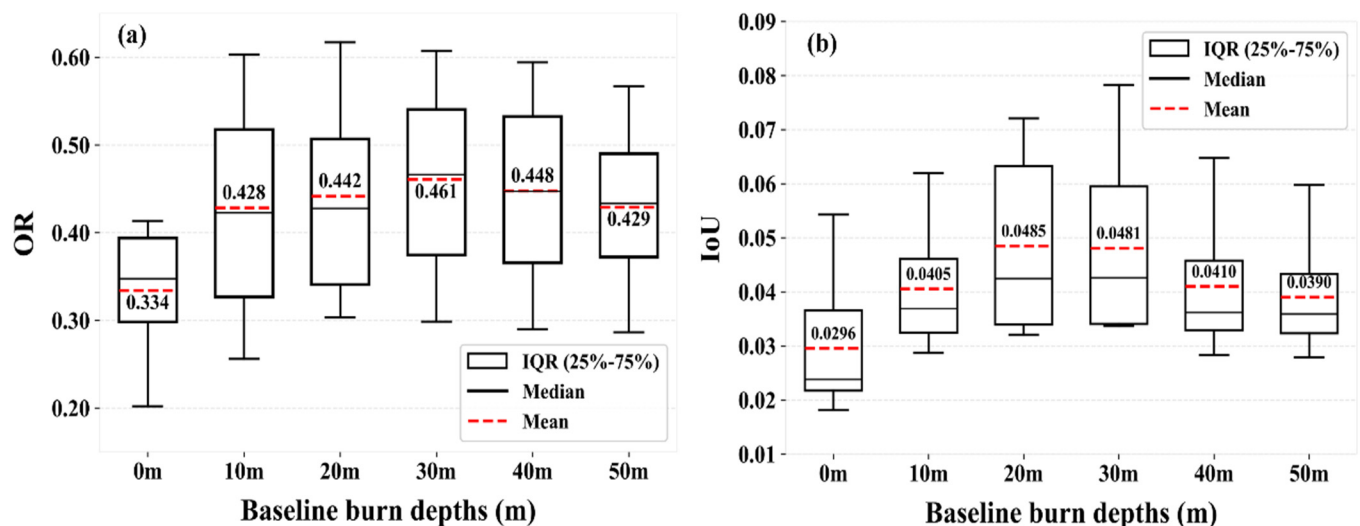


Figure 13. Accuracy diagram for different baseline burning depths. (a) OR with different baseline burn depths; (b) IoU with different baseline burn depths.

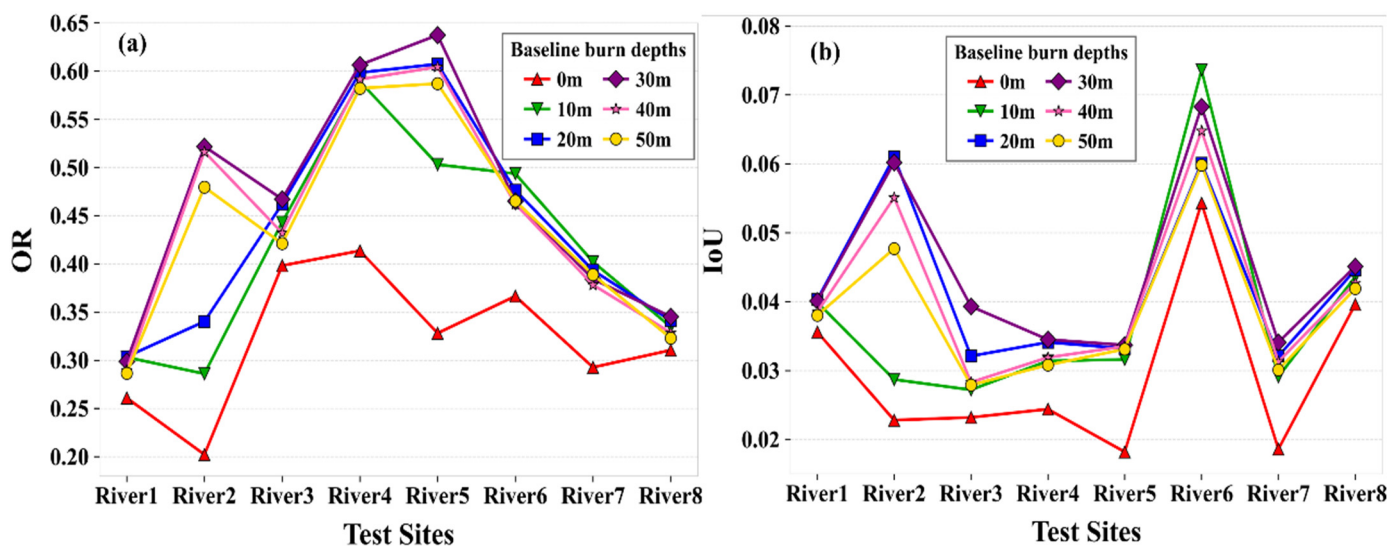


Figure 14. Variations in river network extraction accuracy (OR and IoU) with stream burning depths across eight study areas with diverse characteristics. (a) OR at different baseline burn depths in different regions. (b) IoU at different baseline burning depths in different regions.

To further assess the influence of terrain data quality on extraction performance, four global DEM products—COP30, NASADEM, AW3D30, and ASTER GDEM—are evaluated under the same experimental settings, and the results are shown in Figure 15. Figure 15 shows that COP30 consistently outperforms the other DEMs under both uncorrected and stream-burned conditions, reflecting its superior vertical accuracy. AW3D30 and NASADEM exhibit comparable performance, while ASTER GDEM yields the poorest results due to its larger residuals. Importantly, after employing the proposed adaptive stream burning framework, extraction accuracy is significantly improved for all DEMs, and the performance gap among different DEMs is reduced significantly. This demonstrates that the integration of extracted high-confidence rivers effectively compensates for intrinsic terrain data limitations, yielding more realistic river networks. Among all tested DEMs, COP30 is recommended as the preferred data source for high-precision river network extraction.

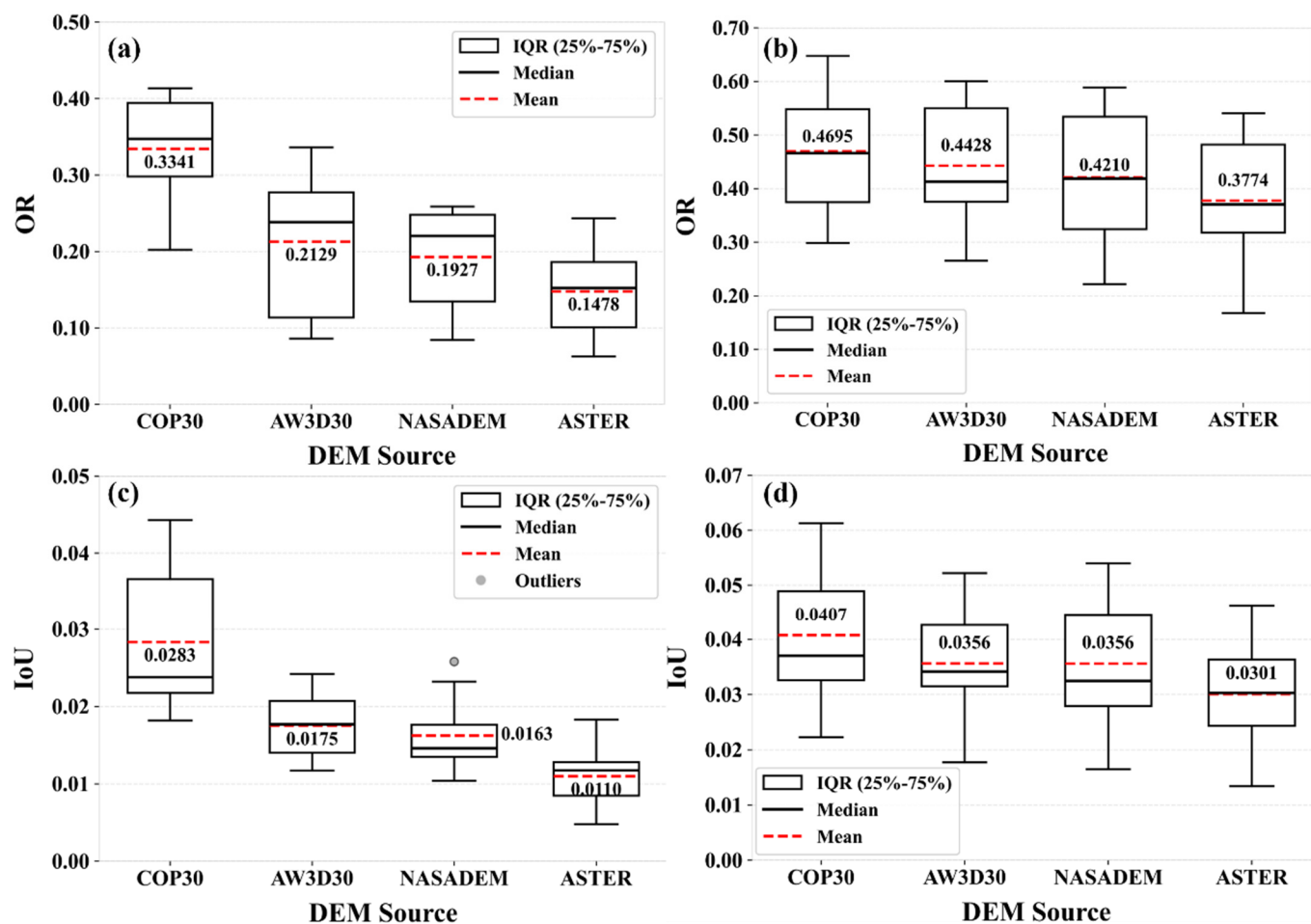


Figure 15. Comparison of river network extraction accuracy for four DEMs with and without the proposed processing across the eight study areas. (a) OR with uncorrected DEMs; (b) OR with stream-burned conditions; (c) IoU with uncorrected DEMs; (d) IoU with stream-burned conditions.

Furthermore, we specifically investigated the sensitivity of the dynamic flow accumulation threshold (A_ϕ in Equation (10)) under contrasting topographic gradients. The results reveal a clear “terrain-dependent” sensitivity. In high mountain valleys (e.g., Yarlung Zangbo River), the extraction accuracy is relatively insensitive to variations in A_ϕ . This is because the steep valley walls naturally constrain the hydrological flow direction, making the flow accumulation weight less critical for defining channel paths. Conversely, in extremely low-lying plains (e.g., Chuhe River), the accuracy demonstrates high sensitivity to A_ϕ . Due to the lack of dominant terrain gradients, the flow direction is easily disturbed by DEM noise. Therefore, A_ϕ becomes a critical factor in distinguishing effective channel flow from background noise: a value that is too low may amplify noise, while a value that is too high may disconnect small tributaries. Based on these experiments, setting A_ϕ to a percentile range of 75–95% of the cumulative flow volume provides a robust balance, ensuring that main channels are sufficiently deepened while preserving tributary connectivity across diverse terrains.

6.2. Performance Evaluation Under Different Topographical Conditions

To validate the applicability of our method, river network extraction results across regions with diverse heterogeneous backgrounds are illustrated in Figure 16. Figure 16a–d demonstrate the river extraction in typical humid regions characterized by dense vegetation. These regions are often severely disrupted by dense canopy cover and water turbidity. Nevertheless, this method effectively extracts river networks in these scenarios. Figure 16a

shows that this method accurately captures the continuous meandering rivers, demonstrating robust recognition. The method also demonstrates excellent adaptability across varying spatial scales (river width range: 10–100 m). It extracts tributary networks while effectively eliminating spurious rivers. The method also exhibits outstanding adaptability in urban areas. As illustrated in Figure 16d, in the highly urbanized Chuhe River region, the extracted river network exhibits remarkable correspondence with actual river networks. Figure 16e,f demonstrate the performance within arid and semi-arid environments. Such regions have surface cover, vegetation, and soil exposure, posing challenges for precise river network extraction. Figure 16b,h demonstrate the performance in complex water systems such as braided river networks. For example, for the braided river network of the Yarlung Zangbo River (Figure 16h), the extracted river network exhibits high consistency with the actual river in terms of overall orientation and spatial position. In cold climate zones, Figure 16g demonstrates the performance for rivers in northern Siberia. This region is characterized by extensive permafrost distribution, with river morphology being susceptible to glacial processes such as snowmelt. This method effectively captures the complete outline and meandering morphology of the main river channel. The proposed method is applicable to river network extraction across diverse topographical conditions, demonstrating excellent efficiency and robustness in multiple topographical conditions.

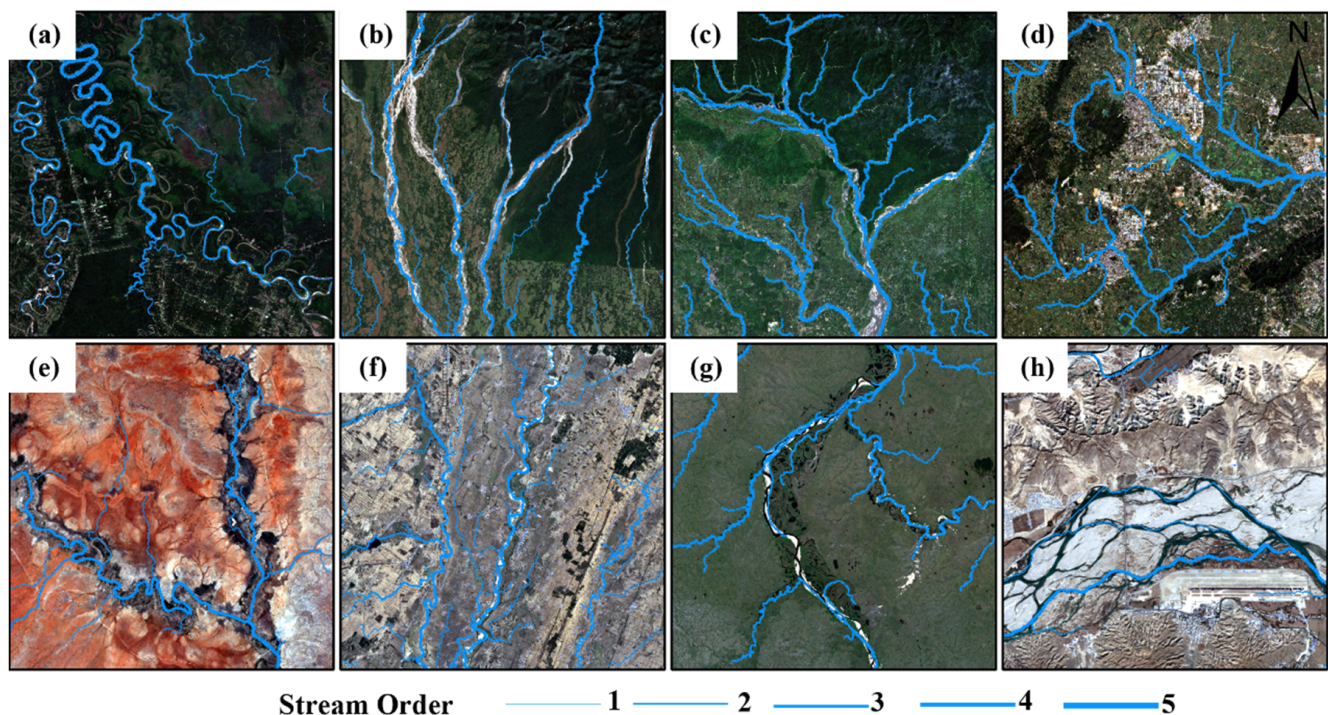


Figure 16. Performance evaluation under different topographical conditions. (a) Rivers on the Bolivia plains; (b,c) rivers of the Kamen River region in India; (d) Chuhe river region; (e) Genale River in Ethiopia; (f) rivers of Dongliao region; (g) Anabar River; (h) Yarlung Zangbo River in Tibetan Plateau.

6.3. Limitations and Future Work

On the one hand, the performance of the RGBT model relies on the representativeness and completeness of the training samples. Although the current dataset covers eight distinct regions, certain rare hydrological scenarios are still underrepresented, such as estuaries subject to strong tidal influences. This may introduce uncertainties when applying the model to unfamiliar hydro-environments. To address this, future work will focus on expanding the training dataset using large-scale river images and incorporating semi-supervised or self-supervised learning strategies to improve generalization performance.

On the other hand, the spatial resolution of Sentinel-2 imagery limits the extraction of narrow rivers. Rivers with a width smaller than the pixel size are inevitably affected by the mixed pixel phenomenon, leading to the loss of topological connectivity. While the adaptive stream burning strategy partially compensates for this limitation, the first-order headwater rivers may still be underrepresented. Future work will explore integrating higher-resolution optical imagery to further improve the detection capabilities of these micro-scale river channels.

Future work will focus on expanding the training dataset using large-scale river images and incorporating semi-supervised or self-supervised learning strategies to improve performance. And we will also explore the integration of higher-resolution optical imagery to further improve small-channel extraction capability.

7. Conclusions

This study proposes a novel method for mapping river networks, aiming to address common challenges in existing approaches, such as spatial position deviation, network topology fragmentation, and structural incompleteness. We propose a river network extraction method integrating multi-scale linear river enhancement with regional growth techniques to capture river vectors at different scales. Based on this, an adaptive stream burning algorithm is proposed for adaptive terrain correction. By generating a conditional DEM, the method achieves accurate river network extraction and classification.

Comprehensive experiments across eight representative regions with diverse topographical conditions demonstrate that the proposed method achieves accurate and robust performance. Quantitative assessments against manually digitized reference networks show that the proposed method outperforms traditional DEM-based extraction, AGRSDEM-enhanced DEMs, and mainstream hydrographic products (MERIT Hydro, GRWL, and HydroSHEDS) in terms of positional accuracy, network continuity, and morphological consistency. In all three benchmark basins, the proposed method yields the lowest offset distances, with displacement distributions concentrated within the low-error range (0–40 m). Notably, the advantages are most significant for small-scale tributaries, highly meandering rivers, and braided river systems. The incorporation of adaptive stream burning significantly reduces the DEM discrepancies, confirming strong capability. Overall, the proposed method provides a consistent and accurate solution for high-resolution river network mapping, supporting hydrological modeling, flood and waterlogging disaster management, and biogeochemical cycles.

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