

RESEARCH ON THE INFLUENCE MECHANISM OF
MULTI-SCALE TERRAIN AUTOMATIC RIVER NETWORK
EXTRACTION BASED ON CHANGE POINT DETECTION
TECHNOLOGY

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Abstract

DEM-based river network extraction is sensitive to drainage thresholds, terrain and data resolution. This study applies four change-point detection (CPD) algorithms to three DEM resolutions (12.5, 30 and 90 m) across mountainous, hilly and plain landscapes (36 experiments). Kernel-based CPD performed best in most combinations, attaining the highest F1-scores in mountains at 90 m (0.89), hills at 30 m (0.88) and plains at 12.5 m (0.75). PELT and Binary Segmentation produced similar thresholds, whereas the Mann–Whitney U test yielded higher values; thresholds varied approximately linearly with DEM resolution. The results show that DEM resolution, terrain and algorithm jointly affect extraction accuracy. Coarser data can suppress false channels in mountains, whereas finer data preserve smaller channels in plains. These findings support terrain-specific selection of DEM resolution and CPD algorithm for automatic river network extraction.

Key words: Change Point Detection algorithm, Digital Elevation Model, GIS, multiscale analysis, river network extraction

Introduction. Digital elevation models (DEMs) provide a widely used basis for river-network extraction, often using D8 flow routing [1]. However, selecting

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flow-accumulation thresholds remains partly subjective and may require repeated adjustment across DEM resolutions and geomorphic settings, limiting consistency in multi-scale applications. Prior studies have addressed individual challenges through multifractal analysis of DEM-derived stream networks and flow-threshold selection [2]; the natural-rule-based-connection (NRBC) method for connecting river segments extracted from high-resolution imagery [3]; the DeepRiver deep-learning model with an adaptive loss function [4]; and a two-stage approach using multi-temporal remote sensing and path tracking to delineate connected river networks [5]. Other research combined Sentinel-1 radar and Sentinel-2 multispectral imagery to derive water and sediment masks for DEM stream burning, improving extracted network accuracy [6]. Nevertheless, these approaches do not directly resolve how terrain type, DEM resolution, and change-point detection (CPD) algorithm interact in automatic threshold determination. Therefore, this study compares four CPD algorithms under three DEM resolutions and three terrain types (36 combinations), evaluating extraction accuracy to identify terrain-specific algorithm–resolution choices.

Materials and methods. As shown in Fig. 1, study areas representing plains, hills, and mountains were selected. The plain area (Shunde–Panyu Water Network Area) covers a $45\text{ km} \times 35\text{ km}$ grid with dense, meandering tidal and anthropogenically influenced channels. The hilly region (Zhaoqing Qixingyan–Dinghu Hills, $40\text{ km} \times 25\text{ km}$) includes transitional terrain with seasonal streams and clear basin boundaries. The mountainous area (Shaoguan Danxia Mountain–Jinjiang Mountainous Watershed, $60\text{ km} \times 40\text{ km}$) features steep topography and dendritic drainage controlled by ridge lines. Multi-resolution DEMs

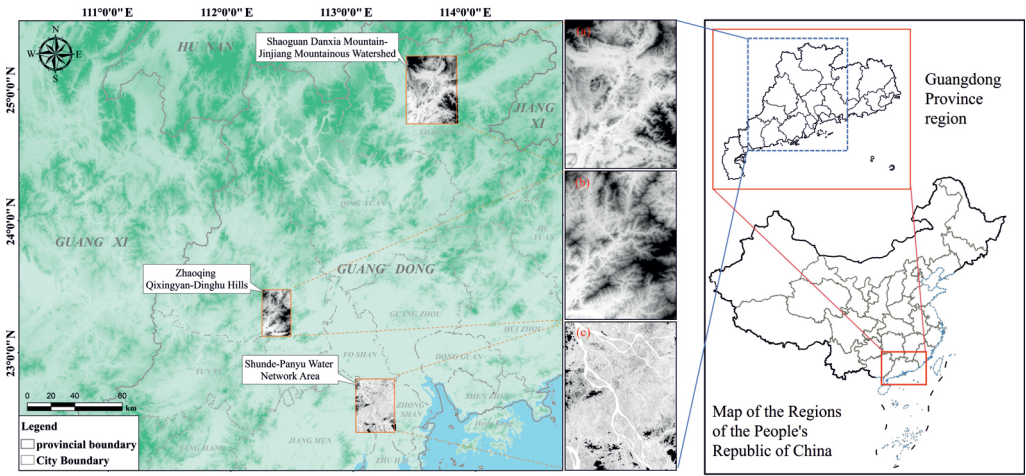


Fig. 1. Geographical overview map of the study area: (a) Shunde–Panyu Water Network Area; (b) Zhaoqing Qixingyan–Dinghu Hills; (c) Shaoguan Danxia Mountain–Jinjiang Mountainous Watershed

were used: 12.5 m (ALOS PALSAR, NASA) for plains, 30 m (SRTM, USGS) for hills, and 90 m (GDEM V3, CAS) for mountains. River network data were obtained from the National Earth System Science Data Center and OpenStreetMap, and refined via Google Earth interpretation to remove non-fluvial water bodies for hydrological consistency.

Methodology and design concept. The flow-threshold–first-order-tributary relationship exhibits an exponential change and a single optimal threshold [7, 8]. We therefore selected four parametric and non-parametric CPD algorithms capable of detecting a single change point in such sequences.

Pruned exact linear time (parameterization). Assuming a normal distribution, global optimal change point detection is achieved by minimizing the penalty likelihood function [9]

$$(1) \quad F(t) = \min_{0 \leq \tau < t} \{F(\tau) + C(y_{(\tau+1):t}) + \beta\}.$$

Binary segmentation (parameterization). Binary Segmentation recursively identifies an optimal change point, partitions the sequence and repeats until no significant change point remains [10]

$$(2) \quad C(\tau) = \frac{n}{\tau(n-\tau)} \left(\frac{1}{\tau} \sum_{i=1}^{\tau} y_i - \frac{1}{n-\tau} \sum_{i=\tau+1}^n y_i \right)^2.$$

Mann–Whitney U test (non-parametric). Change points are located by comparing rank sums without assuming an underlying data distribution [11]

$$(3) \quad U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1.$$

Kernel-based CPD (Non-parametric). Kernel-based CPD maps data into a reproducing kernel Hilbert space (RKHS) to detect distributional changes [12]

$$(4) \quad \widehat{\text{MMD}}^2 = \frac{1}{m(m-1)} \sum_{i=1}^m \sum_{j \neq i}^m k(x_i, x_j) + \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{j \neq i}^n k(y_i, y_j) - \frac{2}{mn} \sum_{i=1}^m \sum_{j=1}^n k(x_i, y_j).$$

Design of river network extraction process. The workflow comprises hydrological preprocessing, CPD-based threshold analysis and river network extraction with accuracy evaluation (Fig. 2).

GIS 10.8 and Python 3.12 were used for iterative calculations (Fig. 2). Extraction accuracy was evaluated using the F1-score

$$(5) \quad \text{F1} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} * 100\%.$$

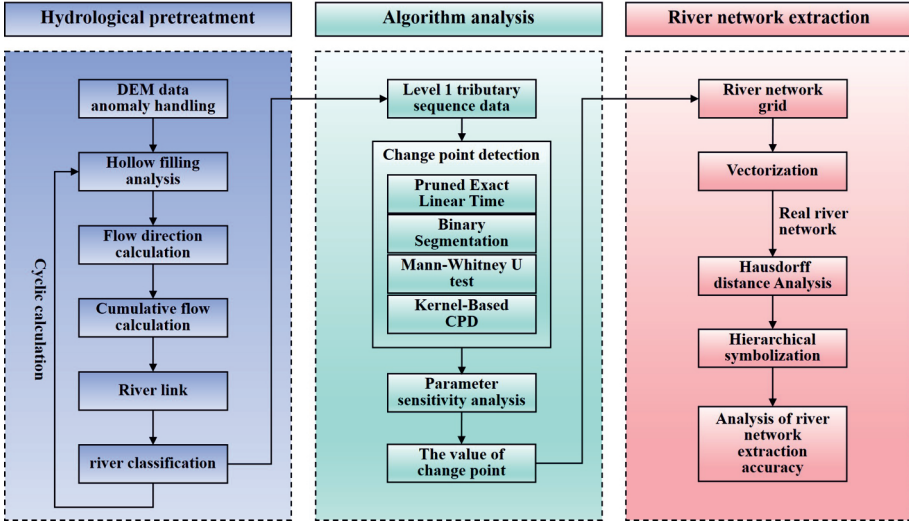


Fig. 2. Flowchart for extracting and analyzing hydrological river networks

Precision represents the fraction of extracted segments that match the reference; Recall represents the fraction of reference rivers extracted. Spatial discrepancy was measured by Hausdorff distance. True positives (TP) fall within $2 \times \text{DEM}$ resolution of reference rivers, while false positives (FP) lie beyond this distance. True rivers (TR) are the reference network corrected using Google Earth imagery.

Results. Four CPD algorithms were applied to cumulative-flow sequences of first-order tributaries for the three terrains and three DEM resolutions to identify optimal change points.

Sensitivity analysis and mutation detection. First, the PELT algorithm ($\beta = 0.1$, $\text{MinSeg} = 5$) verified statistical significance via mean differences and signal-to-noise ratios, proving stable for long sequence analysis. Second, the binary segmentation algorithm ($\text{MinLen} = 5$, $\text{SigThresh} = 1.0$) utilized F statistic distributions to accurately identify potential change nodes. Third, the Mann–Whitney U test evaluated significance levels, sequence length, and window smoothing effects to locate optimal mutation points, showing strong adaptability to non-normal data. Finally, the kernel-based CPD method ($\text{bandwidth} = 0.5$, $\text{MinSeg} = 10$, $\alpha = 0.05$) maximized test statistics to capture nonlinear structural changes. These complementary methods enhance detection robustness. The optimal threshold results under these sensitivity conditions are presented in Fig. 3.

Detection thresholds were algorithm-dependent and varied approximately linearly with DEM resolution, with similar values for PELT and Binary Segmentation but higher thresholds for the nonparametric Mann–Whitney U test.

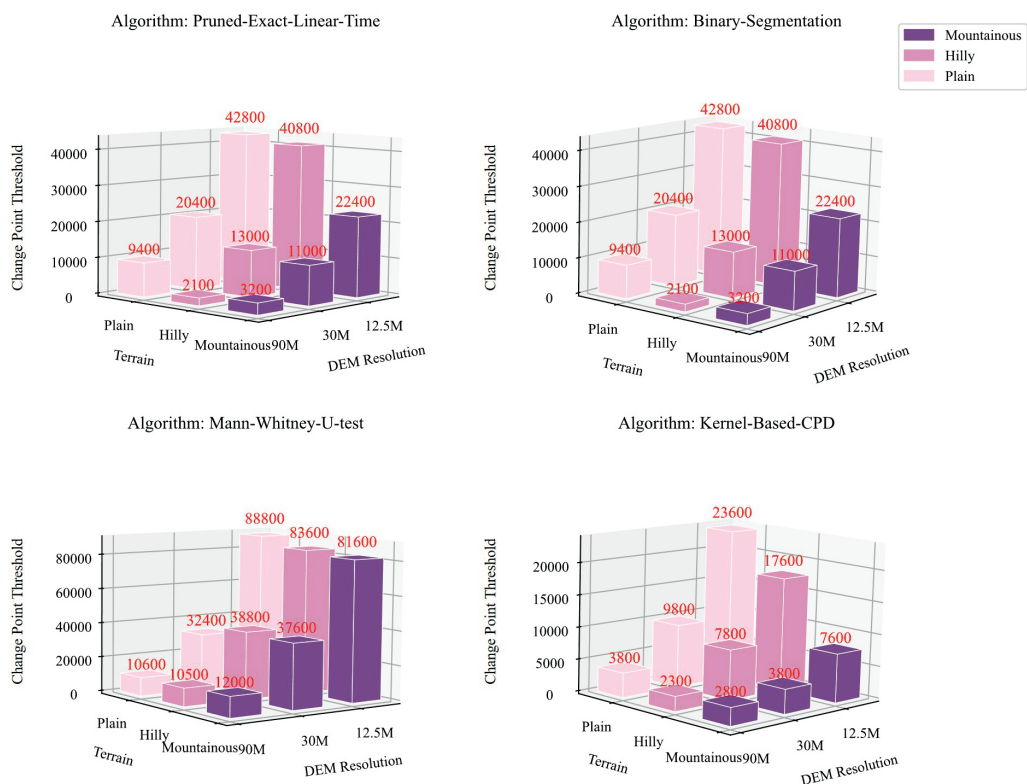


Fig. 3. CPD algorithm parameter settings and mutation information

Spatial distribution characteristics of river networks. Terrain and DEM resolution jointly affected extraction (Fig. 4), Kernel-based CPD had the strongest overall performance; the optimal resolutions were 90 m in mountains, 30 m in hills and 12.5 m in plains, reflecting different trade-offs between channel detail and false detection.

In mountainous terrain (Fig. 4a), the D8 algorithm applied to the 12.5 m DEM identified branch gullies as narrow as 5 m but also produced many false positives for non-river gullies, resulting in a 34.1% false-extraction rate. With the 30 m DEM, omitted tributaries were less than 10 km and mainly located in headwater areas. The 90 m DEM best represented the main channel, with false- and missed-extraction rates of 6.83% and < 3%, although channel-bend details were poorly captured. In (Fig. 4b), the 30 m DEM showed the best overall match, reducing both over-extraction at 12.5 m and omissions at 90 m, with false- and missed-extraction rates of 8.6% and 3.5%, respectively. In plain areas (Fig. 4c), all DEMs captured main channels (~ 160 m width), while the 12.5 m DEM achieved 82% accuracy for 20–50 m channels, outperforming coarser resolutions. However, channels < 10 m remained poorly extracted across all resolutions, with frequent omissions and discontinuities.

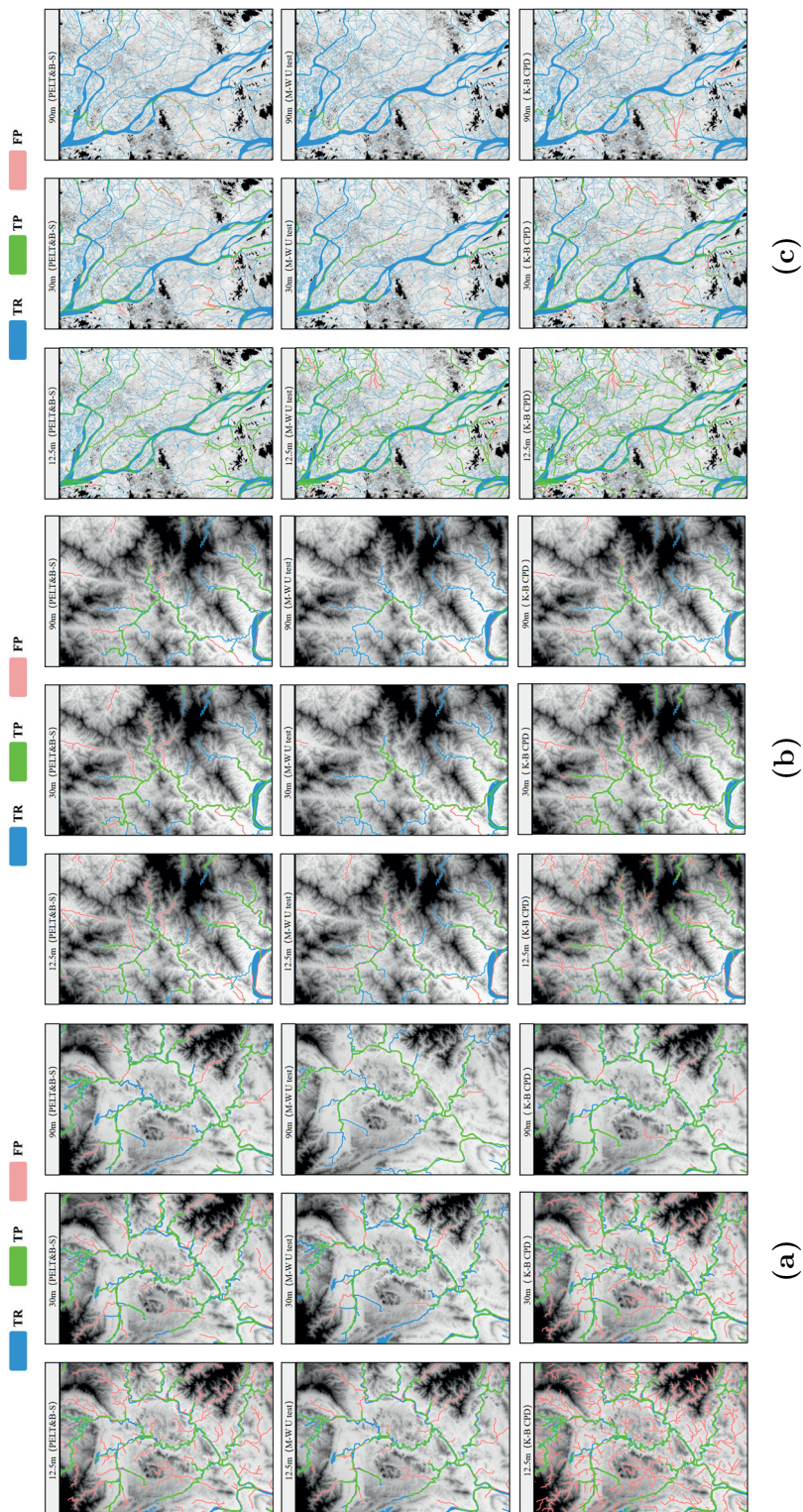


Fig. 4. Multi-scale DEM-CPD-terrain extraction river network results: (a) Mountainous; (b) Hilly; (c) Plain.
TR, true river; TP, true positive; FP, false positive

Differences in precision indicators. The F1-Score accuracy data under the 36 combined experiments are summarized as follows to verify the cross-influence law of algorithm–resolution–terrain on river network extraction. In mountainous areas, PELT and Binary Segmentation produced identical F1-Scores of 0.70, 0.85, and 0.79 at 12.5 m, 30 m, and 90 m, respectively; Mann–Whitney U yielded 0.84, 0.82, and 0.84; and Kernel-Based CPD yielded 0.58, 0.76, and 0.89. In hilly areas, PELT and Binary Segmentation again showed identical values of 0.72, 0.74, and 0.64; Mann–Whitney U gave 0.74, 0.64, and 0.55; and Kernel-Based CPD gave 0.72, 0.88, and 0.69. In plain areas, PELT and Binary Segmentation both produced 0.69, 0.57, and 0.43; Mann–Whitney U produced 0.72, 0.64, and 0.46; and Kernel-Based CPD produced 0.75, 0.67, and 0.48. These results confirm that extraction accuracy is jointly controlled by terrain type, DEM resolution, and CPD algorithm.

Discussion. River network extraction depends on the interaction of DEM resolution, terrain and CPD method. In mountains, finer DEMs retain small gullies but may generate false channels; at 90 m, kernel-based CPD better suppresses these errors, although channel bends are less detailed. Parametric methods (PELT and Binary Segmentation) retain useful detail at intermediate resolution, while kernel-based CPD is more robust under coarser representation. Hills favour 30 m data, whereas plains require 12.5 m to retain smaller channels, although channels below 10 m remain difficult to extract. Therefore, neither high resolution nor a single CPD method is universally optimal; method–resolution combinations should be selected for the terrain and required mapping detail.

Conclusions. Across 36 terrain–resolution–algorithm combinations, river extraction accuracy varied substantially. Kernel-based CPD achieved the highest F1-scores for mountainous terrain at 90 m (0.89), hilly terrain at 30 m (0.88) and plains at 12.5 m (0.75). PELT and Binary Segmentation returned identical F1-scores within each tested terrain–resolution combination. In mountains, the coarser DEM reduced spurious channel extraction but lost some bend detail; in hills, 30 m data balanced detail and omissions. In plains, kernel-based CPD decreased from 0.75 at 12.5 m to 0.48 at 90 m, and channels narrower than 10 m remained difficult to detect. These findings show that extraction performance depends on matching terrain characteristics, DEM resolution and CPD method rather than using a uniform setting. The proposed matching approach can guide multi-scale river network extraction and warrants further validation with additional geospatial data.

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