Low-Altitude Remote Sensing and Satellite Imagery for River Discharge Retrieval: A Postprint

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Abstract

Accurate monitoring of discharge in small and medium-sized rivers is of great significance for ecological stability in arid regions. However, precise remote sensing retrieval of flow in small and medium-sized rivers presents difficulties. Taking the Zhongfengchang section of the Kashi River in Nileke County, Xinjiang as an example, and based on the relationship fitting method, a power function relationship model between river width, water depth, and discharge was constructed using measured hydrological data, UAV data, and satellite data. The temporal characteristics of satellite data were utilized to retrieve discharge at the monitored river section for 24 different periods. The retrieval results show that: when discharge is 0~50 m3 · s-1 and 50~100 m3 · s-1, the hydraulic geometry discharge retrieval based on river width yields the optimal performance, with Root Mean Square Errors (RMSE) of 7.15 m3 · s-1 and 2.81 m3 · s-1, respectively; when discharge is 100~200 m3 · s-1 and >200 m3 · s-1, the hydraulic geometry discharge retrieval based on water depth and river width performs best, with RMSE of 13.37 m3 · s-1 and 1.06 m3 · s-1, respectively. The research findings can provide a new method for refined monitoring and management of runoff in small and medium-sized rivers in hydrological data-scarce regions, and also hold high reference value for flood disaster prediction, hydroenergy resource development, and aquatic ecosystem restoration.

Full Text

Preamble

Runoff Estimation with Low-Altitude Remote Sensing and Satellite Images

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Abstract: Accurate monitoring of runoff from small and medium-sized rivers is of great significance for ecological stability in arid regions. However, precise remote sensing retrieval of flow in small and medium-sized rivers remains challenging. Taking the Zhongfengchang river section of the Kashi River in Nilka County, Xinjiang as a case study, this research constructed a power function relationship model between river width, water depth, and discharge based on the relationship fitting method, using measured hydrological data, unmanned aerial vehicle (UAV) data, and satellite data. Leveraging the temporal characteristics of satellite data, the runoff of the monitored river section was retrieved for 24 different periods. The inversion results demonstrate that when discharge ranges from 0–50 $m^3 \cdot s^{-1}$ and 50–100 $m^3 \cdot s^{-1}$, the hydraulic geometry-based runoff retrieval using river width alone performs optimally, with root mean square errors (RMSE) of 7.15 $m^3 \cdot s^{-1}$ and 2.81 $m^3 \cdot s^{-1}$, respectively. When discharge ranges from 100–200 $m^3 \cdot s^{-1}$ and >200 $m^3 \cdot s^{-1}$, the hydraulic geometry-based retrieval using both water depth and river width achieves the best performance, with RMSE values of 13.37 $m^3 \cdot s^{-1}$ and 1.06 $m^3 \cdot s^{-1}$, respectively. These findings provide a novel method for refined monitoring and management of runoff in small and medium-sized rivers in hydrologically data-scarce regions, and offer valuable reference for flood disaster prediction, hydropower resource development, and water ecosystem restoration.

Keywords: unmanned remote sensing; Sentinel-2; river discharge; relationship fitting method; estimation

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1. Study Area Overview

This study selected the Zhongfengchang hydrological monitoring cross-section at the outlet of the upper Kashi River as the research object (Fig. 1). The Kashi River is located within Nilka County, surrounded by mountains on three sides, originating from the Yilianhabierga Mountains and flowing from east to west. The total river length is 315 km, with a watershed area of 2,800 km^2. The watershed exhibits a narrow, willow-leaf shape, with elevations ranging from 800 to 4,600 m. The river's multi-year average flow velocity is 127.9 $m \cdot s^{-1}$, and the multi-year average runoff is 3.902$×10^{8}$ m^3. Its water sources are primarily ice-snow meltwater, supplemented by precipitation.

2.1 Research Methods

This study combines low-altitude remote sensing data, measured hydrological data, and satellite data based on the relationship fitting method to construct a power function model for river discharge retrieval. The specific workflow is illustrated in Fig. 2. By utilizing the high-precision digital surface model (DSM) data obtained from UAV aerial photography, the Zhongfengchang river section was uniformly segmented to generalize the hydraulic characteristic relationships. Based on these relationships, measured hydrological data were used to determine the empirical parameter values required for discharge retrieval, enabling river flow estimation with Sentinel-2 satellite data, followed by accuracy verification of the inversion results.

2.1.1 Hydraulic Characteristic Relationship Construction

1) **River segment division.** Due to erosion, transport, and deposition processes during natural river development, it is difficult to use a unified relationship to describe cross-sectional shape characteristics at different locations. Dividing the target river segment into multiple shorter reaches allows for the derivation of width-depth relationship curves that characterize cross-sectional shapes within these reaches.

2) **Width-depth relationship curves for divided segments.** Elevation data were extracted for each divided segment to obtain river width data corresponding to different water depths, enabling the plotting of width-depth relationship curves for each segment's cross-section.

3) **Fitting the average hydraulic characteristic relationship curve.** Based on the width-depth relationship curves of the divided segments, the average river width at the same water depth across all segments was calculated. Origin software was used to fit the width-depth relationship curve representing the target segment's cross-sectional shape characteristics and obtain the functional equation, allowing calculation of the corresponding water depth (or width) for any given width (or depth).

4) **Discharge retrieval.** Based on the relationship fitting method, a functional relationship between discharge, river width, and water depth was constructed. The water area of the river segment was extracted from satellite data to obtain the generalized river width. Since measured hydrological data do not record actual river width, but the empirical parameters (A, B, C) in the retrieval method require width data for calibration, the fitted equation was used to derive river width from water depth, thereby enabling parameter calibration. Ultimately, changes in observed river width or water depth can be used to retrieve river discharge.

2.1.2 Deep Learning Convolutional Neural Network Model

Deep learning convolutional neural networks represent a machine learning algorithm based on data representation. They utilize spatial and spectral information from satellite imagery to extract image features at a deep level, achieving higher accuracy for water body identification in remote sensing images compared to methods such as neural networks, support vector machines, and normalized difference water index (NDWI), while avoiding complex preprocessing procedures. This study employed the Keras convolutional neural network to extract water bodies from remote sensing images and obtain water area. Fig. 3 illustrates the complete water extraction process using the Keras CNN.

The Keras-based remote sensing image water identification method consists of four main steps: (1) **Image preprocessing.** Existing models and methods were used to suppress or eliminate various errors during image imaging. (2) **Data labeling.** The 10 m resolution bands of Sentinel-2 (Red, Green, Blue) were used for false-color composition. Water bodies in the composite images were labeled by saving polygon vertices, creating an image of the same size as the original with white background, and setting pixels within the polygons to black. In the labeled images, white represents land and black represents water. (3) **Image segmentation and training set establishment.** To enable model training for water identification, remote sensing images were segmented into 16$×$16 pixel patches, which were combined with labeled images to create training sets. (4) **Model construction and training with Keras CNN.** The Keras CNN in this study comprised 3 convolutional layers, 3 max pooling layers, 1 input layer, and 1 output layer. The convolutional and max pooling layers were primarily used for water extraction from remote sensing images. Through forward propagation and backpropagation training processes, the model parameters were determined. Finally, inputting false-color remote sensing images yields water body extraction results with 99.54% accuracy.

2.1.3 Hydraulic Parameter Calculation

Hydraulic gradient and roughness are essential parameters in many hydrological prediction models. However, research has demonstrated that accurate discharge prediction can still be achieved without these parameters. The relationship fitting method constructs a power function model based on the hydraulic relationships between river width, water depth, and discharge, enabling river runoff retrieval. This method is applicable to rivers with power-function cross-sections, triangular cross-sections, and rivers with large width-depth ratios. The calculation formula is:

$$Q = A \cdot W^B \cdot H^C \tag{1}$$

where A, B, and C are empirical parameters; Q, H, and W represent discharge ($m^3 \cdot s^{-1}$), water depth (m), and river width (m), respectively.

Since direct river width retrieval from remote sensing data may be affected by mountain shadows, clouds, ice, and snow, leading to significant errors, using the ratio of water area to river segment length produces smaller errors and higher accuracy. The calculation formula is:

$$W = \frac{S}{L} \tag{2}$$

where W, S, and L represent river width (m), water area (m^2), and river segment length (m), respectively.

2.1.4 Accuracy Assessment

This study employed three accuracy assessment metrics to verify discharge retrieval results: relative accuracy (RA), root mean square error (RMSE), and mean percentage error (MPE). The calculation formulas are:

$$RA = \frac{Q_{sim}}{Q_{obs}} \times 100\% \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{sim} - Q_{obs})^2} \tag{4}$$

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Q_{sim} - Q_{obs}}{Q_{obs}}\right| \times 100\% \tag{5}$$

where Q_{sim} represents the predicted discharge value ($m^3 \cdot s^{-1}$), Q_{obs} represents the measured discharge value ($m^3 \cdot s^{-1}$), and n represents the number of retrieved discharge values.

2.2.1 Satellite Remote Sensing Data

Sentinel-2 remote sensing data offer high spatial resolution, short revisit cycles, and relatively simple preprocessing methods, making them widely applicable for water identification and analysis. This study utilized 24 Sentinel-2 images from different periods corresponding to measured data. Based on Sentinel-2 band characteristics and threshold settings, remote sensing data within the study area were screened. The 10 m resolution bands (Red, Green, Blue) were selected for false-color composition, and the Keras CNN model was applied for water extraction.

2.2.2 Low-Altitude Remote Sensing Data

The UAV data used in this study were collected from the Zhongfengchang section of the Kashi River in Nilka in October 2020, during the dry season when water levels were low and flow velocity was slow, with water depth generally not exceeding 50 cm. This timing maximized the acquisition of riverbed topography data. The study employed a Phantom 4 Advanced UAV to obtain high-precision low-altitude imagery. The main steps for acquiring high-precision topographic data of the Zhongfengchang section were: (1) **Setting UAV flight trajectory.** Based on the geographic location of the Zhongfengchang hydrological monitoring cross-section, flight routes were planned with the river channel as the center at an altitude of approximately 100 m. To ensure consistency in takeoff points across multiple flights, point markers were used to record the landing coordinates and surrounding reference features. (2) **UAV aerial operation.** Consistent flight altitude and routes were maintained for each flight, with each flight line maintaining uniform height above ground to ensure 70%–80% overlap between adjacent UAV images for subsequent geometric correction and mosaicking. (3) **Image stitching and processing.** Pix4D mapper software was used to automatically process UAV images, generating orthophotos and digital surface models (DSM) of the Zhongfengchang section. Finally, in the ArcGIS 3D Analyst module, 200 cross-sectional topographic data points were uniformly extracted from the river segment, and above-water cross-section data were combined with measured water depth data from rods to generate complete river cross-sections.

2.2.3 Measured Data

The measured data used in this study were obtained from the Zhongfengchang hydrological station, including measured discharge and water level data from 2019–2021 (Fig. 4). To verify the reliability of discharge retrieval, the measured hydrological data were divided into two parts based on the hydraulic geometry model between river width and water depth: a calibration period (2019–2020) and a validation period (2021). The calibration period data were used to determine the empirical parameters A, B, and C in Equation (1), while the validation period data were used for discharge retrieval and accuracy evaluation.

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3. Results and Analysis

3.1 River Cross-Section and Water Depth Relationship Curve

From the Zhongfengchang hydrological station's 200 m river segment, 200 cross-sections were uniformly extracted. Elevation data for each segmented cross-section were obtained using ArcGIS imagery to plot width-depth relationship curves for each cross-section (Fig. 5).

3.2 Fitting the Average Hydraulic Characteristic Curve

Based on the hydraulic characteristic relationship curves of the 200 cross-sections in the Zhongfengchang segment, the average river width at the same water depth across all cross-sections was calculated to plot the average width-depth relationship curve, representing the target segment's cross-sectional morphology (Fig. 6). Origin software was used to obtain the fitted equation for the width-depth relationship curve. This software employs the Levenberg-Marquardt iterative method, a global optimization algorithm, to iteratively calculate the best-fit equation and residual analysis (Table 1). The fitting performance was excellent, with correlation coefficients reaching 0.9999, residual sum of squares of 0.001, and root mean square errors of 0.008 and 0.009, accurately reflecting the variation characteristics between river width and water depth in the Zhongfengchang segment. According to Table 1, the generalized equation was used with Equation (2) to obtain generalized river width, enabling calculation of corresponding water depth. Since measured hydrological data only recorded water depth, water level, and discharge but not river width, the W-H equation could derive river width data to complete the calibration process requiring width participation for parameters A, B, and C.

3.3 Hydraulic Characteristic Parameter Extraction

Sentinel-2 satellite data were used to obtain the water area of the 200 m Zhongfengchang river segment through the Keras CNN model. Since the UAV remote sensing data and Sentinel-2 satellite data did not perfectly coincide, the Sentinel-2 data were used as the baseline, with upstream and downstream boundaries each expanded by 10 pixels (100 m) to obtain the generalized river width of the target segment. The Keras CNN model achieved a water extraction accuracy of 99.54%. Table 2 shows the water area, generalized width, and generalized water depth for 24 different periods. The generalized river width calculated using Equation (2) and the fitted equation from Table 1 yielded the generalized water depth.

3.4 Discharge Retrieval

Based on the relationship fitting method, measured hydrological data from the calibration period were used to divide discharge into four levels: 0–50 $m^3 \cdot s^{-1}$, 50–100 $m^3 \cdot s^{-1}$, 100–200 $m^3 \cdot s^{-1}$, and $ 200m{3}·s{-1}.ThedetailedresultsareshowninTable3.Fig.7comparestheinversionresultswithmeasureddata.Table3reflec
1},Equation(1)usingriverwidthasthehydrauliccharacteristicvariableperformedbest,withRMSEof7.15m{3}
1}.Whendischargeis50–100m{3}·s{-1},Equation(1)usingbothwaterdepthandriverwidthperformedoptimally,
1}.Whendischargeis100–200m{3}·s{-1},Equation(1)usingbothvariablesalsoperformedbest,withRMSEof13.
1},closelymatchingmeasureddata.Whendischargeis > 200m{3}·s{-1},Equation(1)usingwaterdepthaloneper
13.60m{3}·s{-1})thanthatusingbothvariables(RMSE = 1.06m{3}·s{-1}).Overall,whendischargeis <
100m{3}·s{-1},Equation(1)usingriverwidthaloneshowslargererrors,whiledischarge >
100m{3}·s{-1}$ yields smaller overall errors, though retrieval accuracy is slightly lower for the 100–200 $m^3 \cdot s^{-1}$ range compared to >200 $m^3 \cdot s^{-1}$.

4.1 Research Results Comparison and Analysis

Recent studies have achieved significant progress in discharge retrieval using various remote sensing data. Wang et al. [28] employed the same research method as this study, constructing power function models between discharge and river width/depth for retrieval and accuracy evaluation. Their results showed RMSE of 4.65 $m^3 \cdot s^{-1}$ when discharge was <200 $m^3 \cdot s^{-1}$, with good evaluation results and an average qualification rate of 86.5%, though retrieval accuracy could be further improved. In this study, validation period measured discharge data were divided into four levels, with each level's parameters A, B, and C in Equation (1) calibrated separately. The evaluation results show that when discharge is 0–50 $m^3 \cdot s^{-1}$, retrieval accuracy is superior to similar studies; when discharge is 50–100 $m^3 \cdot s^{-1}$, retrieval performance is second best, providing reference value for refined water resource management; when discharge is 100–200 $m^3 \cdot s^{-1}$, retrieval performance is good and overall superior to other formulas; when discharge is >200 $m^3 \cdot s^{-1}$, Equation (1) using both width and depth performs optimally, with average qualification rate of 99.24% and false alarm rate of 0.76%. All indicators demonstrate that discharge retrieval accuracy in the Zhongfengchang segment is superior to comparable research results.

4.2 Applicability of Typical River Channels

The Zhongfengchang cross-section of the Kashi River is a typical triangular cross-section with a large width-depth ratio, where river width and water depth vary with discharge fluctuations and can be well characterized by width variations. As shown in Fig. 8, triangular cross-sections are common in mountainous areas, featuring one steep bank and one gentle bank. When river width changes, discharge shows the same trend. In plain and hilly areas, rectangular and compound cross-sections are common, characterized by small hydraulic gradients and low flow velocities. Compound cross-sections have large width-depth ratios and are suitable for characterizing discharge variations using river width, whereas rectangular cross-sections with small width-depth ratios are unsuitable for width-based discharge characterization.

This study constructed width-depth hydraulic characteristic relationship curves and utilized the temporal characteristics of Sentinel-2 satellite data to retrieve discharge for 24 different periods, achieving spatiotemporal expansion of runoff. This method has certain applicability for rivers where discharge can be characterized by width variations but has limitations and may produce large errors when applied to rivers with small width-depth ratios, such as trapezoidal or rectangular cross-sections.

4.3 Influence Factors and Sensitivity Analysis

Factors affecting discharge retrieval accuracy primarily include river segment length and the retrieval process. First, river segment length significantly impacts retrieval accuracy. Generalized river width is calculated by extracting water area from satellite imagery using Equation (2). However, excessively long segments inevitably introduce errors between extracted and actual water areas, affecting final results. Therefore, shorter segments yield more precise hydraulic geometry characteristics at hydrological cross-sections. Based on 200 m DSM data, 200 cross-sections were uniformly extracted, and the final retrieval accuracy confirmed that shorter segments produce more accurate results [22,29].

Second, the retrieval process requires river width and depth data for empirical parameter calibration, which also influences results. If the discharge values in the calibration period vary widely, direct parameter calibration may cause large biases in retrieval results. This study adopted a discharge classification approach, calibrating comprehensive parameters separately for each discharge level to accurately simulate various flow conditions and reduce retrieval errors. The good simulation results demonstrate that discharge classification provides valuable reference for power function model retrieval.

4.4 Cross-Section Topography and Hydraulic Geometry Acquisition

Many scholars have used the relationship fitting method to obtain hydraulic characteristic variables for discharge retrieval. Target river cross-sections are typically parabolic or triangular [14,18,28,30]. Although the relationship fitting method is unsuitable for low width-depth ratio trapezoidal sections in plain areas, it remains applicable to most rivers, especially mountainous rivers or mid-upstream reaches that typically have high width-depth ratios and are often hydrologically data-scarce. This research method provides a fast, convenient new approach for temporal discharge prediction in data-scarce regions, applicable to flood disaster prediction and refined water resource management.

In discharge retrieval research, elevation data at hydrological monitoring cross-sections are crucial [19,31]. This study obtained underwater topography during the dry season using UAV DSM data to generate complete river cross-sections. However, for perennially flowing or turbulent rivers, the following measures can be adopted: (1) **Wading measurement.** When water depth is shallow ($ $50 cm) and flow is slow, depth can be measured using rods or visual estimation, combined with above-water topography from UAVs to generate complete cross-sections. (2) **Sonar detection and manual boat measurement.** For deep or turbulent rivers, underwater cross-section data can be obtained through unmanned boat sonar detection or manual boat surveys combined with rod measurements. Sonar is generally suitable for rivers deeper than 50 cm, while manual boat measurement is appropriate for large rivers with large width-depth ratios. (3) **Fitting water surface topography.** For remote or mountainous rivers where underwater topography is difficult to obtain, water surface topography from UAV surveys can be fitted to underwater topography (Fig. 9). Fitting types include parabolic, triangular, and trapezoidal forms [19,31], with selection based on geographic environment and actual conditions. (4) **Determining cross-section topography based on base discharge.** For wide rivers with slow flow, multiple base discharge values (Qi) at different depths can be selected based on actual conditions to obtain cross-section topography for discharge retrieval, particularly applicable to complex river environments such as braided rivers.

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5. Conclusions

This study uniformly segmented the river reach based on the relationship fitting method, constructed functional equations between river width and water depth, and retrieved discharge. The influence of the number of segmented cross-sections on retrieval accuracy and the relationship between discharge classification and retrieval precision were analyzed. The main conclusions are:

1) Based on measured hydrological data, low-altitude remote sensing data, and satellite data, the relationship between river width, water depth, and discharge was fitted to construct models. The width-depth average relationship curve was developed to generalize river segment shape characteristics. Shorter segmentation yields more accurate fitting results. The power function relationship model demonstrated good simulation performance in the Zhongfengchang segment, showing high reliability for retrieving discharge in small and medium-sized rivers and providing a new solution for runoff retrieval in ungauged or data-scarce regions.

2) The relationship between discharge classification and retrieval accuracy shows that when discharge >200 $m^3 \cdot s^{-1}$, using both river width and water depth as hydraulic characteristic variables yields optimal retrieval performance with an average qualification rate of 99.24%, enabling flood disaster prediction. When discharge is 100–200 $m^3 \cdot s^{-1}$, retrieval performance is slightly lower (RMSE = 13.37 $m^3 \cdot s^{-1}$). When discharge is <100 $m^3 \cdot s^{-1}$, using river width alone performs well (RMSE = 2.81 $m^3 \cdot s^{-1}$), enabling refined water resource management. When discharge is 0–50 $m^3 \cdot s^{-1}$, performance is slightly lower (RMSE = 7.15 $m^3 \cdot s^{-1}$) compared to 50–100 $m^3 \cdot s^{-1}$.

3) This research method, based on the relationship fitting method and utilizing high-precision low-altitude remote sensing data and long-term satellite data, enables historical backtracking of discharge in hydrologically data-scarce regions to analyze spatiotemporal runoff variations. The method has limitations and is more suitable for mountainous rivers or rivers with large width-depth ratios. Application to compound cross-section rivers may produce larger errors and requires further research.

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Note: Figure translations are in progress. See original paper for figures.