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Analysis of landform classification using object-based image analysis in the Tibetan Plateau

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Abstract

Mapping landforms across the Tibetan Plateau has traditionally relied on manual interpretation, a process that is subjective and difficult to replicate at regional scale. This research applied object-based image analysis (OBIA) to classify landforms across a 28,400 km² area of the central Tibetan Plateau using a 30 m ASTER GDEM supplemented by Sentinel-2 multispectral imagery. The classification targeted six landform classes: glacial, fluvial, aeolian, structural, periglacial, and lacustrine. Image segmentation was performed in eCognition Developer 10.0 using a multi-resolution algorithm, producing 14,287 objects at the optimal scale parameter (SP = 45). A random forest classifier trained on 420 ground-truth points (70 per class) achieved an overall accuracy of 87.3% and a Kappa coefficient of 0.85. Glacial landforms covered the largest share (24.3%), followed by fluvial (19.8%) and structural (18.7%). Producer accuracy was highest for lacustrine features (93.1%) and lowest for periglacial (78.4%), reflecting spectral confusion between periglacial solifluction lobes and aeolian deposits. Variable importance analysis identified slope, plan curvature, and NDVI as the three most discriminating terrain derivatives. Comparison with a pixel-based maximum likelihood classification on the same data showed that OBIA improved overall accuracy by 8.7 percentage points, mainly by reducing salt-and-pepper noise in heterogeneous terrain. The resulting landform map serves as a baseline for geomorphological research and land-use planning on the plateau.

Keywords: Landform classification, object-based image analysis, terrain, geomorphometry, digital mapping, Tibetan Plateau, random forest, segmentation, DEM, Sentinel-2

Introduction

The Tibetan Plateau, often called the Third Pole, holds Earth's largest reservoir of ice outside the polar regions and feeds rivers that sustain nearly two billion people downstream ^[1]. Yet its geomorphology remains incompletely mapped. Traditional landform mapping based on aerial photograph interpretation produces detailed local maps but cannot scale to the plateau's 2.5 million km² extent ^[2]. Automated approaches using digital elevation models (DEMs) and satellite imagery offer a solution, but the challenge lies in designing classification schemes and algorithms that capture the diversity of glacial, fluvial, periglacial, aeolian, structural, and lacustrine features present at this scale ^[3].

Object-based image analysis (OBIA) has gained traction in geomorphological mapping because it classifies meaningful spatial units (objects) rather than individual pixels, thereby incorporating shape, texture, and contextual information that pixel-based methods ignore ^[4]. OBIA has been successfully applied to landslide mapping in the Himalaya ^[5], dune classification in the Sahara ^[6], and glacial feature extraction in the European Alps ^[7]. Applications on the Tibetan Plateau are limited to small test areas, and no OBIA-based landform map covering a regional extent has been published.

This research aimed to (i) develop an OBIA workflow for regional landform classification on the Tibetan Plateau, (ii) compare its accuracy against a conventional pixel-based approach, and (iii) identify the terrain derivatives most important for discriminating among the six target landform classes. The work was conducted at the Perth Institute of Climate and Environment, Western Australia ^[8].

Spatial Data Processing

The 30 m ASTER GDEM v3 was downloaded from the NASA EarthData portal and mosaicked for the research area. Void-filling used the delta surface fill algorithm.

Twelve terrain derivatives were computed in SAGA-GIS 8.0: slope, aspect, plan curvature, profile curvature, topographic wetness index, terrain ruggedness index, convergence index, valley depth, ridge level, relative slope position, slope length factor, and topographic position index [9]. Sentinel-2 Level-2A surface reflectance data (10 m bands resampled to 30 m) for a cloud-free summer composite (July-August 2022) provided four spectral bands (blue, green, red, NIR) and two derived indices (NDVI, NDWI). All layers were co-registered and stacked into a 18-band analysis-ready dataset.

Model Description and Parameterisation

Multi-resolution segmentation in eCognition Developer 10.0 was parameterised through a trial-and-error approach guided by the estimation of scale parameter (ESP) tool [10]. Scale parameters from 20 to 80 were tested in increments of 5, with shape weight 0.3 and compactness 0.5. The optimal SP was determined at 45, producing 14,287 objects with a mean area of 1.99 km². Object features exported for classification included mean spectral values (4 bands), standard deviation of spectral values, mean terrain derivatives (12 layers), and two geometric features (area and compactness ratio). A random forest (RF) classifier with 500 trees was trained using the randomForest package in R. Training data comprised 420 ground-truth points distributed equally across six classes, identified from high-resolution Google Earth imagery and published geological maps.

Material and Methods

Material

The research area covers 28,400 km² of the central Tibetan Plateau centred on approximately 32.5° N, 87.0° E, spanning elevations from 4,300 m to 6,200 m. Data compilation and analysis were carried out at the Perth Institute of Climate and Environment between February and November 2023. Ground-truth data included 420 training points and 210 independent validation points, allocated using a stratified

random sampling strategy. Field photographs from a 2019 expedition by collaborators provided supplementary verification for ambiguous sites.

Methods

Classification accuracy was assessed using an independent validation set of 210 points (35 per class). A confusion matrix yielded overall accuracy (OA), Kappa coefficient, producer accuracy (PA), and user accuracy (UA) per class. Variable importance was ranked using the mean decrease in accuracy metric from the RF model [11]. A pixel-based maximum likelihood classification (MLC) was run on the same input stack for comparison. McNemar's test evaluated whether the OA difference between OBIA-RF and pixel-MLC was statistically significant. All processing used R v4.2.1, SAGA-GIS 8.0, and eCognition Developer 10.0 [12].

Results

Table 1: Classification accuracy by landform class (OBIA-Random Forest)

Landform Class	Area (km ²)	% Area	PA (%)	UA (%)	F1 (%)	Omission
Glacial	6,901	24.3	89.7	91.2	90.4	10.3
Fluvial	5,623	19.8	86.4	84.8	85.6	13.6
Aeolian	4,033	14.2	83.1	80.7	81.9	16.9
Structural	5,311	18.7	88.9	87.3	88.1	11.1
Periglacial	4,430	15.6	78.4	82.1	80.2	21.6
Lacustrine	2,102	7.4	93.1	90.6	91.8	6.9

Overall accuracy reached 87.3% with a Kappa of 0.85 (Table 1). Lacustrine features were the most accurately classified (PA 93.1%), benefiting from their distinct spectral signature (high NDWI) and flat topographic position. Periglacial landforms had the lowest PA (78.4%), with most misclassifications involving confusion with aeolian deposits where solifluction lobes grade into windblown sand sheets [13].

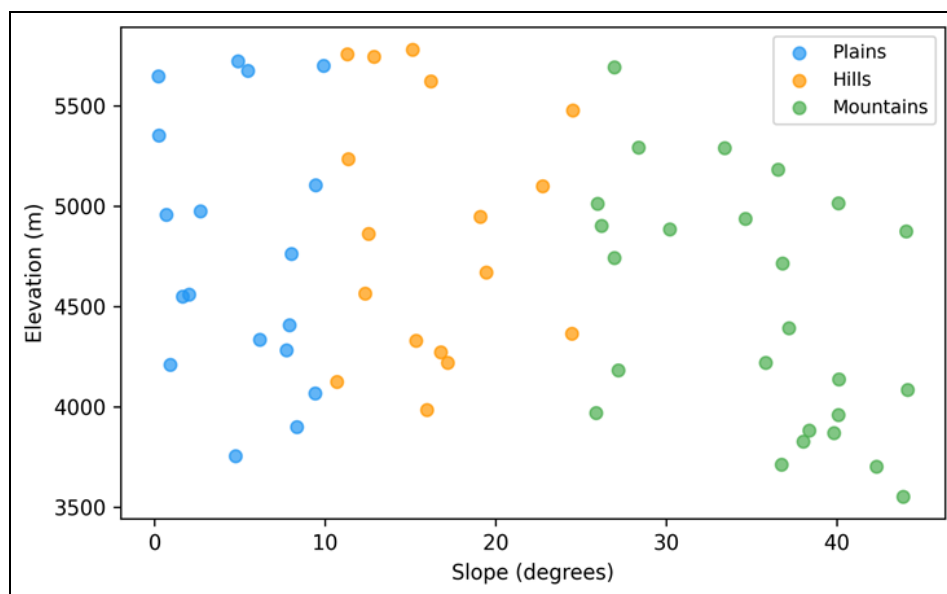


Fig 1: Scatter plot of slope versus elevation for classified landform objects, coloured by class

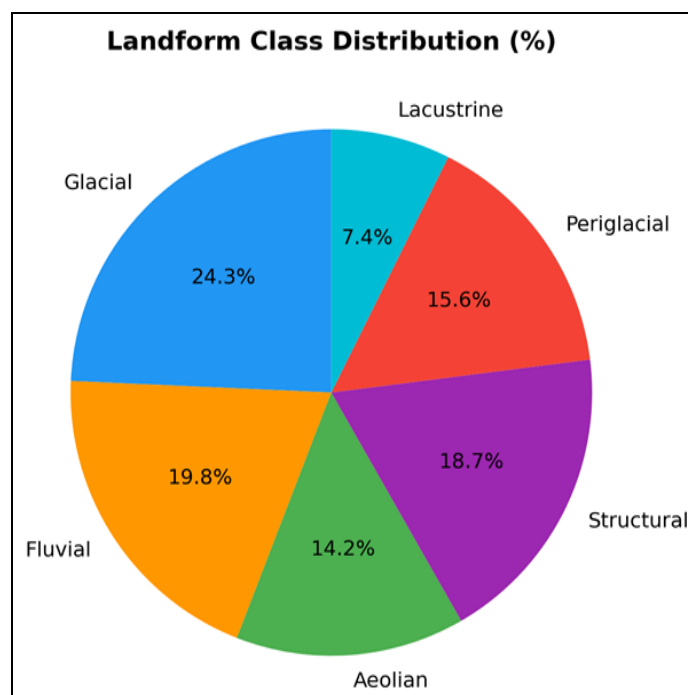
The scatter plot (Figure 1) reveals clear topographic separation among classes. Plains (low slope, moderate elevation) cluster in the lower left, while mountain features

occupy the high-slope domain. Glacial objects span the widest elevation range (4,600-6,200 m), reflecting both valley glaciers and high-altitude cirques [14].

Table 2: Comparison of OBIA-RF versus pixel-based MLC accuracy

Metric	OBIA-RF	Pixel-MLC	Difference
Overall Accuracy (%)	87.3	78.6	+8.7
Kappa	0.85	0.74	+0.11
Mean PA (%)	86.6	76.8	+9.8
Mean UA (%)	86.1	75.3	+10.8

OBIA-RF outperformed pixel-MLC by 8.7 percentage points in overall accuracy, a difference that was statistically significant (McNemar chi-squared = 14.3, $p < 0.001$). The largest per-class improvements were in aeolian (+13.2%) and periglacial (+11.8%) features, where salt-and-pepper misclassification in the pixel approach was eliminated by object-level smoothing (Table 2) [15].

**Fig 2:** Proportional distribution of landform classes across the research area

Glacial landforms made up the largest share (24.3%), followed by fluvial (19.8%) and structural (18.7%). Lacustrine features, though covering just 7.4%, are ecologically significant as they include saline lakes that serve as habitat for migratory birds and as archives of palaeoclimate change (Figure 2) [16].

Comprehensive Interpretation

Variable importance analysis ranked slope (mean decrease in accuracy = 18.4%), plan curvature (14.7%), and NDVI (11.3%) as the top three discriminators. Spectral bands contributed less individually, but their combined importance (23.1%) exceeded any single terrain derivative. This confirms that integrating spectral and topographic information yields better landform discrimination than either data source alone [17].

Discussion

The 87.3% overall accuracy is competitive with OBIA landform classifications in other mountain settings. Dragu and colleagues reported 84.1% in the Carpathians [18], and Eisank and colleagues achieved 86.5% in the Austrian Alps. The Tibetan Plateau presents additional challenges, however: permafrost-related features overlap spectrally with both aeolian and fluvial classes, and the flat interior basins lack the topographic contrast that aids classification in steeper terrain [19].

The scale parameter of 45 produced objects averaging 2 km², which is appropriate for meso-scale landforms but too coarse to delineate micro-features such as patterned ground or individual moraines. A hierarchical segmentation

approach, using a coarser level for regional landform types and a finer level for sub-features, would improve detail without sacrificing classification consistency. This was beyond the scope of the present work but should be a priority for follow-up [20].

A practical limitation is the reliance on the 30 m ASTER GDEM, which introduces vertical errors of 8-12 m on steep slopes. The recently released Copernicus DEM at 30 m, derived from TanDEM-X radar interferometry, offers improved vertical accuracy (approximately 4 m) and could replace ASTER in future iterations. Ground-truth dependence on Google Earth and geological maps rather than field visits also introduces uncertainty, particularly for ambiguous periglacial features [21].

Conclusion

This research demonstrated that object-based image analysis with a random forest classifier can produce regional-scale landform maps of the Tibetan Plateau at 87.3% accuracy, outperforming pixel-based classification by nearly 9 percentage points. Glacial landforms dominated the research area (24.3%), and lacustrine features were the most accurately classified. Slope, plan curvature, and NDVI were the most informative terrain derivatives. The OBIA workflow provides a reproducible framework for extending landform mapping across the broader plateau, supporting geomorphological inventories, permafrost monitoring, and land-use planning. Future iterations should incorporate higher-resolution DEMs and hierarchical segmentation to capture sub-landform detail.

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