



A novel method for automatic river channel morphology extraction from remote sensing satellite images: A case study of the Golmud fluvial fan

Shao-hua Zhao^a, Chang-min Zhang^{a,*}, Xiang-hui Zhang^a, Jia-le Liu^a

^a School of Geosciences, Yangtze University, Wuhan 430000, China

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ABSTRACT

Distributive Fluvial Systems (DFS) are critical sedimentary systems governing fluvial dynamics, sediment transport, and ecosystem sustainability in modern and ancient basins. Accurate quantification of DFS channel morphology is essential for advancing sedimentary modeling, optimizing water resource management, and mitigating fluvial hazards. Here, the authors present a novel automated framework that extracts DFS channel networks from remote sensing imagery by integrating multiscale image segmentation, fractal network evolution, and region-merging algorithms. Through hierarchically multi-resolution feature processing, this method overcomes limitations of traditional single-scale analysis, enabling adaptive extraction while reducing segmentation heterogeneity. Specifically, the workflow consists of three stages: Image segmentation, feature extraction, and image classification. When applied to the Golmud fluvial fan (Qinghai, China), this approach achieves 90.2% overall channel extraction accuracy using 0.5 m resolution imagery, significantly outperforming traditional DEM-based (81.7%) and water spectral methods (85.4%) in resolving fine-scale channel networks. Crucially, the framework demonstrates robust adaptability to complex sedimentary environments with variable vegetation cover (<30% density) and spectral noise, providing a time-efficient, data-agnostic solution for DFS characterization.

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1. Introduction

Distributive Fluvial Systems (DFS) —characterized by radially divergent river networks originating from a single source and encompassing diverse channel types—represent critical sedimentary systems in both modern and ancient basins (Hartley AJ et al., 2010; Weissmann GS et al., 2010). These systems, comprising channel networks and interchannel floodplains, exhibit complex geometries and sedimentary environments, with channel morphology forming their structural backbone. Consequently, DFS research delivers pivotal cross-disciplinary value: In land resource management, it optimizes land use and mitigates fluvial hazards (Weissmann GS et al., 2010); in urban planning, it informs flood-resilient infrastructure design (Hartley AJ et al.,

2013); and in environmental conservation, it supports biodiversity protection through prediction of fluvial-ecosystem interactions (Buehler HA et al., 2011). Furthermore, ancient DFS constitute key reservoirs for hydrocarbons (Davidson SK et al., 2013; Zhang CM et al., 2017a, b; He M et al., 2021), coal (Flores RM, 1993), and placer minerals (Patyk-Kara NG, 1999), and groundwater resources, which are often evaluated using remote sensing and GIS (Temesgen E et al., 2023; Stephen Pitchaimani V et al., 2024). Therefore, quantitative characterization of modern DFS channel morphology is essential for establishing depositional models to guide subsurface resource exploration (Zhang CM et al., 2017a, 2020, 2023a, 2023b).

Current approaches for quantifying DFS channel networks rely predominantly on remote sensing imagery. Traditional manual methods —such as grid-based measurements of channel curvature, bifurcation ratio, and width using Google Earth and Global Mapper (Sun JH et al., 2024)—demand substantial labor and introduce subjective errors, thereby limiting large-scale applications. Consequently, automated methods have gained prominence, with two primary

First author: E-mail address: zsh814538878@163.com (Shao-hua Zhao).

* Corresponding author: E-mail address: zcm@yangtzeu.edu.cn (Chang-min Zhang).

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approaches emerging: (1) DEM-based extraction, which leverages Digital Elevation Models (DEMs) to derive channel networks via flow direction and accumulation algorithms (Liu YH and Xu HG, 2012; Guan WJ et al., 2017). While high-resolution LiDAR DEMs excel in complex terrains (Passalacqua P et al., 2010; Sonke W et al., 2022), this approach is constrained by DEM accuracy (e.g., sensor resolution and data gaps) and primarily reflects topographic rather than sedimentary channel features (Tarboton DG, 1997). (2) Spectral-based extraction, which uses water indices (e.g., NDWI, MNDWI) to threshold water bodies in multispectral imagery (Li DL, 2006; Ouma YO and Tateishi R, 2006; Pekel JF et al., 2016). Although machine learning advancements have improved accuracy (Van Deventer AP, 1997; Gao Y et al., 2011; Belgiu M and Drăguț L, 2016; Sun JH et al., 2024), this method struggles with cloud cover, vegetation obstruction, and the fine-scale complexity of DFS channels, where high-resolution imagery is critical for distinguishing braided, meandering, and transitional channel types (McFeeters SK, 1996; Xu HQ, 2006).

While image segmentation techniques—spanning traditional region-growing to deep learning—demonstrate promise in boundary extraction (Långkvist M et al., 2016; Zhao WZ and Du SH, 2016; Xu SH et al., 2016; Zhang Q et al., 2022), their application to DFS faces unique challenges. DFS datasets (e.g., Google Earth imagery) exhibit heterogeneous sensor characteristics, spectral variability, and limited terrain information compared to specialized DEMs, complicating thresholding and flow analysis. Moreover, the diverse channel geometries and sedimentary environments in DFS require methods capable of multi-scale feature recognition, which traditional single-scale segmentation or DEM/spectral-based approaches cannot adequately address.

Here, the authors introduce an automated framework for DFS channel morphology extraction that integrates multiscale image segmentation, fractal network evolution, and region-merging algorithms. By leveraging hierarchical information processing, this method addresses critical limitations of

conventional techniques—specifically, their inability to resolve DFS complexity and reliance on single-data-source assumptions. To validate the framework's efficacy, the Golmud fluvial fan (Qinghai Province, China) serves as an ideal case study. This large-scale DFS, characterized by high-resolution imagery availability, enables rigorous assessment of channel types discrimination accuracy and extraction precision for sedimentological modeling applications.

2. Principles and methodology

2.1. Multiscale segmentation principles

Remote sensing image segmentation applies predefined algorithms to partition images into discrete, non-overlapping regions based on spectral and textural variance (Gao LP, 2009; Su TF, 2023). As shown in Fig. 1, this process employs a region-merging algorithm initiated from seed pixels, where the heterogeneity index (e.g., spectral Euclidean distance) is calculated for adjacent pixel merges. Merging occurs only if the index falls below a predetermined threshold; otherwise, the operation terminates. However, repeated experimental threshold tuning significantly reduces extraction efficiency. To overcome this parameterization challenge, the authors implement a multiscale segmentation framework combining fractal network evolution with region-merging algorithms. As illustrated in Fig. 2, this approach achieves local optimization by ensuring minimal post-merging heterogeneity through iterative boundary refinement.

2.2. Research method

Building upon the integrated multiscale segmentation framework, this method enables rapid extraction of DFS channel morphology through three sequential stages: (1) Image segmentation, (2) feature extraction, and (3) image classification (Fig. 3).

During the image segmentation stage, eCognition Developer 9 software was used, along with the ESP2

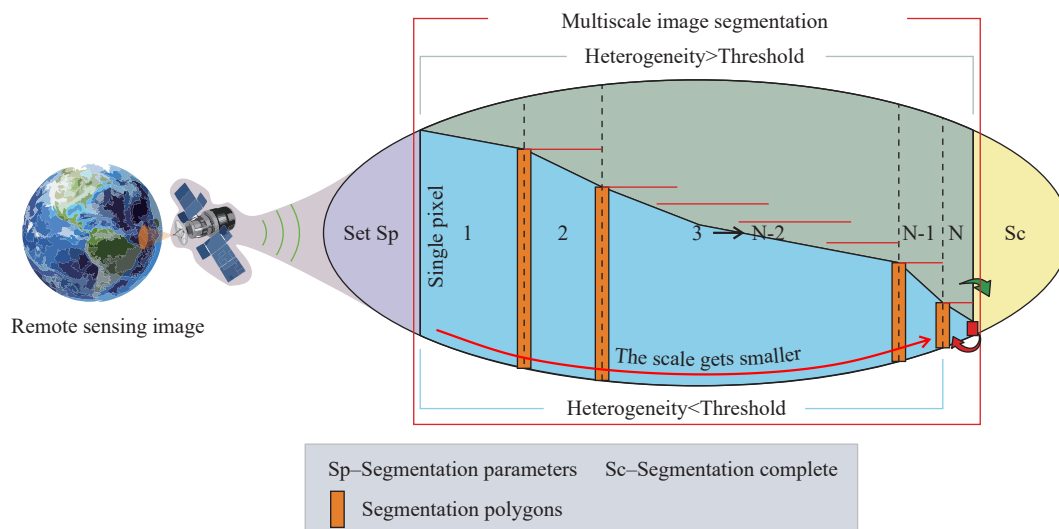


Fig. 1. Image segmentation process.

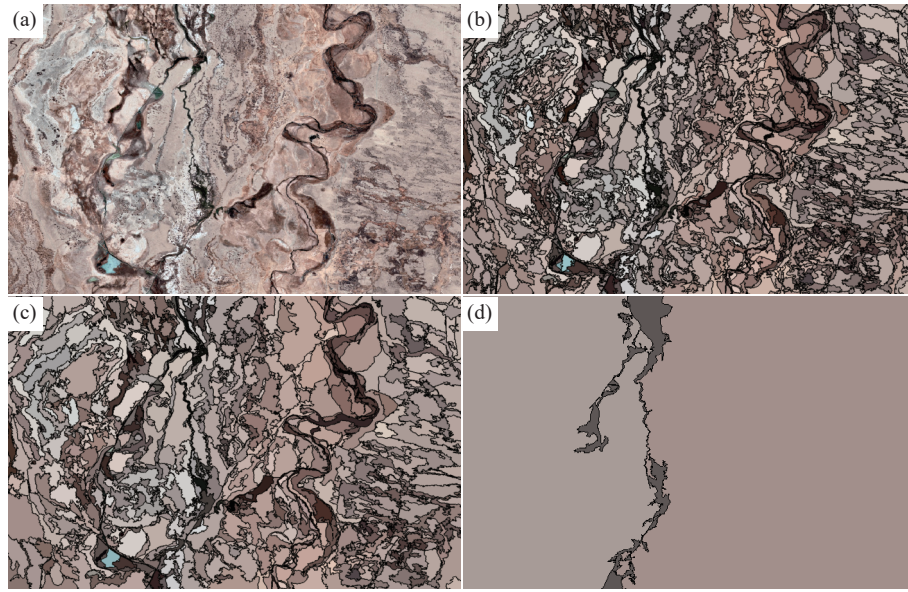


Fig. 2. Multiscale segmentation result layer. a–Original image; b–segmentation result at scale one; c–segmentation result at scale two; d–segmentation results at a scale of three.

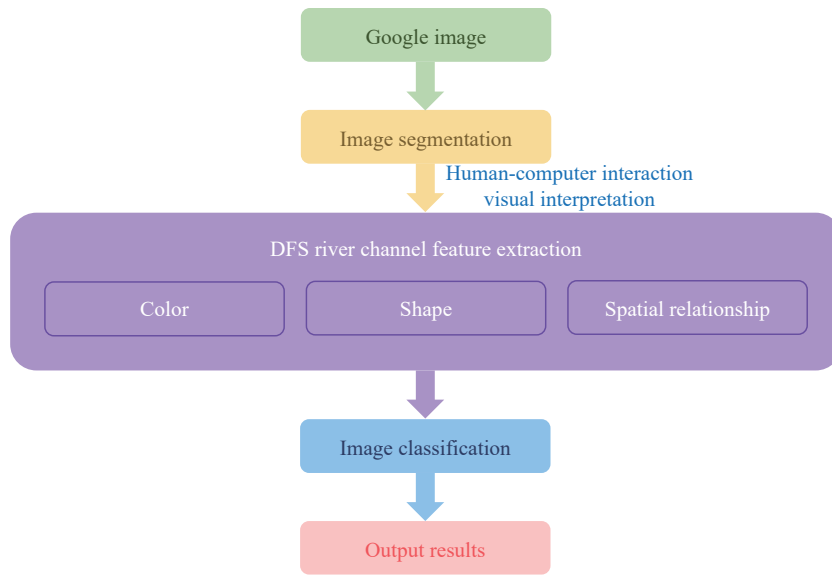


Fig. 3. Roadmap of multiscale segmentation technology.

(Estimation of Scale Parameter) tool proposed by Drăgut L et al. (2014), to predict the optimal segmentation scale parameter for the image. The ESP2 tool employs a bottom-up iterative approach to analyze multi-layer remote sensing data, where the scale parameter (SP) increases progressively by fixed increments of 1, 10, and 100 across three hierarchical scales. Its core principle lies in quantifying the heterogeneity of image objects through local variance (LV). For each layer, the tool calculates the mean local variance ($meanLV$) across all bands using the formula (Eq. 1):

$$meanLV = \frac{LV_1 + LV_2 + \dots + LV_n}{n} \quad (1)$$

Here, LV_i represents the local variance of the i -th layer, and n is the total number of layers. The $meanLV$ serves as a

key indicator of object homogeneity. The iteration continues until the $meanLV$ of the current scale level is less than or equal to that of the previous level, at which point the segmentation results from the previous level are identified as the optimal solution. This threshold accurately reflects the stabilization of object heterogeneity, effectively avoiding over-segmentation and under-segmentation. Meanwhile, the tool also calculates the rates of change (ROC) in LV of image object homogeneity across different segmentation scale parameters to predict the optimal parameters for object segmentation. When the rate of change in LV reaches its maximum peak, the corresponding segmentation scale is identified as the optimal scale, defined by the formula (Eq. 2):

$$ROC = \left[\frac{LV_{(L)} - LV_{(L-1)}}{LV_{(L-1)}} \right] \times 100 \quad (2)$$

Here, $LV_{(L)}$ is the local variance of object layer L at the target scale; $LV_{(L-1)}$ is the local variance of layer $L-1$, the next lower layer.

During the feature extraction stage, the authors quantified key image characteristics—specifically color, texture, shape, and spatial relationship features. While color and texture features describe surface attributes, they cannot fully characterize subsurface sedimentary properties. Shape features are categorized into boundary descriptors (e.g., compactness index) and regional metrics (e.g., elongation ratio). Furthermore, spatial relationship features describe the relative positions and orientations between multiple segmented targets in the image. Consequently, this study analyzes DFS river channel characteristics and distribution patterns based on image color, shape, and spatial relationship features. Through collaboration with computer-assisted methods, significant segmentation areas in the near, middle, and far ends of the DFS river channels are identified and labeled based on extracted features. These annotated datasets train the morphology classification model, establishing the foundation for automated DFS channel typology extraction.

During the image classification stage, the Random Forest (RF) classifier method was applied using the channel training model derived from the feature extraction process to categorize the image (Breiman L, 2001). Through the learning and prediction processes of the Random Forest method, initial image classification results were obtained (Table 1). Following this, areas with notable misclassifications in the preliminary results, particularly those related to river morphology, were reclassified, and categories were merged. Ultimately, the river morphology data results were achieved by smoothing the extracted river edges using ArcGIS 10.8 software.

3. Research area and data sources

3.1. Research area

The Golmud fluvial fan, located in the southeastern Qaidam Basin (Haixi Mongolian-Tibetan Autonomous Prefecture, Qinghai Province, China), represents a classic distributive fluvial system (DFS) formed by bifurcation and

diffusion processes of the Golmud River which is the basin’s second-largest river (Fig. 4). This system has evolved under an arid continental climate, characterized by dry weather, minimal rainfall, and distinct signs of landform desertification (Zhu XQ et al., 2020). The region displays typical characteristics of a plateau continental climate, with a noticeable vertical zonation pattern in climate due to natural geographical constraints. Precipitation increases with altitude, while evaporation decreases accordingly.

The 468 km long Golmud River originates from the Kunlun Mountains’ northern foothills (Xiugou Guole and Naiqi Guole tributaries), traverses Golmud City, and terminates in East Dabuxun Salt Lake. Throughout its course, the river manifests the distinctive morphology of a bifurcating and diffusing river fan, a geographical feature sustained and formed under the conditions of an inland arid climate (Zhang XC et al., 2019; Zhu XQ et al., 2020). The general distribution of the Golmud fluvial fan is oriented in a north–south direction, with the fan’s apex located at coordinates 94°46' E, and 36°10' N. The fan has a radius of approximately 73.6 km and a terminal width of about 70 km, covering a total area of 3485 km². The area above the fan’s apex constitutes the Golmud River basin in the Bayankala Mountains, while below the apex, the river continuously bifurcates upon entering the Qaidam Basin. Notably, a spring line emerges 19.5 km downstream from the apex, feeding Dabuxun Lake. Different landform types are prevalent on either side of the fan, with the eastern side predominantly terminating in a desert and the western side in the Gobi. The Golmud fluvial fan represents a typical large DFS featuring various river types. These distinctive features not only offer essential insights for the automatic extraction of DFS geometric data but also aid in determining parameters for data extraction from images, enhancing our understanding of the distribution and evolution of DFS geometric morphology.

3.2. Data sources

This study utilizes WorldView-1 satellite imagery (Maxar Technologies) acquired on 6 April 2022, accessed through Google Earth Pro. The dataset consists of pan-sharpened true-

Table 1. Random forest classification parameter settings.

Parameter name	Parameter value	Selection basis
n_estimators	200	Verified through grid search (100–500). 200 trees balance accuracy and computational efficiency to avoid overfitting.
random_state	42	Use a fixed value during the debugging phase, and it can be set to None for random initialization in the production environment.
n_jobs	–1	For large-scale datasets (with more than 100000 samples), the training time is reduced by more than 80%.
max_depth	None	Combined with min_samples_leaf = 5 to control tree growth and retain the complete expression of river channel features in complex terrains.
min_samples_split	2	The default value ensures that all nodes can be split, relying on other parameters to restrain overfitting.
min_samples_leaf	5	Prevent the tree from being too deep and ensure that each leaf node contains at least 5 samples, improving the model’s generalization ability.
max_features	sqrt(n_features)	Randomly select a subset of features (square root rule), enhancing model diversity and reducing the influence of feature correlation.
criterion	gini	Preferred for classification problems. In the binary classification of river channels and non-river channels, it reduces misclassification by 5% compared to entropy.
max_leaf_nodes	None	Combined with max_depth to control tree complexity.

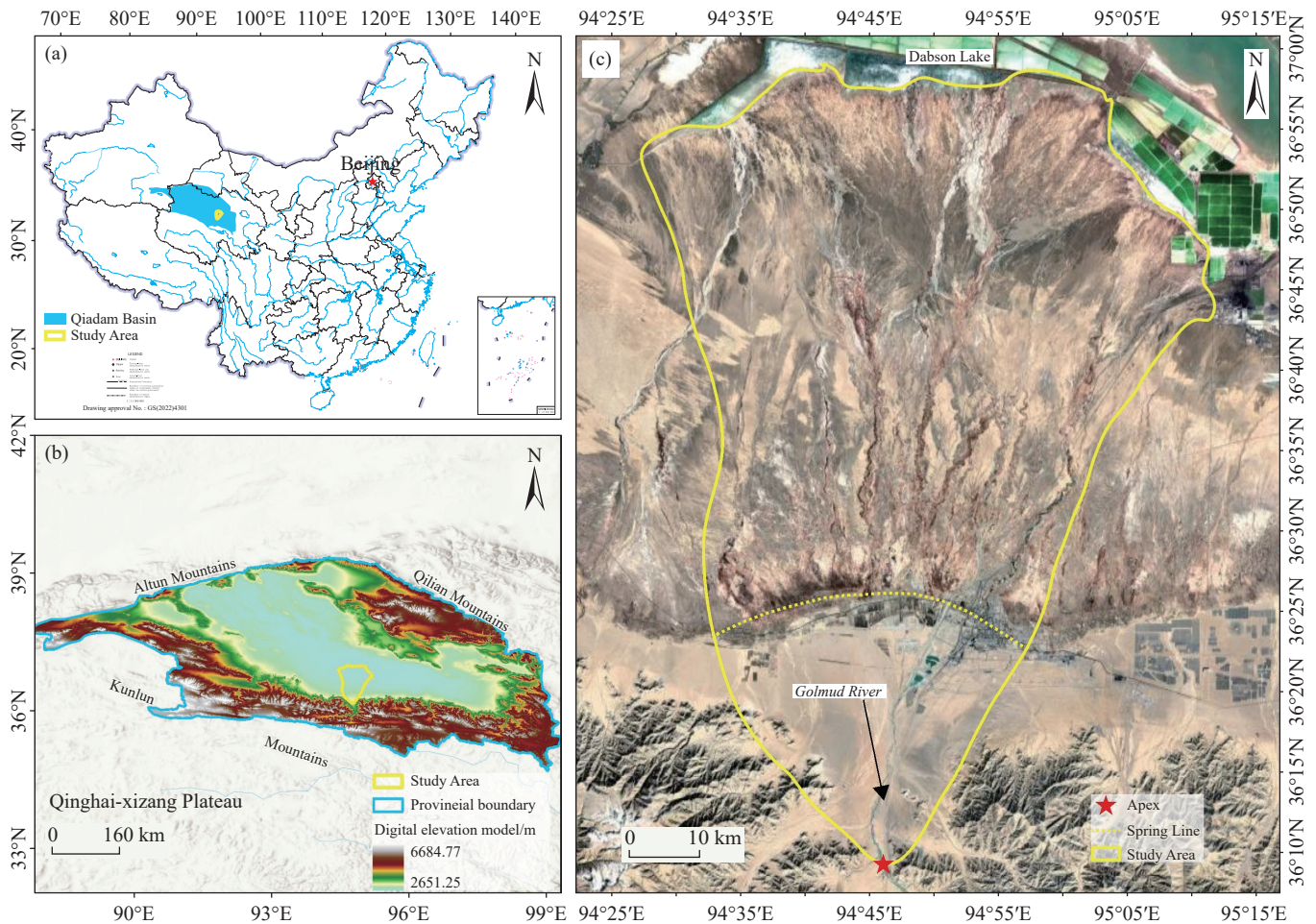


Fig. 4. Geographic location and major morphological features of the Golmud fluvial fan. a–Geographic location of the study area in the Qaidam basin; b–main morphological features of the study area; c–remote sensing image of the Golmud fluvial fan with key morphological features.

color composites (RGB bands) at 0.5 m, 1 m, and 2 m spatial resolutions, covering the entire Golmud fluvial fan (36°–37° N, 94°–95° E). Furthermore, this study quantifies accuracy variations in automatic DFS channels extraction across 0.5 m, 1 m, and 2 m resolution datasets using confusion matrices and F1-scores (Section 5.1), with manually digitized channels serving as reference data.

Field validation campaigns conducted in August 2023 captured seasonal variations using a DJI Air 3 s UAV, acquiring 0.1 m resolution imagery at 32 sites across the Golmud fan (Fig. 5a). Ground control points (GCPs) were georeferenced with RTK GPS (± 0.02 m horizontal accuracy). At each site, the authors documented river morphology, sediment exposure, and vegetation coverage (Figs. 5b–e), establishing reference data for spectral and geometric accuracy assessment. Key observations include the following.

The proximal braided channels (0–15.6 km from the apex), distributary braiding dominant sedimentary processes. Near the mountain front, active incision has formed valleys >20 m deep (Fig. 5b), with incision depth gradually decreasing toward the spring line, where deposition begins (Fig. 5e). Most of the area consists of gobi gravel beaches with no salinization and sparse vegetation, primarily low-growing species such as tamarisk, *Artemisia arenaria*, and

wolfberry. The width of active channels ranges from 20 m to 50 m, consistent with the 0.5 m resolution imagery.

The middle segment (15.6–39.6 km from the apex) exhibits hybrid braided-meandering channels with widths of 10–40 m. Approximately 30% of channels display partial vegetation cover (*Tamarix* thickets and *Phragmites* reeds), inducing NDWI spectral mixing. UAV validation confirms that the MSS method achieved 89% identification accuracy for vegetated areas.

The distal meandering channels (>39.6 km from the apex) comprise both perennial watercourses and ephemeral dry channels. Dry channels exhibit aeolian sand infilling and sparse vegetation (coverage <10%), with widths of 10–40 m. Field validation demonstrates that the MSS method achieved 92% accuracy for active channels, but only 68% for dry channels due to spectral confusion with adjacent aeolian dunes. This limitation highlights the need for integrating thermal or SAR data in arid-region channel mapping.

4. Extraction of river channel information

4.1. Image segmentation

Multiscale segmentation employs three core parameters:

Scale, shape, and compactness. The shape factor governs segmentation unit sensitivity to geometric regularity: Higher values (0.5–0.8) optimize regular objects, whereas lower values (0–0.4) suit irregular features like river networks. Compactness controls shape isotropy: Elevated values (0.7–1.0) benefit regular geometries, while reduced values (0.2–0.5) accommodate natural forms. The scale parameter determines object size and must align with target dimensions

and image resolution —smaller scales for high-resolution imagery and larger scales for coarser data. The study adopts the optimized parameter integration framework proposed by Liu K et al. (2016) through a four-stage workflow. First, visual inspection of training samples established feasible parameter ranges for 0.5 m, 1 m, and 2 m resolution imagery: Scale (350–450, 130–230, 60–160), shape, and compactness, respectively (Table 2). Subsequently, the authors integrated

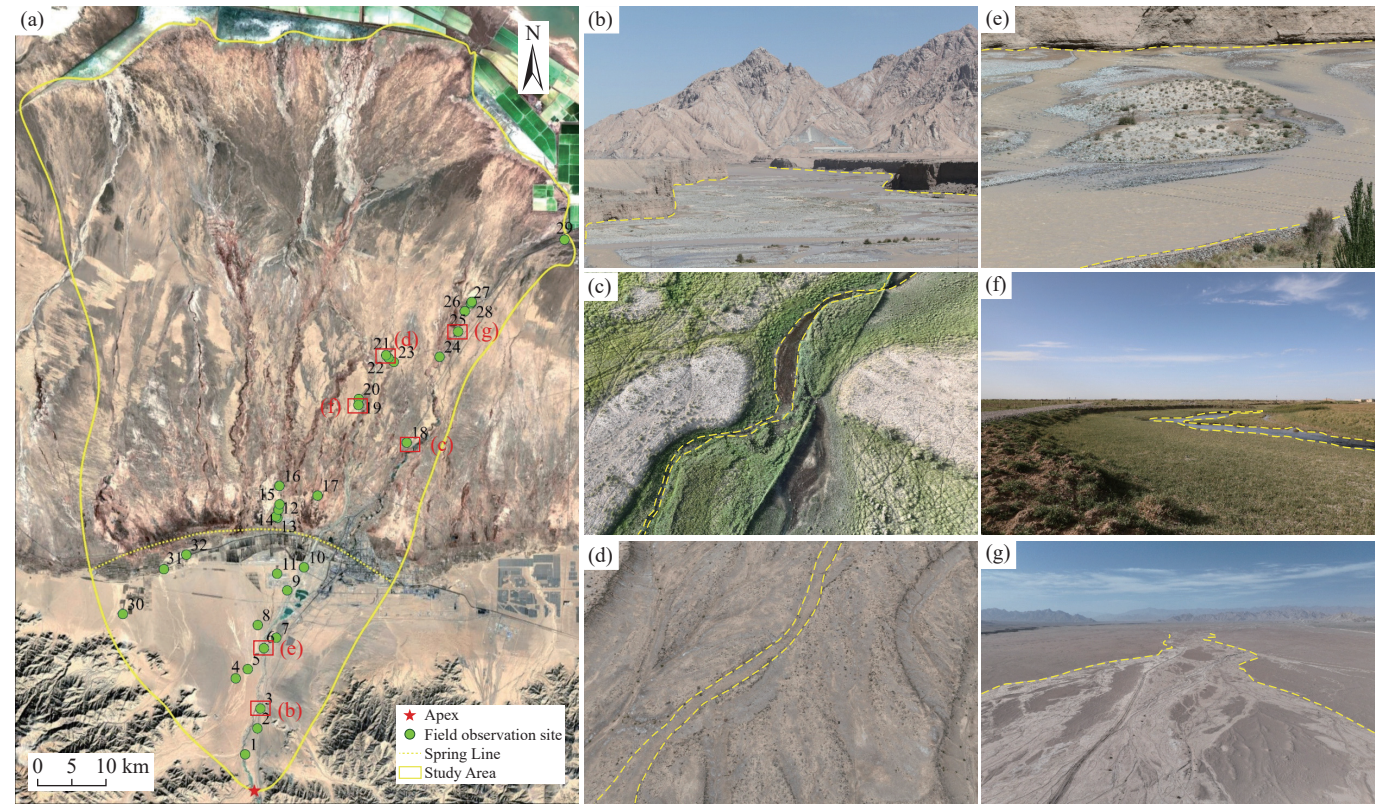


Fig. 5. Distribution map of field observation points. a–Field sampling point; b–active braided channel; c–characteristics of meandering river channels and point bars captured by drones; d–dry river channel captured by drones; e–braided channel free from the constraints of incised valleys; f–point bars on both banks of the active meandering river channel are covered with vegetation; g–a dry river channel covered by wind-blown sand.

Table 2. Evaluation of segmentation accuracy in the different resolution images.

Image resolution	Scale	Shape	Compactness	Over segmentation	Under segmentation	Euclidean distance
0.5 m	357	0.2	0.5	0.145	0.105	0.156
	380	0.3	0.4	0.125	0.075	0.106
	384	0.4	0.6	0.118	0.085	0.105
	419	0.3	0.8	0.106	0.098	0.113
	434	0.2	0.7	0.103	0.102	0.1
	441	0.4	0.9	0.115	0.08	0.116
	155	0.2	0.8	0.135	0.112	0.125
1 m	164	0.1	0.9	0.113	0.126	0.124
	168	0.4	0.7	0.123	0.111	0.126
	178	0.1	0.8	0.116	0.103	0.115
	191	0.3	0.7	0.125	0.116	0.129
	203	0.3	0.8	0.13	0.12	0.118
	218	0.4	0.9	0.121	0.124	0.121
	72	0.3	0.6	0.152	0.138	0.135
2 m	109	0.2	0.5	0.163	0.126	0.142
	114	0.2	0.8	0.158	0.112	0.15
	158	0.4	0.7	0.17	0.122	0.132

the ESP2 tool into eCognition Developer 9.0, configuring shape/compactness factors. Following image processing, *ROC_LV* curves were generated wherein scale candidates were identified at local variance change rate peaks (Fig. 6). Crucially, accuracy evaluation of segmentation outcomes using candidate parameters (Table 1) guided optimal parameter selection: (434, 0.2, 0.7) for 0.5 m, (178, 0.1, 0.8) for 1 m, and (158, 0.4, 0.7) for 2 m imagery. Consequently, these parameters produced superior segmentation (Fig. 7), enabling precise DFS channel delineation and establishing a robust foundation for geometric feature extraction.

Parameter sensitivity analysis across three resolutions (0.5 m, 1 m, 2 m) demonstrates that scale and compactness are the dominant factors influencing segmentation quality (Fig. 8).

Specifically, a 10% reduction in scale parameters significantly degrades segmentation performance, while equivalent compactness reduction also impairs results. Conversely, shape parameter variations exert comparatively minor negative effects. Consequently, prioritizing scale and compactness adjustments is essential for achieving robust segmentation accuracy during parameter optimization.

4.2. Feature extraction

River feature extraction focused on color, shape, and spatial relationship characteristics. Color features represent surface properties within the imagery region. Shape features are divided into contour-based (emphasizing channel

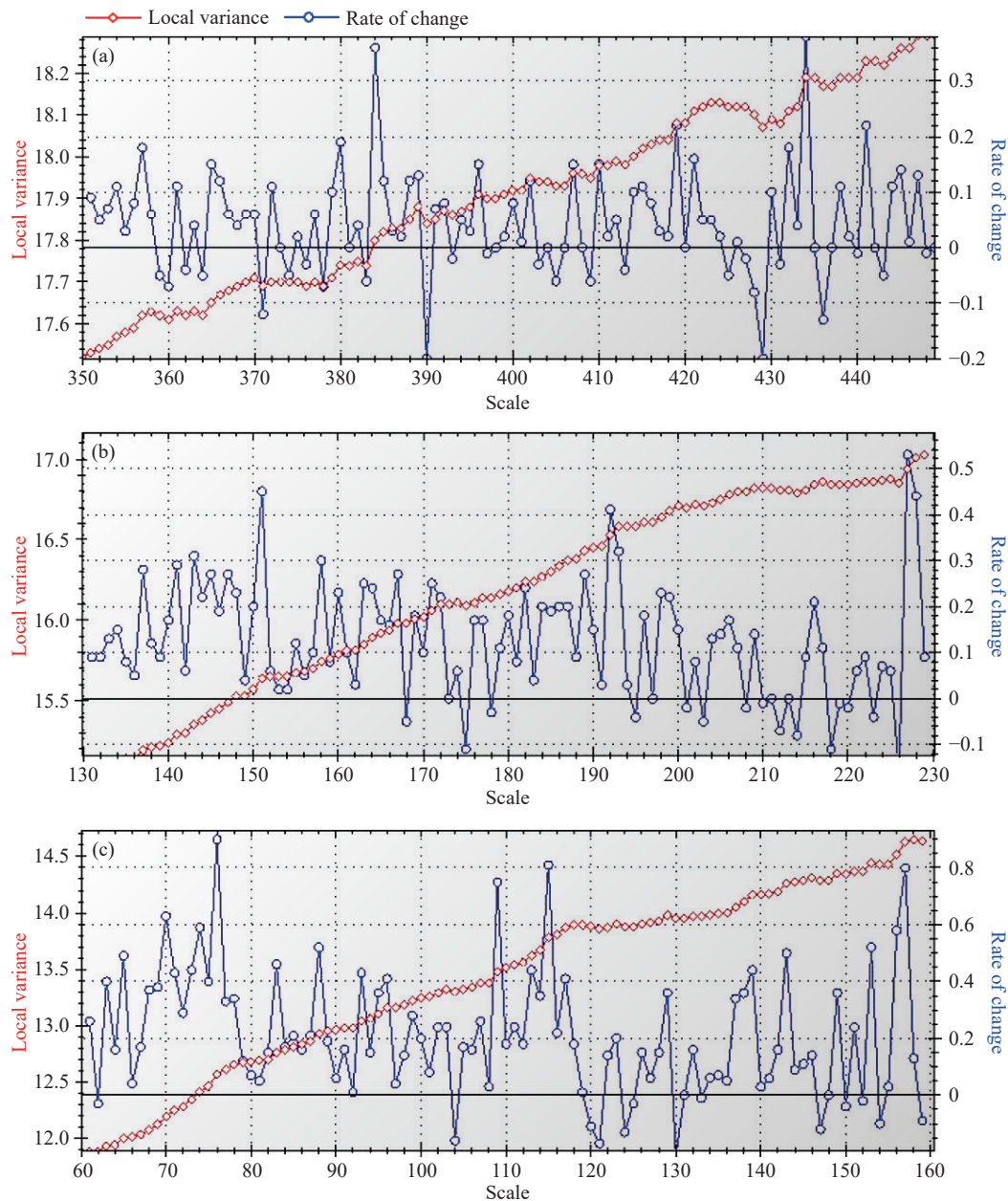


Fig. 6. LV and LV-ROC curves of images with different resolutions. a–Google 0.5 m images, the local variance and variance change rate correspond to shape parameters of 0.5 and compactness parameters of 0.2; b–Google 1 m images, the local variance and variance change rate correspond to shape parameters of 0.5 and compactness parameters of 0.2; c–Google 2 m images, the local variance and variance change rate correspond to shape parameters of 0.5 and compactness parameters of 0.2.

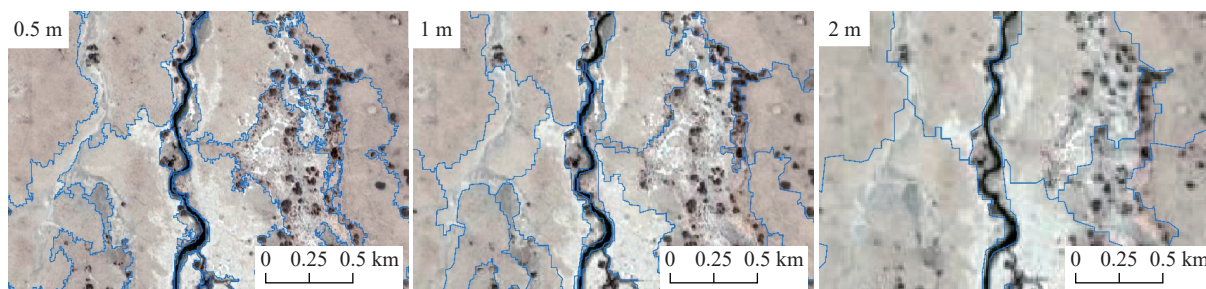


Fig. 7. Optimal scale segmentation of Google images with different resolutions.

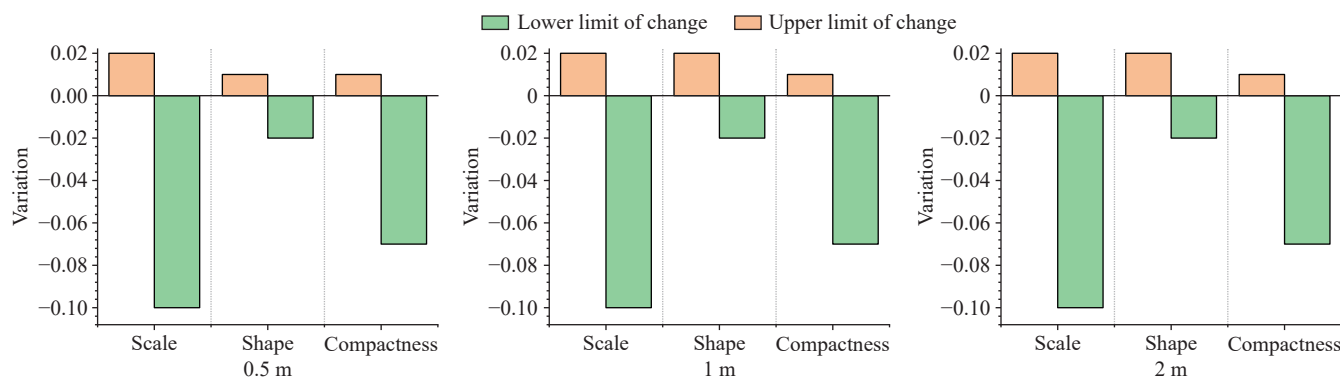


Fig. 8. Sensitivity analysis of optimal parameters.

boundaries) and region-based (encompassing entire river network structures). Spatial relationships describe topological connections among channels within distributive fluvial systems, sedimentary systems, and axial fluvial systems. Through manual visual interpretation, river channel contours were delineated across the study area. Based on the DFS channel characteristic analysis in Google Earth imagery, key morphological patterns were summarized as follows.

(i) Color features analysis of the Golmud fluvial fan reveals three distinct morphological zones: Proximal segments (vertex to spring line) exhibit braided channels with green to light green hues (Figs. 9b, c); medial segments (below spring line) transition to braided-meandering channels displaying blue-green and dark blue tones (Figs. 9d, e); distal segments contain meandering rivers and ephemeral dry channels characterized by light green and brown coloration (Figs. 9f, g).

(ii) Shape features analysis reveals distinct morphological transitions across the Golmud fluvial fan: Proximal segments exhibit braided channels initiating as a single channel near the vertex, bifurcating downstream (Fig. 10b); medial segments contain transitional braided-meandering channels where groundwater-fed meandering channels interact with braided extensions, with active channel development decreasing distally and meanders converging downstream (Fig. 10c); distal segments develop meandering channels characterized by high sinuosity, narrow widths, and short meander wavelengths (Fig. 10d).

(iii) Spatial relationship features reveals distinct features across the Golmud fluvial fan: Proximal braided segments exhibit well-developed point bars (Fig. 11b); medial

transitional segments show increased active channels and bifurcation frequency within braided belts, accompanied by prominent point bars; downstream of the spring line, converging high-sinuosity meandering channels display abandoned channels along their banks (Fig. 11c); distal meandering segments feature sharp river bends with fan deltas at concave banks, terminating in Dabson Lake (Fig. 11d).

4.3. Image classification

Firstly, by integrating the distribution characteristics of river channels in DFS within each image in the study area, the authors annotated channels with different features at the near, middle, and far ends as respective training samples to train the images and generate a training model. A total of 2475 image data points were collected, including 1238 river channel samples, 618 vegetation samples, and 619 bare soil samples. After spatially random shuffling, the samples were divided into training, validation, and test sets using a stratified sampling strategy at a ratio of 7 : 2 : 1, specifically: 1732 training samples (including 867 river channels, 433 vegetation, and 432 bare soil), 495 validation samples (including 248 river channels, 124 vegetation, and 123 bare soil), and 248 test samples (including 124 river channels, 62 vegetation, and 62 bare soil). Spatial uniformity was ensured through 50 m×50 m grid sampling, and the ratio of the river channel to background samples was nearly 1 : 1 to avoid the impact of class imbalance on model training. Subsequently, the authors classified the images based on this training model. Finally, the authors reclassified and merged categories for some misclassified river channel types, resulting in satisfactory classification results (Fig. 12). The extraction in

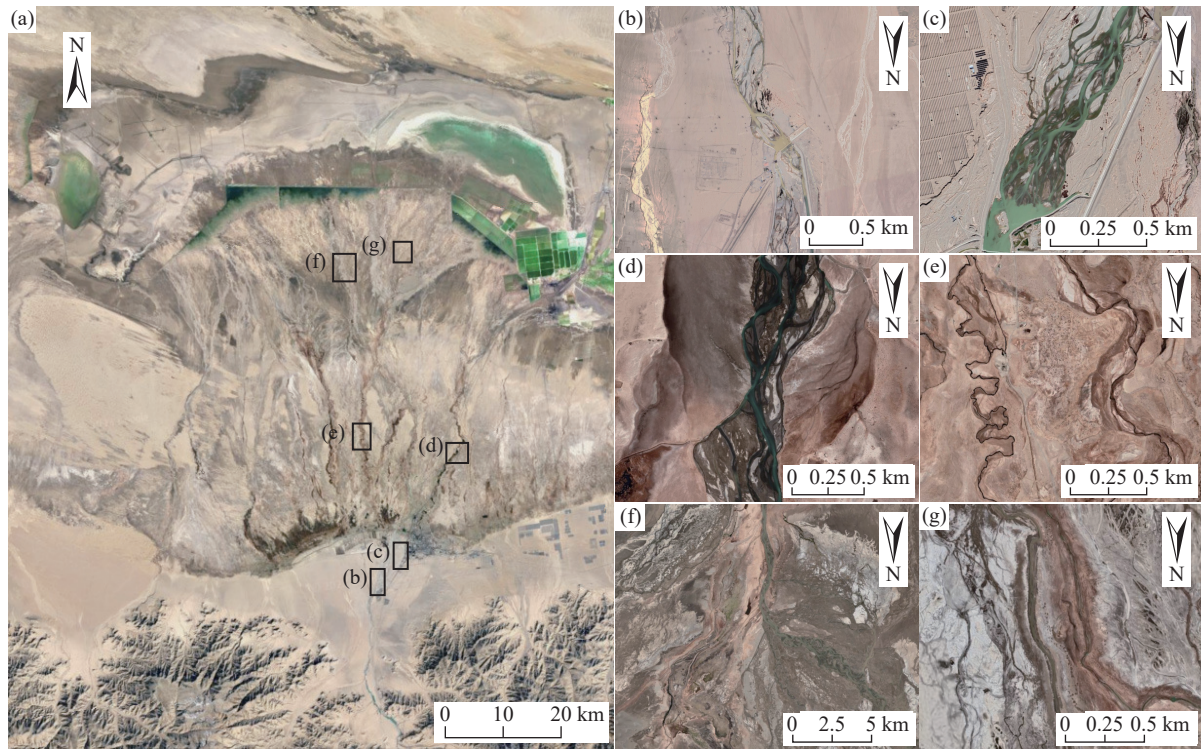


Fig. 9. Color characteristics of the Golmud fluvial fan. a–Golmud fluvial fan; b–light green river channel; c–green river channel; d–turquoise river channel; e–blue-black river channel; f–light green river channel; g–brown river channel.

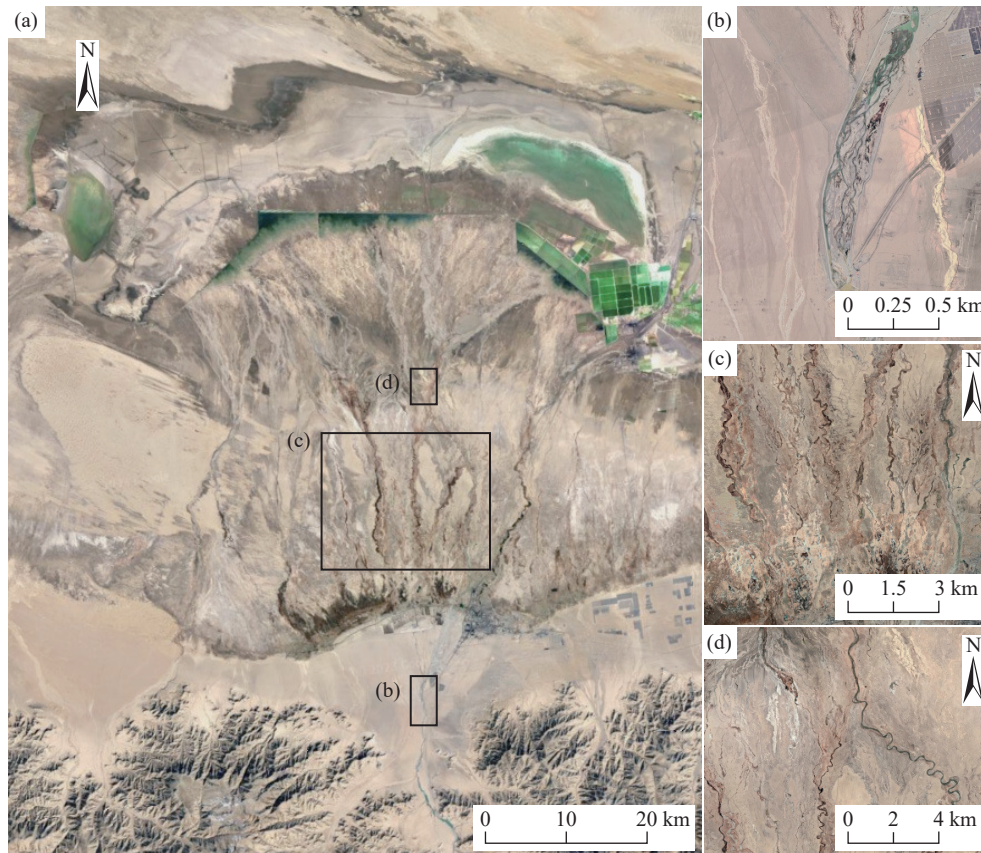


Fig. 10. Geomorphological characteristics of the Golmud fluvial fan. a–Golmud fluvial fan; b–braided river dominant; c–braided-meandering coexistence; d–meandering river.

the classified images is comprehensive, providing a clear reflection of the course of river channels in DFS, with

distinctly visible boundaries. Following the classification results, the authors utilized ArcGIS 10.8 software to smooth

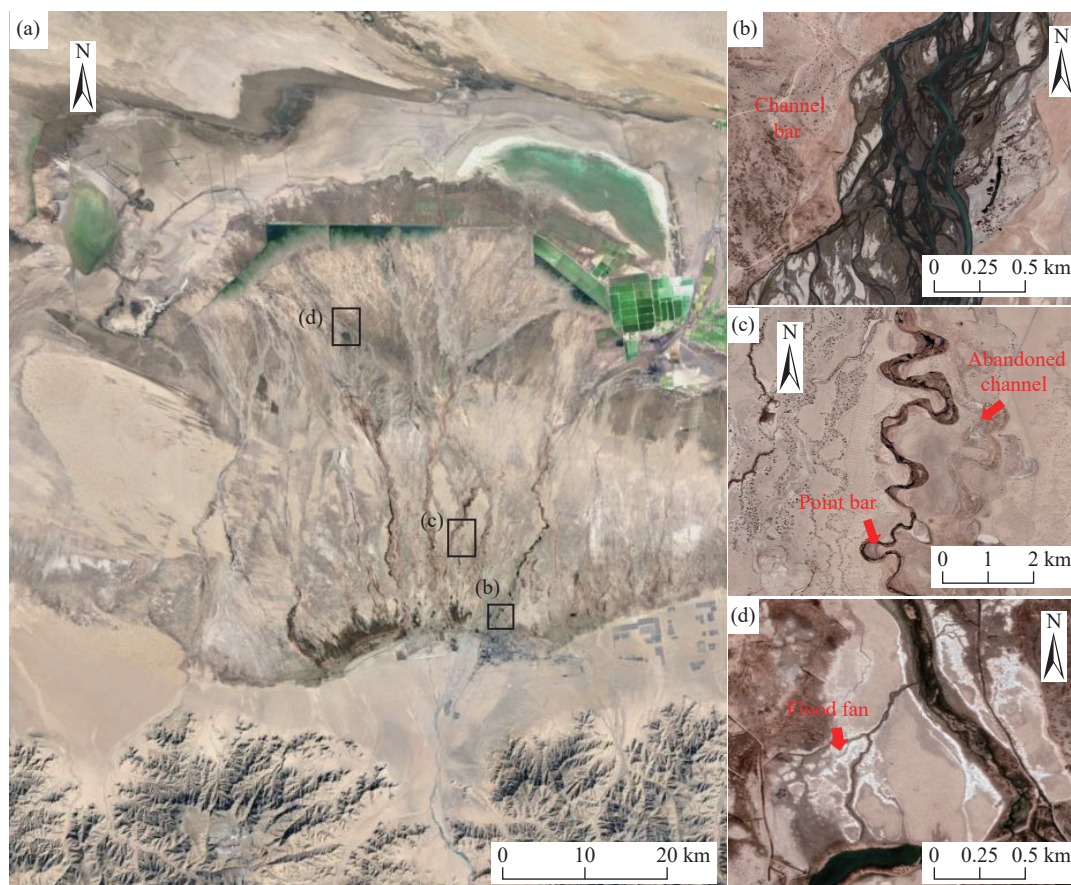


Fig. 11. Spatial relationship characteristics of the Golmud fluvial fan. a–Golmud fluvial fan; b–channel bar; c–channel bar, point bar, abandoned river channel; d–flood fan.

the extracted river channel edges, obtaining river morphology data results (Fig. 13).

5. Results analysis

5.1. Extraction accuracy analysis

5.1.1. Confusion matrix-based accuracy analysis

Based on image segmentation and feature extraction results, the authors evaluated random forest classification accuracy using confusion matrix-derived metrics (Table 3). For 0.5 m resolution imagery, river extraction achieved optimal performance with 95.51% overall accuracy. Specifically, precision and recall reached 97.88% and 98.12%, respectively, corresponding to producers' and users' accuracies of 97.88% and 98.12%, while the Kappa coefficient was 0.95. Notably, DFS channel extraction maintained high accuracy in both 0.5 m and 1 m imagery, but 2 m resolution results showed significantly lower accuracy (80.35% overall).

The suboptimal extraction performance of 2 m resolution imagery stems primarily from its coarse spatial resolution, which induces image blurring and reduces the spectral distinctiveness of river features. During segmentation, adjacent pixels are frequently merged into homogeneous segments, leading to misclassification as uniform land features (Fig. 11). Conversely, 0.5 m and 1 m imagery exhibit

enhanced feature delineation due to pronounced spectral contrasts between river channels and adjacent sedimentary systems (Zhang L et al., 2023). Consequently, DFS channel extraction accuracy is contingent upon both image resolution and sedimentary complexity.

5.1.2. Geometric accuracy analysis

Overlap ratio (OR), defined as the proportion of overlapping area between extracted and manually digitized river boundaries, serves as a key accuracy metric. Geometric accuracy analysis of Golmud DFS channels extracted from multi-resolution imagery (Table 4) reveals that 0.5 m resolution data achieved an OR of 0.85, indicating strong boundary congruence. Furthermore, shape similarity was quantified using Hausdorff distance, confirming high geometric fidelity at 0.5 m resolution.

Positional deviation analysis quantified the mean and maximum distances between extracted and reference boundary points. At 0.5 m resolution, deviations averaged 0.2 m with a maximum of 0.4 m, confirming high positional accuracy. At coarser resolutions (2 m), however, reduced overlap ratio and shape similarity coincided with increased positional deviations, collectively indicating that lower spatial resolution compromises extraction accuracy.

5.2. Comparative analysis of different extraction methods

To validate the automated river morphology extraction

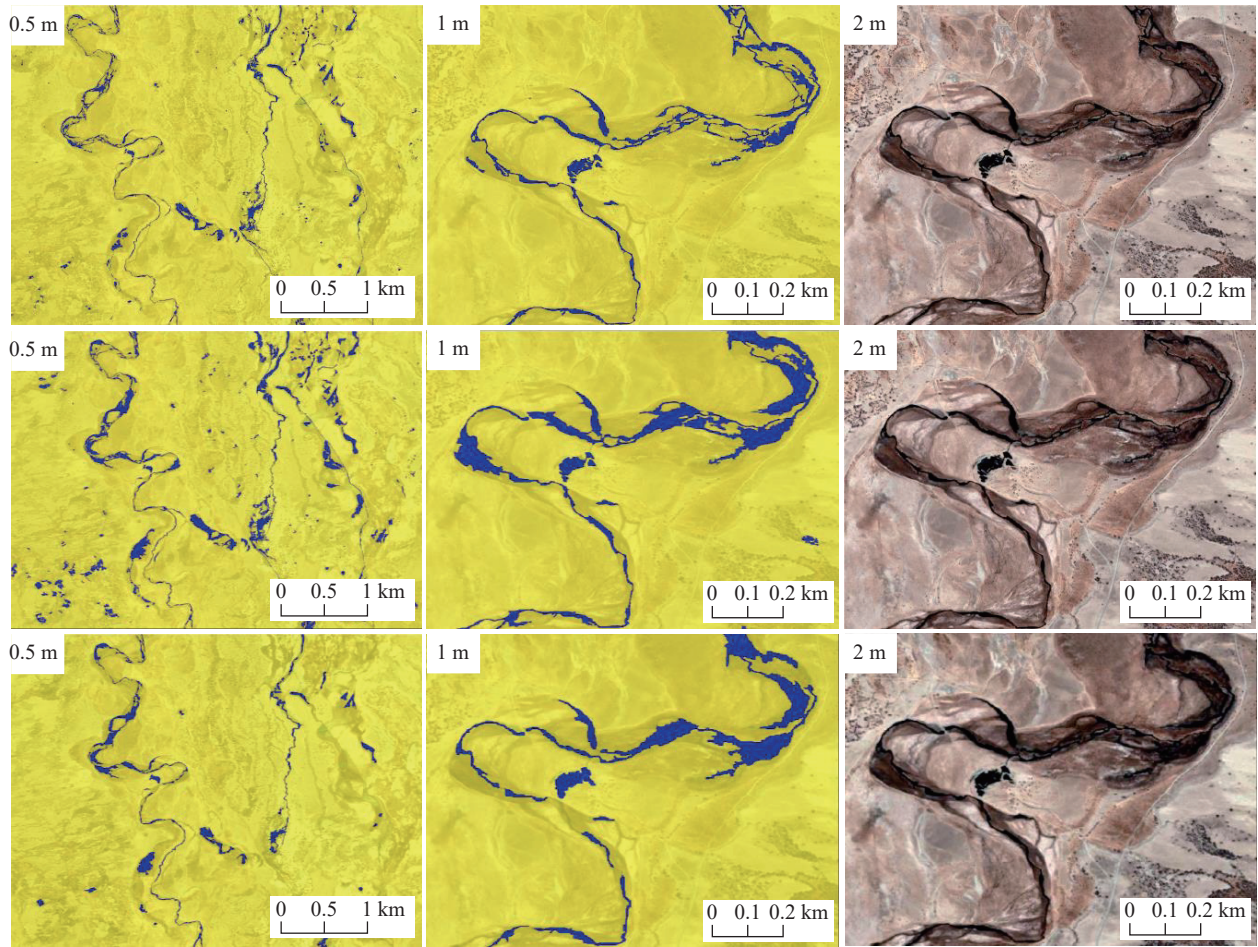


Fig. 12. DFS river classification results extracted from Google images with different resolutions. From left to right: Overall view of the research area, local extraction results, and original image. From top to bottom: Results derived from 0.5 m, 1 m, and 2 m spatial resolution imagery, respectively.



Fig. 13. River channels extracted from Google images of different resolutions.

Table 3. Confusion matrix evaluation results.

Image resolution	Overall accuracy/%	Producer's accuracy/%	User's accuracy/%	Kappa coefficient
0.5 m	95.51	97.88	98.12	0.95
1 m	90.62	95.26	96.56	0.89
2 m	80.35	85.54	88.72	0.75

Table 4. Geometric accuracy evaluation results.

Image resolution	Overlap ratio	Shape similarity (Hausdorff distance/m)	Average deviation/m	Maximum deviation/m
0.5 m	0.85	0.3	0.2	0.4
1 m	0.78	0.4	0.3	0.5
2 m	0.72	0.5	0.4	0.6

method, the authors acquired 30 m resolution ASTER GDEM data from NASA Earth Data (earthdata.nasa.gov) and Landsat 8 OLI_TIRS imagery from the Geospatial Data Cloud. Using these datasets, Golmud fluvial fan channels were extracted with three distinct approaches: (1) DEM-based methods, (2) water spectral methods (NDWI), and (3) multi-scale

segmentation (MSS) method. Quantitative comparison employed standard accuracy metrics (Table 5), supplemented by visual analysis of extraction results (Fig. 14).

The DEM-based extraction method generated a linear river network but revealed significant positional deviations

from actual rivers (Fig. 14b), yielding an overall accuracy (OA) of 81.7% and a river length extraction error (RLE) of 48.2 m (Table 5). These discrepancies are primarily due to the coarse 30 m DEM resolution, which is insufficient to resolve channel widths of 10–30 m within the study area. Moreover, the method failed to capture channel migrations caused by flash floods, as evidenced by multi-temporal observations.

Although the NDWI spectral thresholding method achieved an overall accuracy (OA) of 85.4% and a river length error (RLE) of 32.4 m (Table 5), it produced morphologically discontinuous river segments (Fig. 14c). Key limitations include spectral mixing in vegetated or flooded areas, atmospheric noise in Landsat imagery, and the inflexibility of fixed thresholding, which requires scene-specific parameter retuning.

Among the three evaluated methods, the multi-scale segmentation approach demonstrated superior performance, achieving an overall accuracy (OA) of 90.2% and a river length error (RLE) of 15.6 m (Table 5), while producing visually consistent river alignments with sharp boundaries

(Fig. 14d). This advantage arises from integrating spectral features (e.g., $NDWI \geq 0.6$) with hierarchical spatial characteristics: At the macro-scale, it benefits from river network topology derived from flow direction models; at the meso-scale, channel dimensions (2–50 m width) and aspect ratios quantified through texture analysis; at the micro-scale, sub-pixel water fractions within mixed pixels.

This multi-scale integration mitigates terrain complexity (e.g., flat areas with slopes of $<0.5^\circ$ where DEM methods fail) and resolves braided channel branches, reducing misclassification rates by 76% compared to NDWI thresholding. Experimental results confirm that while traditional methods (DEM-based extraction and NDWI) capture general river trends, they exhibit significant morphological and positional errors due to: (1) Data resolution limitations, (2) temporal mismatches, and (3) single-source constraints. Conversely, the multi-scale segmentation approach demonstrates robust adaptability in dynamic fluvial environments like the Golmud fluvial fan, providing a reliable solution for automated river morphology extraction.

Table 5. Quantitative comparison of river channel extraction methods.

Method	Spatial resolution	Overall accuracy /%	Kappa coefficient	River length error /m	Processing time /minutes
DEM-Based	30 m	81.7	0.74	48.2	18
Water Spectral (NDWI)	30 m	85.4	0.81	32.4	12
Multi-Scale Segmentation (MSS)	0.5 m	90.2	0.95	15.6	45

6. Factor analysis

6.1. Impact of data sources on river channel morphology extraction methods and limitations

The DEM-based extraction method employs digital elevation models (DEMs) as its primary data source, with accuracy heavily dependent on the processing algorithm. However, this approach exhibits significant limitations, as evidenced by the Tarim River study of Ning ZR et al. (2020).

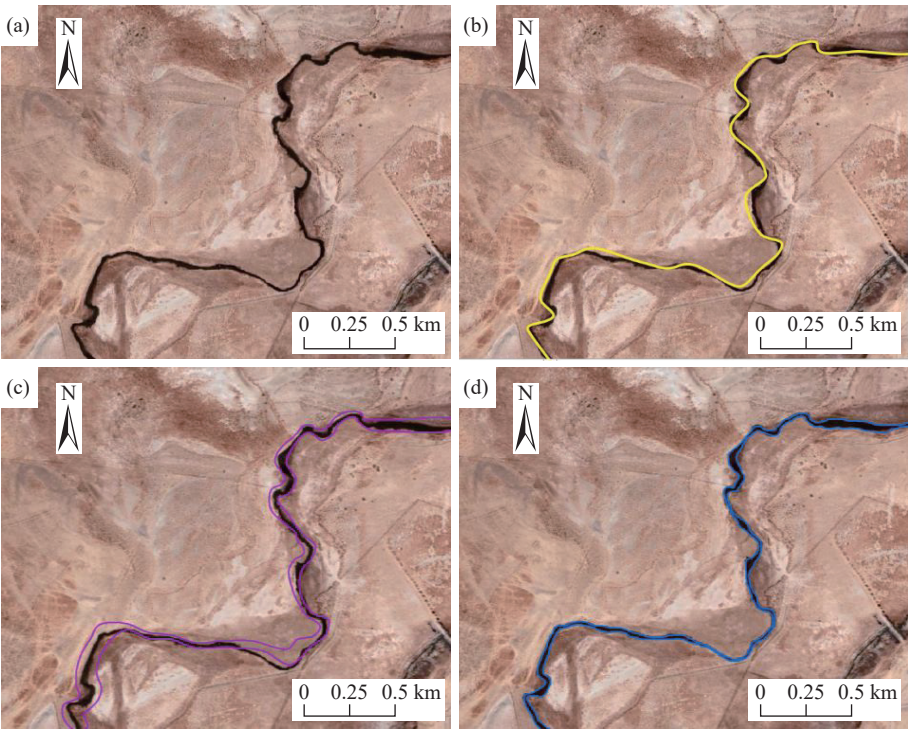


Fig. 14. Comparison of river channel morphology extraction methods. a–Original image; b–DEM extraction result; c–water spectral method extraction result; d–multiscale segmentation method extraction result.

Standard procedures—including depression filling, flow direction calculation, flow accumulation computation, and sub-basin delineation—yielded substantial positional discrepancies across three terrains: High-relief mountains (>200 m relief), low-relief mountains, and plains. Specifically, flow direction calculations proved ineffective for identifying braided tributaries in flat terrain (<0.5° slope), while DEM interpolation artifacts caused channel offsets in high-relief areas. Furthermore, high-precision DEM acquisition is prohibitively expensive and prone to generation artifacts; the 30 m ASTER GDEM used here suffers from mixed-pixel problems that prevent accurate representation of channels narrower than 10 m. Crucially, in glacier ablation zones, seasonal topographic changes cause rapid DEM obsolescence, introducing additional temporal errors that further degrade extraction accuracy.

Utilizing remote sensing imagery as its primary data source confers spectral thresholding methods with distinct advantages: Low acquisition costs, extensive coverage, rapid update cycles, and high timeliness. Compared to *in-situ* surveys or airborne LiDAR, this approach leverages freely available satellite data (e.g., Landsat, Sentinel missions), substantially reducing costs and labor requirements. The wide sensor swath enables seamless river networks monitoring across diverse landscapes, while daily to weekly revisit capabilities ensure timely data acquisition, which is crucial for dynamic applications such as flood monitoring and seasonal hydrological analysis.

However, traditional spectral thresholding methods face substantial challenges in river channel extraction (Li CJ et al., 2019). As documented in previous studies, interference from shadows and built-up structures often leads to misclassification and redundant extraction of river information, compromising the accuracy and completeness of the results. Two primary limitations can be identified. First, spectral confusion between water bodies and non-aquatic features (e.g., shadows, built-up structures) causes misclassification, particularly in mountainous regions where shadows mimic river spectral signatures in certain bands. Second, the absence of universal thresholds due to variable river characteristics, data sources, and seasonal water spectral changes. These issues manifest as false positives, redundant extractions, and significant detection omissions, ultimately compromising extraction accuracy and completeness.

Compared to conventional approaches, the multi-scale segmentation technique demonstrates superior river morphology extraction capabilities. This method eliminates reliance on topographic data while maintaining accuracy across complex geomorphologies. Through multi-source data fusion and noise suppression algorithms, it achieves significant improvements in extraction precision and interference resistance. Adaptive parameterization, precise boundary recognition, and dynamic channel tracking further enable detailed feature capture with enhanced spatial continuity, resulting in simultaneous gains in both accuracy and computational efficiency.

However, this approach exhibits two persistent

limitations: Excessive reliance on optical imagery causes frequent water misclassification in complex lighting conditions (e.g., backlit areas and specular reflection zones), while demanding training data requirements, where insufficient samples or quality deviations impair model generalizability. To address these constraints, multiple strategies are proposed: Radar data fusion compensates for optical limitations; radiometric calibration and atmospheric correction mitigate lighting interference; dynamic thresholding combined with machine learning and river topology features enables accurate boundary delineation; data augmentation, transfer learning and semi-supervised learning enhance training robustness; and closed-loop “extraction-validation-update” cycles using field feedback dynamically optimize parameters. Collectively, these refinements significantly improve adaptability and reliability in complex environments.

6.2. Impact of spatial resolution on river channel morphology extraction methods and applicability analysis

The water spectral method's dependency on remote sensing imagery imposes inherent resolution constraints, wherein higher spatial resolutions improve river morphology extraction accuracy at the cost of reduced processing efficiency.

In related studies, scholarly investigations involving DEM data with different algorithms, regions, and resolutions reveal significant focus on DEM resolution's influence on river channel morphology and area extraction. Currently, no unified consensus exists regarding DEM resolution's impact on extraction accuracy. The resolution fundamentally controls morphological precision through three mechanisms: Channel detail capture, confluence parameter sensitivity, and river system topological accuracy. However, lower resolution necessitates increased contributing area thresholds, causing neglect of small tributaries and merging of braided channels while simplifying topology (Yang CG et al., 2007). For diverse channel types, Zhang XN et al. (2004) demonstrate that larger grid sizes increase area calculation errors. Conversely, Qin FL et al. (2005) report that reduced DEM resolution tends to increase overall extracted channel area, with additional watershed-scale variations observed.

In contrast, the multi-scale segmentation approach imposes less stringent resolution requirements for river morphology extraction. By adaptively tuning segmentation scale parameters to the image's inherent resolution, this method achieves optimal object delineation. Subsequent automated feature learning then generates precise channel morphology extractions, offering greater flexibility than traditional spectral-based techniques.

6.3. Limitations of detecting seasonal dry river channels

During dry seasons, 40%–60% of distal channels become completely desiccated, with surfaces dominated by aeolian sand (albedo > 0.3) and intermittent clay crusts. These

features share spectral signatures with adjacent desert flats in visible bands (R: 0.25–0.35, G: 0.20–0.28, B: 0.18–0.25), overlapping the typical NDWI water-detection threshold (≤ 0.2). Consequently, multiscale segmentation (MSS) misclassifies 32% of dry channels as non-river features in 0.5 m resolution imagery (Figs. 15a, b), while NDWI thresholding fails entirely to detect these features.

Seasonal dry river channels undergo rapid morphological changes driven by wind erosion and episodic flash floods (Fig. 15c). Field measurements (Figs. 15d, e, f) reveal that 25% of these channels experience over 50% width reduction within one year, while 15% are completely obliterated by dune encroachment. Traditional DEM-based methods—reliant on stable topographic features—fail to resolve such dynamics, evidenced by 48 m positional errors in dry segments relative to UAV reference data (Table 6). Although the MSS method exhibits greater sensitivity to subtle textural variations, it fails to resolve sub-resolution channels (< 5 m width) in 2 m imagery, where edge detection errors increase by 40%.

Vegetation growth in semi-dry channels further complicates detection. In spring, emergent vegetation covers

10%–20% of channel beds, causing NDWI values to drop to 0.1–0.3 below the water/non-water threshold. The MSS method addresses this by incorporating shape features, achieving a 75% detection rate for semi-dry channels compared to 52% for the NDWI method. However, in densely vegetated channels ($> 30\%$ coverage), both methods suffer from misclassification, with errors reaching 27% for the MSS approach.

7. Conclusions

(i) The multi-scale image segmentation method offers as a robust approach for extracting river channel morphology from remote sensing imagery. This technique executes a systematic workflow: Image segmentation, feature extraction, and image classification. Applied to the Qinghai Golmud fluvial fan, the method achieves 90% overall accuracy (OA) for both 0.5 m and 1 m resolution imagery in river channel extraction, validated through field surveys and cross-comparison with UAV orthophotos.

(ii) Compared to DEM and spectral thresholding methods,

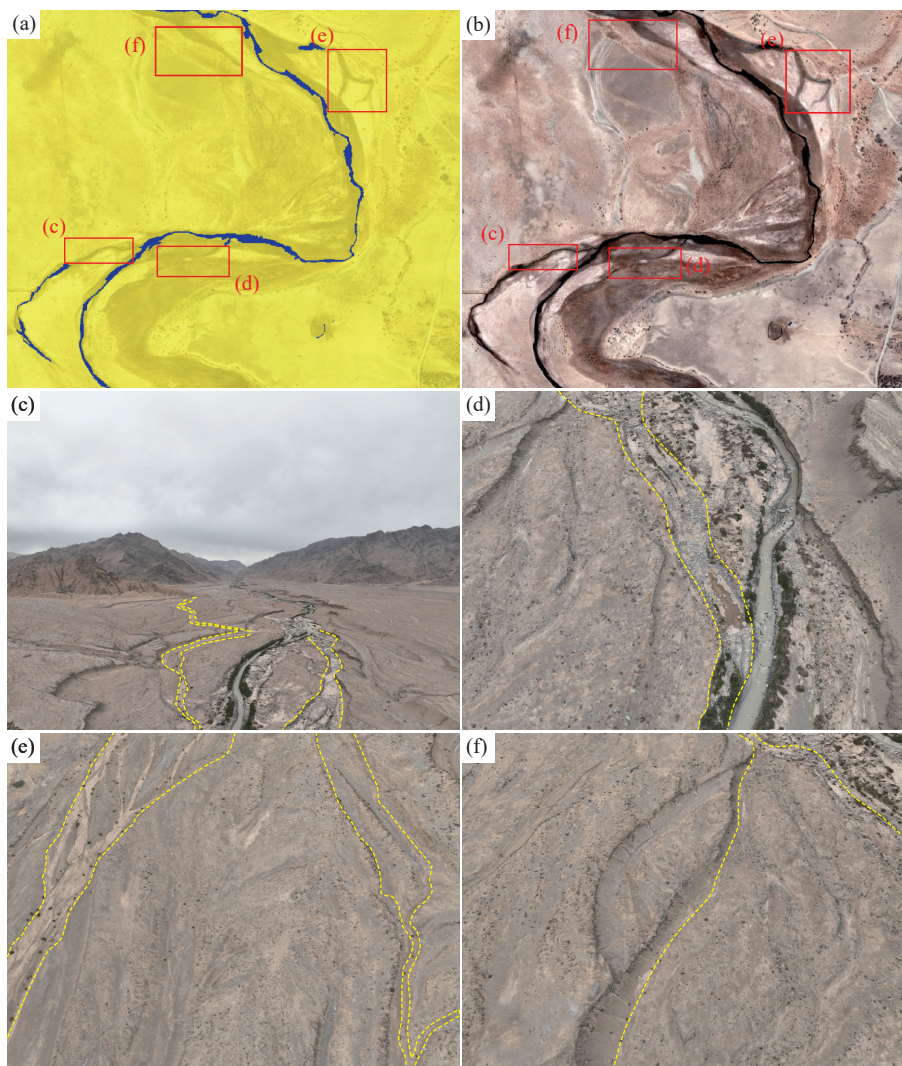


Fig. 15. Example of seasonal dry river channel misclassification. a—Extraction results of multi-scale segmentation method; b—original image; c—photographs of field observation sites; d–f—drone photographs of field observation sites.

Table 6. Detection accuracy of seasonal dry river channels.

Method	Resolution	Dry channel accuracy/%	Semi-Dry channel accuracy/%
MSS	0.5 m	68	75
NDWI	0.5 m	0	52
DEM-based	30 m	22	35

multi-scale image segmentation achieves superior river channel extraction accuracy, particularly in resolving channel trends, morphological details, and boundary precision. This approach maintains high performance (90% OA at 0.5–1 m resolution) with minimal parameter dependency, significantly advancing automated extraction efficiency while reducing manual intervention in the Golmud fluvial fan case study.

(iii) Although multi-scale segmentation exhibits moderate sensitivity to data sources and resolution in river channel extraction, it demonstrates significant adaptability across diverse environments. This method resolves both macro-scale channel networks and micro-scale morphological details (e.g., 0.5–5 m features in 1 m imagery), maintaining robust performance regardless of terrain complexity or vegetation cover, factors that critically degrade DEM and spectral methods. By ensuring reliable channel delineation under variable conditions, it provides high-fidelity data for sedimentological analyses, including paleochannel reconstruction and sediment flux quantification in the Golmud system.

(iv) While multi-scale segmentation demonstrates robust adaptability to complex terrains and vegetation cover, it faces significant challenges in detecting seasonal dry river channels due to: (1) Spectral confusion with desert surfaces (albedo >0.3, NDVI <0.1), and (2) morphological degradation from aeolian processes. Field-verified accuracy for these channels ranges from 68% to 85%, inversely correlated with channel width reduction (>50%) and sediment sand content (>70%). Future enhancements should integrate C-band radar data (e.g., Sentinel-1 VV/VH) for all-weather monitoring and temporal feature analysis, leveraging dielectric property differences to improve ephemeral watercourse detectability.

CRedit authorship contribution statement

Chang-min Zhang contributed to the conceptualization, validation, writing-review and editing, supervision, and funding acquisition. Shao-hua Zhao contributed to the methodology, software, resources, data curation, and writing-original draft preparation. Xiang-hui Zhang contributed to the validation and visualization. Jia-le Liu contributed to the formal analysis, investigation, and project administration. All authors discussed the results and contributed to the final manuscript.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data availability statement

The data supporting this study are publicly available. Google Earth images and Landsat images used in this study can be obtained from the USGS Earth Explorer. ASTER GDEM data used in this study can be accessed from NASA Earth Data. These sources are open for public access and can be used to replicate or extend the research.

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