Postprint: Extraction of Check Dam Systems in Small Watersheds on the Loess Plateau Based on Deep Learning Integrated with OBIA

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Date: 2023-12-06T00:00:00+00:00

Abstract

Check dams play an irreplaceable role in preventing soil erosion on the Loess Plateau; therefore, accurate extraction of check dam areas and check dam locations is of great significance for studying soil and water conservation on the Loess Plateau. Existing image classification methods lack consideration of the topographic features of check dams and are prone to misclassification as terraces or mounds. In addition, automatic extraction research has focused primarily on the extraction of check dam areas, while check dam locations still rely on manual interpretation. Therefore, this study proposes a method for automatic extraction of check dam systems: extracting check dam areas in the Jiuyuangou watershed through deep learning fused with Object-Based Image Analysis (OBIA), and then extracting check dam locations using hydrological analysis methods. The results show that the precision, recall, and F1Score of the check dam areas extracted by this method are 81.97%, 90.94%, and 89.70%, respectively, with the F1Score improving by 21.94% compared with using the OBIA method alone. The automatic identification accuracy of check dam locations is 81.08%, and the completeness is 88.89%, which is similar to the accuracy of previous visual interpretation, and achieves full-element extraction of both check dam areas and check dam locations. The research results can provide important baseline data for analyses such as spatial layout optimization of check dams and soil erosion assessment on the Loess Plateau.

Full Text

Extraction of Check Dam Systems in Small Watersheds of the Loess Plateau Based on Deep Learning Fused with OBIA

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Abstract: Check dams play an irreplaceable role in preventing soil and water loss on the Loess Plateau. Therefore, accurately extracting siltation areas and identifying check dam locations are of great significance for scientific analysis of soil and water conservation. Existing image classification methods lack consideration of the topographic features of check dams, making them prone to misclassification as terraces or mounds. Moreover, automatic extraction research has primarily focused on siltation area extraction, while check dam point identification still relies on manual interpretation. This study proposes an automated method for extracting check dam systems: deep learning fused with object-based image analysis (OBIA) is used to extract siltation areas in the Jiuyuangou watershed, and hydrological analysis methods are then employed to extract check dam points. The results demonstrate that the precision, recall, and F1Score of the proposed method for siltation area extraction reach 90.94%, 81.97%, and 89.70%, respectively—21.94% higher than previous methods. The automatic identification accuracy of check dam points is 81.08%, with a completeness rate of 88.89%. This method provides important foundational data for optimizing the spatial layout of check dams and assessing soil and water loss on the Loess Plateau.

Key words: siltation area extraction; check dam point extraction; object-based image analysis (OBIA); U-Net framework; Loess Plateau

1 Study Area Overview

The Jiuyuangou watershed (110°16 ~110°26 E, 37°33 ~37°38 N) in the Loess Plateau was selected as the study area [Figure 1: see original paper]. Located in Suide County, Shaanxi Province, this watershed features typical loess landforms characterized by fragmented terrain, crisscrossing gullies, deep soil layers, and severe soil erosion. After decades of check dam construction, the area has formed main dam systems and sub-dam systems, making it representative for extracting check dam information. The total study area is 69.29 km^2, with actual siltation areas covering 2.51 km^2 and non-siltation areas covering 66.78 km^2. Based on existing dam system data, the watershed's dam network was divided into 1 main channel dam system unit and 37 sub-dam system units to evaluate the layout of the dam system.

2.1 Data Sources

Data include 0.5 m resolution Google Earth imagery and DEM data from the Shaanxi Provincial Bureau of Surveying and Mapping. After acquisition, projection methods were applied to ensure consistent coordinate systems between datasets, though slight spatial offsets remained. To guarantee subsequent experimental accuracy, ArcGIS was used for image registration and clipping to obtain the final study area remote sensing imagery. High-resolution imagery contains abundant ground object information, making traditional pixel-based analysis methods prone to severe misclassification and "salt-and-pepper" effects. Object-based image analysis (OBIA) technology addresses this issue by utilizing shape, spectral, and texture information from high-resolution imagery, as well as hierarchical features such as semantic relationships between objects.

2.2 Research Approach

This study employs a method combining OBIA and deep learning to more accurately segment ground objects and identify siltation areas and check dam points. First, an object-oriented multiscale segmentation method segments multi-source data while deep learning segments remote sensing imagery. Majority voting then fuses these segmentation results to extract more accurate siltation areas. Next, hydrological analysis of DEM data extracts the river network within the watershed. Finally, neighborhood analysis of flow accumulation values at intersections between siltation areas and the river network determines check dam points, with results validated against reference data. Additionally, a nearest neighbor classification method applied to multiscale segmentation results serves as a comparison to the proposed method. The technical workflow is shown in [Figure 2: see original paper].

2.3.1 Training Dataset

Compared with traditional image processing and machine learning methods, convolutional neural networks (CNNs) and other deep learning models require large amounts of labeled data for training. This experiment selected remote sensing imagery and corresponding DEM data from Suide County (green bounding box area) to train the model, and used Jiuyuangou watershed imagery and DEM data (red bounding box area) to validate model performance. The training sample area features rich data volume and image characteristics, enabling the model to abstract various high-level semantic features and effectively improve accuracy and robustness.

Due to large input image sizes causing high model parameter counts and computational complexity, which reduces training and inference efficiency, large images were divided into 2 km $\times$ 2 km sub-blocks, then further into 256 $\times$ 256 pixel tiles. To preserve geometric and textural features of siltation landforms and avoid edge effects, original images were split into overlapping sub-blocks with a certain overlap rate. Each sample's edges were included in network processing but discarded during output stitching. Data augmentation through elastic deformation simulated local terrain variations, enhanced network classification capability, and reduced required training sample quantities.

2.3.2 U-Net Network Construction

U-Net is an end-to-end fully convolutional neural network architecture offering fast computation and good training results with small sample sizes. Multiple pooling layers enable multi-scale feature recognition. Similar to FCN, U-Net consists of downsampling and upsampling stages. The downsampling stage extracts image features while reducing dimensionality and preserving effective information, thereby avoiding overfitting. The upsampling stage restores feature images to the original size while fusing extracted feature outputs. Unlike FCN, U-Net employs the same number of convolutional layers in both stages and uses skip connections to directly link corresponding layers, enabling more accurate pixel localization and higher segmentation precision.

To improve model prediction accuracy, multi-source data were used as training inputs. Experimental comparisons showed that DEM, slope, and hillshade data significantly improved classification accuracy. Therefore, these three data layers were stacked with remote sensing imagery as integrated network inputs. This multi-source dataset compensates for limitations of single-channel architectures that cannot fully express complex landform features.

2.3.3 Extracting Siltation Area Boundaries

Multiscale segmentation technology was employed to segment study area data. The segmentation parameter selection critically determines final results. Three key segmentation parameters are: segmentation scale, shape index, and compactness. Since siltation surfaces are flat, slope, hillshade, and elevation data were used as segmentation inputs. [Figure 3: see original paper] shows segmentation results under different parameters. With shape index and compactness held constant, smaller scale values produce more fragmented siltation areas, increasing subsequent workload, while excessively large values cause misclassification in complex terrain regions. Based on experiments and previous research in the Wangmaogou sub-watershed, which shares high similarity with Jiuyuangou, optimal parameters were determined as: scale = 50, shape index = 0.4, and compactness = 0.5.

Loess landforms can be divided into positive terrain (hills, ridges) and negative terrain (valleys, basins). Check dams should only be built in negative terrain areas. Following established methods, positive and negative terrain extraction involves depression filling, flow direction calculation, and flow accumulation calculation. A threshold applied to the flow accumulation raster generates the final gully network. Since all check dams must be located at gully bottoms and contain corresponding river sections, only areas overlapping with gullies are considered potential siltation areas; other areas represent network misclassification.

2.3.4 Feature Fusion

Considering that deep learning and OBIA each have advantages and disadvantages, majority voting fuses their results to achieve better image recognition performance and noise robustness with minimal time cost. Majority voting is a collective decision-making scheme where each voter produces a decision for input samples, and the final classification follows the majority decision. After deep learning training, each pixel receives a probability value representing its likelihood of belonging to siltation areas. Following multiscale segmentation, each polygon exhibits internal homogeneity with similar pixel probability values. Therefore, the dominant pixel value within each polygon is assigned as the polygon's final value. This process transforms deep learning features into object-scale features, improving polygon classification accuracy.

2.4 Check Dam Point Extraction

Check dams are typically constructed at water outlets where flow accumulation is greatest. Therefore, after obtaining siltation areas, check dam extraction uses hydrological analysis to identify maximum flow accumulation points. First, DEM data undergoes depression filling to address uneven terrain affecting flow direction generation. Flow direction analysis compares elevation differences between each central pixel and its eight neighbors, assigning flow direction toward the steepest descent. Based on flow direction raster, flow accumulation is calculated and thresholded to extract the river network [Figure 4: see original paper]. Initial analysis tests several thresholds from large to small, selecting the optimal value based on river system extraction effectiveness.

With river network data, check dam points are extracted by intersecting siltation areas with the river network. Flow accumulation is calculated for the entire study area, then clipped by extracted siltation areas to obtain flow accumulation within each check dam range. A moving window analysis (3$×$3 window) identifies the maximum flow accumulation value in each window, assigned to the central pixel. Subtracting this maximum value raster from the original flow accumulation raster yields zero values at check dam locations.

2.5.1 Accuracy Assessment for Siltation Area Extraction

Confusion matrices are commonly used for remote sensing classification accuracy assessment. For all validation pixels, the classification categories are compared with actual categories to calculate accuracy, precision, recall, and F1Score for comprehensive evaluation . Accuracy is a global metric representing the percentage of correctly predicted samples. Precision indicates the probability that predicted siltation areas are actual siltation areas. Recall represents the proportion of actual siltation areas correctly identified. F1Score comprehensively weights precision and recall.

2.5.2 Accuracy Assessment for Check Dam Point Extraction

As check dams are large structures, hydrological analysis may extract points with slight spatial offsets from actual dam centers. Therefore, a 20 m buffer zone is established around each real check dam. Errors <20 m are considered acceptable (correct extraction), while errors >20 m represent extraction failure. Accuracy and completeness metrics are calculated as: Accuracy = (Number of correctly extracted points / Total extracted points) × 100%; Completeness = (Number of correctly extracted points / Number of visually interpreted check dams) × 100%.

3.1 Siltation Area Extraction Results and Analysis

Extraction results from different methods are shown in [Figure 5: see original paper]. Due to spectral variability within identical objects and spectral similarity between different objects, traditional OBIA methods produce fragmented ground patches with unclear edges and internal holes, with some omission errors. Deep learning methods extract ground patches with smoother, clearer edges and fewer internal holes, better representing actual ground edges and providing a foundation for precise check dam point extraction. However, deep learning alone tends to misclassify terraces and mounds as check dams. The deep learning fused with OBIA method achieves the highest precision and recall rates, reaching 90.94% and 81.97% respectively, with an F1Score of 89.70%—21.94% higher than OBIA alone .

3.2 Check Dam Point Extraction Results and Analysis

Check dam point extraction results show 64 total points extracted, with 58 correctly identified, achieving 81.08% accuracy and 88.89% completeness. Spatial distribution analysis reveals higher check dam density along main channels (0–5.09 points/unit area), while sparse areas occur at watershed edges near river sources with lower sediment retention capacity and economic value. Based on river network classification (level 1-4 streams), check dam numbers increase progressively from main channels to tertiary tributaries, demonstrating enhanced watershed control capacity.

4 Discussion

The proposed method effectively extracts siltation areas and check dam points, but several limitations require future improvement: (1) Vegetation cover on check dams affects extraction accuracy. This study used winter imagery to avoid vegetation interference, but summer imagery with crop cover would complicate identification. (2) Point location accuracy depends on siltation area extraction quality. While the OBIA-deep learning fusion method detects most siltation areas, complete identification remains challenging. Future research should explore multispectral imagery and compare multiple deep learning networks optimized for check dam spectral and morphological characteristics. (3) While the method extracts areas and points, automatic classification of check dam types still requires manual interpretation.

5 Conclusions

This study used 0.5 m Google Earth imagery and DEM data to improve the U-Net deep learning architecture, integrating negative terrain river networks to extract siltation areas and determine check dam spatial locations through hydrological analysis. Experimental results in the Jiuyuangou watershed demonstrate: (1) Majority voting fusion of deep learning and OBIA achieves 90.94% precision and 81.97% recall for siltation area extraction, with F1Score of 89.70%. (2) Combining topographic features with hydrological analysis enables automatic check dam point extraction with 81.08% accuracy and 88.89% completeness. (3) Spatial analysis reveals concentrated check dam distribution along main channels and progressive increases from main channels to tributaries, demonstrating enhanced watershed control. This method provides rapid extraction capability and important data support for soil and water loss assessment, check dam construction planning, and siltation agriculture development across the Loess Plateau.

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