Terraced Field Information Extraction by Integrating UAV Imagery and Terrain Indices: Postprint

Authors: Xue Mudan, Zhang Hongming, Yang Jiangtao, Li Xingshu

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Abstract

Currently, there has been certain research progress in the automatic and semi-automatic interpretation of terraced field information from satellite remote sensing and low-altitude remote sensing imagery. However, constrained by limitations such as data acquisition costs, accuracy, and single interpretation methods, existing studies are restricted to extracting terraced field regions over large areas. Conducting precise extraction of terraced field surfaces and area statistics at low cost still requires further research. Using an object-oriented approach, terraced field region segmentation, extraction, and area statistics were performed separately on 0.5m resolution UAV orthophotos, terrain indices, and the combination of both data sources. The results demonstrate that integrating orthophoto data with terrain indices yields superior terraced field surface extraction compared to methods based on single data sources.

Full Text

Preamble

Extraction of Terrace Information Based on UAV Image and Topographic Index

Xue Mudan[1], Zhang Hongming[1]†, Yang Jiangtao[2], Li Xingshu[3] [1]College of Information Engineering, [2]College of Water Resources & Architectural Engineering, [3]Institute of Mechanical & Electrical Engineering, Northwest A&F University, Yangling, Shaanxi 712100, China

Abstract: While research on automatic and semi-automatic interpretation of terrace information from satellite and low-altitude remote sensing imagery has made progress, current efforts are limited to large-scale terrace area extraction due to constraints in data acquisition cost, accuracy, and single-method interpretation approaches. Low-cost, precise extraction of terrace field surfaces and area statistics require further investigation. This study employs an object-oriented approach to segment, extract, and calculate terrace areas using 0.5m resolution UAV orthophotos, topographic indices, and a fusion of both data types. Results demonstrate that combining orthophoto data with topographic indices yields superior terrace field extraction compared to single-source data approaches.

Keywords: terrace; UAV orthophoto; topographic index; object-oriented; supervised classification

0 Introduction

Terrace construction represents a soil and water conservation practice developed on sloping farmland that significantly enhances agricultural potential while providing water retention and soil preservation benefits [1]. Traditionally, visual interpretation has been the primary technique for obtaining terrace information. However, limitations in experiential knowledge and technical costs have resulted in incomplete survey data regarding terrace quantity, area, and distribution, hindering quantitative research on terraces' contributions to soil and water conservation. With advances in high-resolution image acquisition and processing technologies, terrace information extraction based on texture features using Fourier transform algorithms and template matching has become feasible [2-4]. Nevertheless, these methods suffer from numerous omissions and misclassifications due to indistinct, irregular texture patterns and limitations such as fixed window sizes in Fourier transform algorithms and inflexible template dimensions in template matching. Moreover, these algorithms consider only texture and grayscale features while underutilizing color, shape, slope, and other topographic indices of terraces.

Object-oriented classification methods can fully exploit color, shape, and other information from terraces. Researchers such as Zhang Yuguo [5] and Dang Tianmin [6] have employed object-oriented approaches using relatively low-resolution single satellite data sources, employing trial-and-error methods to identify optimal scales (which is subjective and lacks quantitative analysis) and using rule-based methods (requiring manually set rules, also subjective) and K-nearest neighbor (KNN) classification. Post-classification manual adjustment of misclassifications and omissions constitutes a semi-automated terrace region extraction process. Eckert et al. [7] combined four-band multispectral data with DSM data, applying object-oriented classification for terrace extraction, demonstrating that integrating spectral information with DSM yields higher accuracy than using spectral information alone. Compared to satellite data, UAV photogrammetry systems offer advantages in low-cost, high-efficiency, and rapid acquisition of high-resolution imagery. Han et al. [8] compared two data sources for terrace classification: DEM-based approaches and combined DEM-orthophoto-infrared band approaches. However, their study did not analyze classification based solely on orthophoto-infrared band combinations, lacking rigor and persuasiveness. Diaz-Varela et al. [9] combined DEM with multispectral imagery for terrace extraction through object-oriented analysis, though extraction accuracy was affected by high vegetation coverage in the study area.

Existing research combining high-resolution imagery with DEM data for large-area terrace extraction has achieved progress but faces several challenges: (a) nearly all researchers focus on large-area terrace region extraction, with minimal progress on precise field surface extraction and area statistics, failing to meet precision agriculture requirements, and most data sources are costly and difficult-to-acquire satellite imagery; (b) visual interpretation for determining optimal multi-scale segmentation parameters remains at a qualitative stage without quantitative analysis; (c) classification methods are 单一, and accuracy assessment rarely mentions evaluation sample acquisition, though more objective evaluation samples yield more reliable results.

Addressing these limitations, this study leverages the low-cost, high-efficiency, and rapid acquisition advantages of UAV imagery, using 0.5m high-resolution orthophotos captured over Longquan, Gansu Province to develop extraction methods for unvegetated level terraces. Employing object-oriented classification technology, we extract terrace field surfaces from large terrace areas and calculate corresponding areas. First, UAV orthophotos are preprocessed and DEM-derived topographic indices are analyzed. Next, following the optimal scale research method of Hu Zhongwen et al. [10, 11], we select evaluation metrics for optimal segmentation scale based on region merging evolution analysis, followed by classification feature screening. Finally, we apply three supervised methods—KNN, Support Vector Machine (SVM), and Decision Tree (DT)—for classification and compare their accuracy. Results demonstrate that the combined data approach achieves higher terrace extraction accuracy.

1.1 Experimental Data

The study area is located in Longquan Township, Yuzhong County, Gansu Province, within a typical loess hilly region of dryland terraces, with geographic coordinates ranging from 104°10’ 58 to 104°19’ 51 E and 35°34’ 4 to 35°40’ 56 N. Data were acquired in March 2016 using an AF1000 UAV developed by Anxiang Power, equipped with a SONY A5100 camera. Each image covered approximately 340m × 500m with a resolution of 0.05m. During acquisition, wind speed was less than level 4, weather was clear with high visibility, and flights used automatic takeoff/planned route flight/automatic landing mode, with total operation time of approximately 24 hours. Data processing employed Agisoft Photoscan software, importing imagery, POS data, and control points. The entire area was divided into 25 blocks for processing, with approximately 5,000 photos per block. Each block underwent point cloud extraction and stereo model establishment before merging and texture extraction to obtain a Digital Surface Model (DSM) using CGCS2000_3_Gauss_Kruger_CM_105E projection. As the study area had minimal vegetation cover and few buildings during acquisition, point clouds could be classified into ground and non-ground points, with non-ground points treated as noise and filtered to produce a DEM data with 0.5m resolution (30,000 × 24,000 pixels). The planimetric and elevation accuracy of the 1:500 topographic map produced from UAV imagery met the requirements of the "Specifications for Aerophotogrammetric Office Operation of 1:500, 1:1000, 1:2000 Topographic Maps" [12] for plains and hilly areas.

Three 1000×1000 pixel sub-areas with different representative characteristics were selected for testing (Figure 1 [Figure 1: see original paper]). Region 1 contains some hills and buildings, roads, no surface cover, with short and wide field shapes and fewer terraces. Region 2 has some buildings, partial crop residue accumulation on field surfaces, overall slender and narrow field shapes with smooth edges and more terraces. Region 3 includes some buildings, large snow cover on field surfaces, and winding field shapes. These three sub-areas represent the typical surface characteristics of terraces in the sample region.

1.2 Research Methods

This study first preprocesses UAV data to create three data sources: (a) histogram-equalized UAV orthophotos as Data Source 1; (b) seven topographic indices extracted from DEM data—positive and negative terrain index (PN), accumulative curvature (AC), slope (S), profile curvature (PC), coefficient of variation in elevation (CVE), terrain roughness (TR), and hill shade (HS)—with principal component analysis (PCA) applied for dimensionality reduction, producing Data Source 2; (c) combined histogram-equalized orthophotos and PCA-reduced topographic indices as Data Source 3.

Second, object-oriented classification is applied to the three data sources. Finally, classification accuracy is evaluated and areas are calculated. The technical workflow is shown in Figure 2 [Figure 2: see original paper].

1.2.1 UAV Orthophoto Histogram Equalization

High-resolution UAV orthophotos exhibit prominent structural, shape, texture, and detail information, but are susceptible to contrast deficiencies and haze blur due to weather conditions, increasing feature extraction difficulty. Preprocessing methods are typically applied to enhance contrast and improve extraction accuracy. Histogram equalization (HE) [13] is a common contrast enhancement method that adjusts global image properties but performs poorly in certain details. Adaptive histogram equalization (AHE) [14] calculates local histograms to redistribute brightness and alter contrast but may over-amplify noise in uniform regions. Contrast limited adaptive histogram equalization (CLAHE) [15] overcomes AHE's noise amplification by limiting contrast enhancement through clipping in each small region.

This study employs CLAHE to enhance UAV orthophoto contrast and perform defogging preprocessing, leveraging its advantages in both contrast enhancement and noise suppression. The processed results serve as Data Source 1, providing robust data support for subsequent object-oriented analysis.

1.2.2 Terrain Index Calculation and Dimensionality Reduction

Terrain indices in multi-band rasters containing elevation and slope are typically derived directly or indirectly from DEM data, exhibiting significant redundancy. To reduce data redundancy in object-oriented classification, this study applies principal component analysis (PCA) [16] for dimensionality reduction, with results serving as Data Source 2.

Terrace field identification primarily relies on effective segmentation of terrace edge transition zones. Among topographic indices, slope most effectively reveals these changes in visual interpretation. However, identification of which common topographic indices can serve as feature recognition parameters requires definition. This study first calculates seven terrain indices from DEM data using ArcMap 10.5: PN, S, AC, PC, CVE, TR, and HS. Definitions and formulas are as follows:

a) **PN**: The difference between maximum and minimum elevation within an analysis area. Let H_{max} be local maximum elevation and H_{mean} be local mean elevation. PN is calculated as:

$$\text{PN} = H_{\text{max}} - H_{\text{mean}}$$

b) **S**: Surface unit steepness, typically defined as the ratio of vertical height H to horizontal distance L of a slope. Let dH be elevation difference. S is calculated as:

$$S = \arctan\left(\frac{dH}{L}\right)$$

c) **PC**: The rate of elevation change along the direction of maximum slope descent. In this study, slope is expressed in degrees. PC is calculated as:

$$\text{PC} = \frac{dS}{dL}$$

d) **AC**: Ground curvature quantifies terrain surface twisting. Components in vertical and horizontal directions are profile curvature (K_p) and planform curvature (K_c), respectively. Accumulative curvature is their difference. Let K_p be profile curvature and K_c be planform curvature. AC is calculated as:

$$\text{AC} = K_p - K_c$$

e) **CVE**: Reflects elevation variation of grid vertices within an analysis area, expressed as the ratio of standard deviation to mean elevation. Let SD be standard deviation and Z be neighborhood elevation. CVE is calculated as:

$$\text{CVE} = \frac{SD}{Z}$$

f) **HS**: Hill shade simulates illumination from a hypothetical light source at specific direction and solar altitude, generating a 0-255 grayscale image through neighboring pixel calculations. Let Zenith_rad be solar zenith angle in radians, Slope_rad be slope angle in radians, Azimuth_rad be solar azimuth angle in radians, and Aspect_rad be aspect angle in radians. HS is calculated as:

$$\mathrm{HS} = 255.0\times(\cos(\mathrm{Zenith\_rad})\times\cos(\mathrm{Slope\_rad})+\sin(\mathrm{Zenith\_rad})\times\sin(\mathrm{Slope\_rad})\times\cos(\mathrm{Azimuth\_rad}-A$$

g) **TR**: The ratio of surface unit curved area S_{surface} to its projected area on a horizontal plane $S_{\text{horizontal}}$. The formula is:

$$\mathrm{TR} = \frac{1}{\cos(S)}$$

1.2.3 Object-Oriented Classification and Evaluation

This study extracts terrace field surfaces using object-oriented methods. First, optimal multi-scale segmentation parameters are selected for the three data sources and imported as thematic data into eCognition Developer 9.0 for multi-scale segmentation. Classification employs three supervised methods—KNN, SVM, and Decision Tree—with comparative accuracy analysis.

a) Optimal Scale Segmentation. For object-oriented remote sensing image feature extraction, image segmentation quality directly determines subsequent classification accuracy [17]. Recent segmentation research encompasses graph theory, clustering, and classification algorithms [18, 19]. Superpixel-based methods are currently popular [20-22], including SLIC [23], SEEDS [24], LSC [25], Mean Shift [26], Marker-based Watershed [27], and Graph-Cuts [28]. While superpixel segmentation effectively utilizes spectral, texture, and shape features to produce homogeneous objects, it often generates excessive over-segmentation fragments, creating data redundancy that reduces efficiency and robustness in classification and object detection [10]. Therefore, post-processing such as region merging and filtering is necessary.

The widely used FNEA [29] multi-scale segmentation addresses this by performing region merging after initial superpixel segmentation. This bottom-up approach merges individual pixels into progressively larger objects until segmentation parameter conditions are met. Compared to single-pixel spectral methods, multi-scale segmentation better utilizes high-resolution imagery information. eCognition Developer 9.0' s FNEA algorithm involves three main parameters: scale, shape, and compactness, with scale being particularly critical and typically requiring manual setting based on experience, which limits automated interpretation.

This study applies the optimal scale selection method of Hu Zhongwen et al. [10, 11], which performs global evolution analysis in a scale-set model for unsupervised scale set simplification to obtain optimal segmentation scales. Combining

FNEA [29] with hierarchical iterative region merging, the method constructs a hierarchical region structure that records the complete region merging process and scale indices, enabling calculation of segmentation results at any scale. Global evolution analysis based on minimum risk Bayesian decision rules performs scale set simplification, followed by local evolution analysis. When under-segmentation cost weight $C = 1$, the scale set achieves optimal simplification, which is selected as the optimal segmentation scale.

b) Classification Feature Screening. After multi-scale segmentation, a certain number of terrace and non-terrace sample objects are visually interpreted from Region 1’ s three data sources. Classification features are calculated for each band of sample objects (Table 1), followed by boxplot statistical analysis to screen features with strong separability for classification.

Table 1. Classification Features

Feature	Description
Mean	Average value of all pixels in the image object’ s layer
StdDev	Standard deviation calculated from all pixels in the image object’ s layer
Brightness	Sum of image object’ s layer values divided by number of layers containing spectral information
Length/Width	Ratio of eigenvalues from covariance matrix (larger as numerator)
Shape Index	Boundary length of image object divided by square root of its area
GLCM Correlation	Gray-level co-occurrence matrix correlation
GLCM Contrast	Gray-level co-occurrence matrix contrast
GLCM Entropy	Gray-level co-occurrence matrix entropy
GLCM Homogeneity	Gray-level co-occurrence matrix homogeneity

c) Supervised Classification. Multi-scale segmented objects are classified using KNN, SVM, and CART supervised methods.

KNN is a non-parametric, statistics-based classification algorithm. Given training data with known labels, test data features are compared with training features to identify the K most similar training samples. The test data’ s class is assigned as the most frequent class among these K neighbors. Euclidean distance (Equation (8)) calculates inter-object dissimilarity without requiring object matching. For this binary terrace/non-terrace problem, K should be odd.

$$d(x, y) = \sqrt{\sum_{k=1}^{n} (x_k - y_k)^2}$$

SVM, proposed by Cortes and Vapnik [31], solves a convex quadratic programming problem. For linearly inseparable two-class problems, the optimal classification nonlinearly maps samples to a high-dimensional feature space where a linear discriminant function separates classes with maximum margin. This approach offers good generalization for small-sample, nonlinear cases. This study uses a radial basis function (RBF) kernel with genetic algorithms (GA) to optimize parameters (penalty coefficient c and kernel radius g).

Decision Tree is a fundamental classification method with a tree structure representing feature-based instance classification. The CART algorithm [32] uses the Gini coefficient for feature selection, recursively partitioning training data into test and target variables to form a binary decision tree. Object-based decision tree classification is widely applied in feature extraction [33, 34], transforming image classification from pure recognition to a knowledge-informed re-recognition process.

d) Classification Accuracy Evaluation. Accuracy evaluation compares field data with classification results to determine accuracy. This study obtains evaluation samples through visual interpretation, creates ground truth maps in ArcMap 10.5 approximating actual terraces, and calculates actual field surface areas. Using eCognition Developer 9.0' s "Error Matrix based on TTA MASK," classification results are evaluated via confusion matrix [35-37] (Error Matrix). For k total classes and N total samples, N_i represents total samples of class i in test data (Equation (9)), and N_j represents total samples classified as class j (Equation (10)).

$$N_i = \sum_{j=1}^{k} N_{ij}$$

$$N_j = \sum_{i=1}^{k} N_{ij}$$

where N_{ij} is the number of samples that should be class i but were classified as class j. From the confusion matrix, various accuracy statistics are calculated: Producer' s Accuracy (PA) [38], User' s Accuracy (UA), Overall Accuracy (OA), and Kappa coefficient [39] (Equations (11)-(14)).

$$\mathrm{PA}_i = \frac{N_{ii}}{N_i}$$

$$\mathrm{UA}_j = \frac{N_{jj}}{N_j}$$

$$\mathrm{OA} = \frac{\sum_{i=1}^{k} N_{ii}}{N}$$

$$K = \frac{N \sum_{i=1}^{k} N_{ii} - \sum_{i=1}^{k} N_i N_j}{N^2 - \sum_{i=1}^{k} N_i N_j}$$

2.1 CLAHE Processing Results

CLAHE enhancement was applied to UAV orthophotos (Figure 3 [Figure 3: see original paper]). Comparison reveals enhanced images with clearer terrace ridge contours, providing improved data sources for further analysis.

2.2 Terrain Index Calculation and Dimensionality Reduction Results

Seven terrain indices were calculated for three sample regions using ArcMap 10.5, followed by PCA analysis. Correlation matrices are shown in Tables 2 , 3 , and 4 . PN-CVE correlation coefficients are 0.980, 0.975, and 0.978 across regions. PN-S correlations are 0.924, 0.910, and 0.894. CVE-S correlations are 0.939, 0.929, and 0.903. With a correlation threshold of 0.9, CVE, PN, and S show strong associations with redundant information. PCA of the seven terrain indices yields five weakly correlated component combinations: S, PC, AC, HS, and TR as principal components (Figure 4 [Figure 4: see original paper]), where S1, PC1, AC1, HS1, TR1 represent Region 1, and so forth.

2.3.1 Multi-scale Segmentation

Based on the three data sources, the method of Hu Zhongwen et al. [10, 11] was applied with shape factor = 0.5 and compactness factor = 0.8 to construct scale sets and identify optimal segmentation scales. Results were imported into eCognition Developer 9.0 as thematic data for multi-scale segmentation (Figure 5 [Figure 5: see original paper]).

a) Segmentation based on Data Source 1 (Figures 5b, 5f, 5j). Under-segmentation occurs in red and blue boxes due to small spectral differences at terrace edges, interference from cover materials, narrow fields (red boxes), and overly narrow ridges (blue boxes).

b) Segmentation based on Data Source 2 (Figures 5c, 5g, 5k). In Regions 1 and 3 (Figures 5c, 5k), red and blue box areas show clear, well-defined edges. Compared to Data Source 1 segmentation in Regions 1 and 3 (Figures 5b, 5j), Data Source 2 better distinguishes terrace edges. However, in green box areas, Data Source 2 segmentation shows under-segmentation. Region 2 (Figure 5g) exhibits poor segmentation with blurred edges because narrow, low-height terraces cannot be adequately represented by topographic indices. In flat field areas where multiple terraces share the same plane, topographic indices show weaker distinguishability despite large spectral differences.

c) Segmentation based on Data Source 3 (Figures 5d, 5h, 5l). Red and blue boxes across Regions 1-3 show clearly visible edges, combining the advantages of Data Sources 1 and 2 to produce segmentation results closely approximating ground truth.

2.3.2 Supervised Classification

1) Classification Feature Extraction

Features are extracted from multi-scale segmented objects across R, G, B, S, PC, AC, HS, and TR bands. Random terrace and non-terrace samples are selected with balanced representation. For Data Sources 1 and 2, features are calculated for each band (Table 2) and used directly. For Data Source 3, feature optimization is required due to numerous features and data redundancy. Sample features are statistically analyzed via boxplots (Figure 6 [Figure 6: see original paper]), revealing that Mean R, Mean S, StdDev G, StdDev B, StdDev TR, StdDev HS, and S-band texture features (GLCM correlations S, GLCM homogeneity S, GLCM deviation S) show strong discriminative power and are suitable as classification features.

2) Classification and Evaluation

Supervised classification using KNN, SVM, and CART was first conducted on Region 1' s three data sources. Figure 7 [Figure 7: see original paper] shows Region 1 ground truth, while Figures 8 [Figure 8: see original paper]-10 [Figure 10: see original paper] present classification results (red = terrace fields, yellow = non-terrace). Accuracy evaluation is shown in Table 5 .

a) Qualitative Analysis:

- **Data Source 1 classifications** (Figures 8-10, left columns) show misclassification in blue, black, and purple boxes. Blue and purple box misclassifications result from under-segmentation due to small spectral differences, while black box errors may stem from incomplete feature selection or classification method limitations.
- **Data Source 2 classifications** (Figures 8-10, middle columns) show misclassification in black, purple, and green boxes due to indistinct topographic index differences causing under-segmentation, with other errors arising from insufficient topographic feature representation.
- **Data Source 3 classifications** (Figures 8-10, right columns) show varying misclassification degrees across methods, with black box errors in all methods and purple/blue box errors in Figure 10d, attributable to feature selection, training sample differences, and classification methods.

Analysis confirms that multi-scale segmentation quality is the primary factor affecting classification results. Data Source 1 under-segments areas with indistinct spectral changes; Data Source 2 under-segments where spectral differences are large but topographic indices are indistinct; Data Source 3 segmentation

(Figures 5d, 5h, 5l) is superior to both single sources, though classification differences persist due to supervised method variations. This comprehensively validates Data Source 3 as most suitable for terrace field extraction.

b) Quantitative Analysis:

- **Producer' s and User' s Accuracy:** Using KNN, Data Source 1 yields 0.759 and 0.908; Data Source 2 yields 0.744 and 0.771; Data Source 3 yields 0.776 and 0.908. Data Source 3 shows the fewest misclassifications. Similar patterns hold for SVM and CART, with Data Source 3 consistently outperforming single sources.
- **Overall Accuracy and Kappa:** Using KNN, Data Source 1 achieves 0.875 OA and 0.730 Kappa; Data Source 2 achieves 0.809 and 0.600; Data Source 3 achieves 0.887 and 0.739. Data Source 3' s accuracy exceeds single sources across all methods.

Based on Region 1 results, Regions 2 and 3 were processed using Data Source 3. Multi-scale segmentation results are shown in Figures 5h and 5l. Classification results using KNN, SVM, and CART appear in Figure 11 [Figure 11: see original paper], with accuracy evaluation in Table 6 . Comparing Region 1 Data Source 3 results: KNN (OA = 0.887, Kappa = 0.739), SVM (OA = 0.887, Kappa = 0.765), CART (OA = 0.872, Kappa = 0.732). SVM outperforms KNN and CART. Similar analysis of Tables 8 shows SVM superior in Region 2, while CART performs best in Region 3.

Overall, SVM classification outperforms KNN and CART. KNN is simple and effective with low retraining cost but high computational load. CART is interpretable and handles numeric and categorical attributes but biases toward features with more values. SVM solves small-sample classification, improves generalization, and handles high-dimensional and nonlinear problems. Given limited terrace/non-terrace samples with diverse features, SVM is most suitable. Final area statistics based on SVM results are shown in Table 7 . The relatively large gap with visually interpreted areas primarily results from suboptimal SVM kernel function and parameter settings, plus unavoidable visual interpretation errors in reference data.

3 Conclusion

This study demonstrates object-oriented terrace information extraction using high-resolution UAV orthophotos, topographic indices, and their combination. Results show that integrating UAV orthophotos with topographic indices, combined with SVM classification, achieves high extraction accuracy by fully utilizing spectral, texture, shape, and topographic information.

Several improvements are needed: (a) While GA optimizes SVM parameters, more suitable optimization algorithms require exploration; (b) Feature optimization relied solely on boxplot statistical analysis without investigating more rigorous methods; (c) Integration of multiple classification methods (ensemble machine learning) or deep learning approaches warrant further investigation.

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