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Mo Wang

Langfang Natural Resources Comprehensive Survey Center, China Geological Survey, Langfang 065000, Hebei, China

Bo Xu

Langfang Natural Resources Comprehensive Survey Center, China Geological Survey, Langfang 065000, Hebei, China

Wentai Tang

Langfang Natural Resources Comprehensive Survey Center, China Geological Survey, Langfang 065000, Hebei, China

Chuangchuang Liu

Langfang Natural Resources Comprehensive Survey Center, China Geological Survey, Langfang 065000, Hebei, China

Nan Zhao

zhaonan@mail.cgs.gov.cn

Langfang Natural Resources Comprehensive Survey Center, China Geological Survey, Langfang 065000, Hebei, China

Research Article

Keywords: environmental assessment, IR-MAD, mine rehabilitation, restoration persistence, UAV photogrammetry, change detection

Posted Date: July 10th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10041405/v1>

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Additional Declarations: No competing interests reported.

Multi-scale remote sensing reveals surface-restoration trajectories and topographic constraints in the Pingquan mining cluster, Upper Luanhe River Basin

Mo Wang¹, Bo Xu¹, Wentai Tang¹, Chuangchuang Liu¹, and Nan Zhao^{1*}

¹ Langfang Natural Resources Comprehensive Survey Center, China Geological Survey, Langfang 065000, Hebei, China

*Corresponding author: Nan Zhao; email: zhaonan@mail.cgs.gov.cn

Contributing authors: Mo Wang (wangmo@mail.cgs.gov.cn); Bo Xu (xubo@mail.cgs.gov.cn); Wentai Tang (tangwentai@mail.cgs.gov.cn); Chuangchuang Liu (liuchuangchuang@mail.cgs.gov.cn).

Clinical trial number: not applicable.

Abstract

Long-term assessment of mine rehabilitation is limited by a scale mismatch: satellite time series capture regional history but resolve mine surfaces incompletely, whereas unmanned aerial vehicle (UAV) surveys resolve fine landforms but rarely provide historical depth. We integrated GF-series images acquired in 2013, 2016, 2019, and 2022 with 93.2826 km² of centimetre-resolution UAV photogrammetry to reconstruct surface-restoration trajectories across the Pingquan mining cluster, northern China. Regularized iteratively reweighted multivariate alteration detection delineated multispectral change, normalized difference vegetation index differences assigned degradation or recovery direction, and UAV orthophotos and terrain models independently verified surface interpretation and diagnosed stability constraints. Interval degradation declined by 50.1%, while the restoration persistence index increased from 0.206 to 0.373. Nevertheless, the 2013–2022 degradation area remained 1.83 times the recovery area. Validation with 300 independently interpreted UAV points yielded 89.7% overall accuracy (Kappa = 0.84), and satellite–UAV spatial consistency reached 87.4%. The resulting evidence chain links regional trajectories, mine-surface attribution, terrain diagnosis, and management prioritization. It supports differentiated source control, stability monitoring, and low-intervention management in mountainous mining regions, while explicitly restricting “restoration” to remotely observable surface-cover improvement rather than verified recovery of soil, water quality, biodiversity, or ecosystem function.

Keywords: environmental assessment; IR-MAD; mine rehabilitation; restoration persistence; UAV photogrammetry; change detection

Introduction

Open-pit mining reorganizes both landforms and surface processes through topsoil removal, slope excavation, waste-rock disposal, road construction, and tailings development. The resulting landscape contains exposed substrates, fragmented vegetation, artificial cliffs, unstable drainage pathways, and potential routes for sediment and contaminant transport. Short-term greening is therefore an incomplete measure of rehabilitation. Credible monitoring must establish whether disturbance has ceased, whether vegetation gains persist, and whether the restored surface is compatible with long-term geomorphic stability, while reserving claims about soil, water, biodiversity, and ecosystem function for field-based evidence.

Satellite remote sensing provides repeatable regional observations and has shifted mine monitoring from single-date land-cover inventories towards time-series trajectories and multi-indicator assessments (McKenna et al., 2020; Wang et al., 2021; Hu et al., 2022; Zhang et al., 2023; Zhong et al., 2023). In mountainous mines, however, mixed pixels, terrain shadow, seasonal vegetation differences, water-level fluctuations, and spectrally similar bare

surfaces complicate attribution of a changed pixel to a specific mining process. Recent studies in Environmental Monitoring and Assessment similarly show that remote-sensing products become environmentally meaningful only when their inference boundaries and verification requirements are explicit (Wasehun et al., 2024; Safo Kantanka et al., 2025).

UAV photogrammetry addresses part of this limitation by resolving orthophotos, point clouds, and terrain models at centimetre scale (Colomina & Molina, 2014; Westoby et al., 2012; Anderson & Gaston, 2013; Turner et al., 2012; Nex & Remondino, 2014). Yet a recent UAV campaign cannot reconstruct when a disturbance occurred. Moreover, vegetation-index gains are often reported without testing whether steep slopes, shallow substrates, or renewed engineering disturbance compromise their persistence. Three linked gaps therefore remain: satellites provide limited object-level attribution, single-date UAV surveys provide limited historical depth, and vegetation change is frequently interpreted without terrain-based stability diagnosis.

Change detection also involves a methodological trade-off between sensitivity and ecological direction. Regularized iteratively reweighted multivariate alteration detection (IR-MAD) identifies multispectral anomalies but does not determine whether they represent degradation or recovery (Nielsen, 2007). Vegetation indices provide directional information but remain sensitive to phenology and soil background (Tucker, 1979; Huete, 1988; Pettorelli et al., 2005). Their integration can therefore separate where a surface changed from whether vegetation increased or decreased, provided that classification thresholds, validation evidence, and inference limits are reported transparently.

Here we developed an evidence-structured monitoring framework for the Pingquan mining cluster in the Upper Luanhe River Basin; the workflow and intended placement of the framework diagram are shown in Fig. 1. We asked four questions: Did interval degradation weaken between 2013 and 2022? Were satellite-derived recovery signals supported by independent UAV interpretation? Did recovery account for an increasing share of significant directional change? And how did terrain constrain the stability of apparent recovery? The analysis was deliberately confined to observable surface disturbance, vegetation cover, and topography; it did not quantify soil contamination, erosion rates, water chemistry, biodiversity, nutrient cycling, or complete ecosystem recovery.

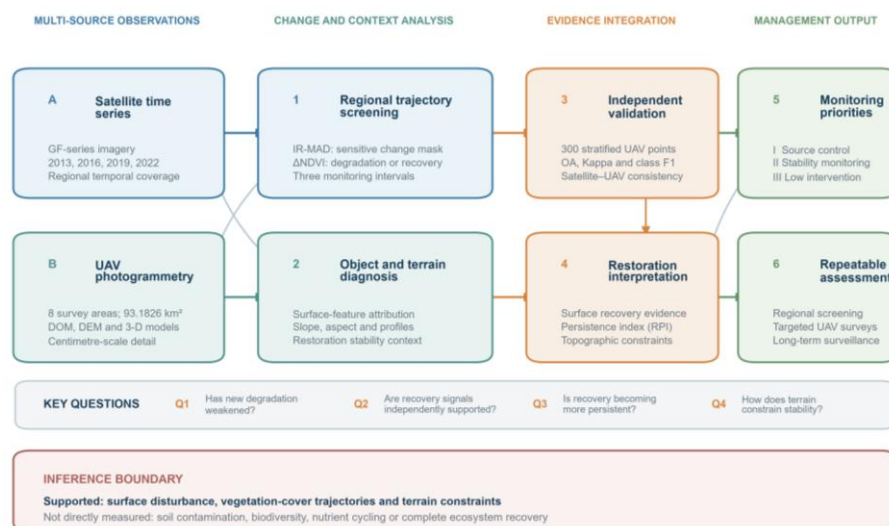


Fig. 1 Multi-scale monitoring workflow linking satellite-derived regional trajectories, UAV-based surface verification, terrain diagnosis, independent validation, and management prioritization.

Materials and methods

Study area

The study area lies in Pingquan City, Hebei Province, within the Baohe River catchment of the Upper Luanhe River Basin (Fig. 2; approximately 118°21'-119°15' E and 40°24'-41°24' N). The eastern Yanshan landscape comprises structurally eroded low mountains, hills, and incised valleys. A temperate continental monsoon climate produces cold, dry winters and warm summers with concentrated rainfall. Zonal vegetation is dominated by warm-temperate deciduous forest and secondary shrub-grass communities, interspersed with cultivated valleys and planted stands. Mountain brown and cinnamon soils coexist with thin skeletal soils on rocky slopes, whereas mining platforms and dumps contain heterogeneous, weakly developed substrates.

Long-term extraction of iron, limestone, and other non-metallic resources has produced dense clusters of open pits, processing facilities, waste-rock dumps, roads, and tailings facilities. Project records list 103 mines and 86 tailings impoundments across Pingquan, indicating a legacy landscape in which active and abandoned disturbances coexist. The eight UAV subareas were selected to represent contrasting monitoring contexts: limestone and iron-mining clusters, pit and dump surfaces, tailings- or reservoir-associated features, upstream river reaches, and a long river corridor. Their purpose was not statistical coverage of all mines, but independent verification across the principal surface-feature types encountered in regional interpretation.

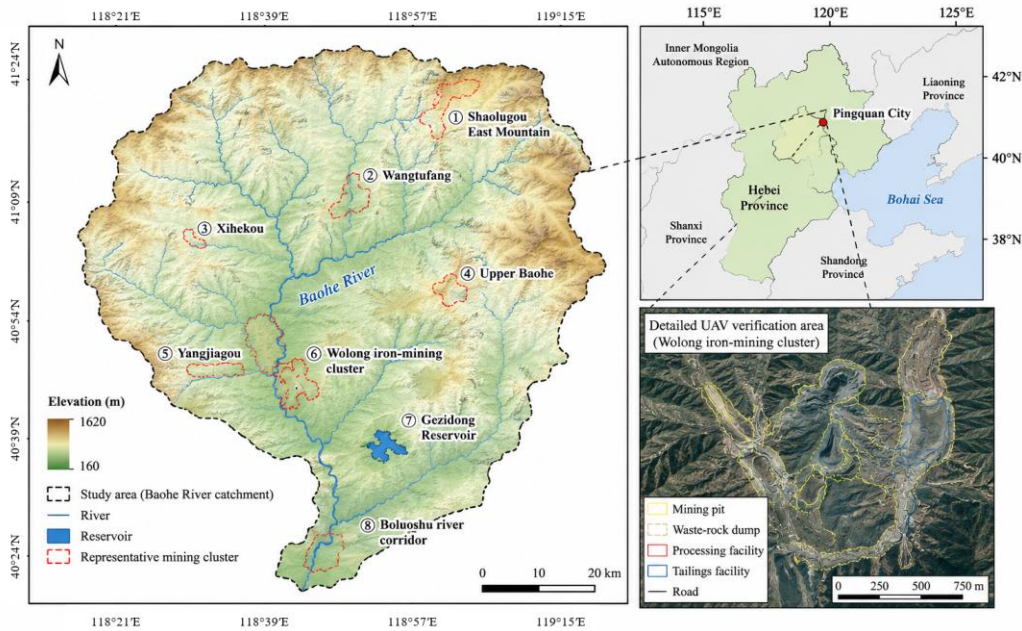


Fig. 2 Location of the Pingquan mining cluster and detailed UAV verification areas.

Satellite and UAV data

Regional change analysis used GF-series imagery acquired on 25 December 2013, 5 April 2016, 25 October 2019, and 19 April 2022. Archived products had undergone radiometric and atmospheric correction. Erdas Imaging photogrammetry tools were used to co-register all scenes to the 2019 reference image, with residual registration errors below 0.18 pixel. Because acquisition seasons differed, no single correction could fully remove phenological effects. We therefore used three safeguards: thresholds estimated from 20 temporally stable reference objects, an IR-MAD mask to exclude spectrally unchanged pixels, and UAV interpretation to reject changes attributable to

shadows, water level, exposed soil, or temporary works. The outputs were consequently treated as directional monitoring signals rather than season-independent biophysical measurements.

UAV surveys were conducted with a DJI M300 RTK platform. In total, 103 ground control points and 42 flights covered 93.2826 km². Forward overlap was 80%, side overlap was 70–75%, and relative flight height ranged from 250 to 400 m. RTK control-point errors were <0.01 m horizontally and <0.025 m vertically. DJI Terra was used for image import, position and orientation checks, aerial triangulation, dense point-cloud reconstruction, orthorectification, and production of digital orthophoto maps (DOMs), elevation/surface models, and three-dimensional models. Mosaics were screened for blur, displacement, distortion, and data voids; colour, brightness, and contrast balancing then reduced inter-image tonal differences. ArcGIS 10.7 supported orthophoto editing, terrain derivation, reclassification, profile extraction, and spatial overlay.

Table 1 UAV survey workload and geometric accuracy. DOM, digital orthophoto map; RMSE, root mean square error

Survey area	Area (km ²)	Control points	Flights	DOM resolution (m)	Planar RMSE (m)
Shaolugou East Mountain	4.2557	7	3	0.046	0.118
Wangtufang	3.7666	8	3	0.056	0.070
Xihekou	1.5236	6	2	0.028	0.079
Upper Baohe	3.1560	7	2	0.027	0.079
Yangjiagou	3.0807	5	3	0.038	0.053
Wolong iron-mining cluster	21.0160	18	9	0.077	0.084
Gezidong Reservoir	9.1630	7	3	0.063	0.038
Boluoshu river corridor	47.3210	45	17	0.063	0.063

Directional change detection

Normalized difference vegetation index (NDVI) was calculated from near-infrared and red reflectance. Twenty temporally stable reference areas representing tailings dams, cropland, grassland, forest, bare ground, and tailings water were used to characterize inter-date variability. Except for turbid water, the standard deviation of NDVI was generally <0.08. A conservative threshold, fixed before classification at twice this empirical standard deviation, assigned $\Delta\text{NDVI} < -0.16$ to degradation, $\Delta\text{NDVI} > 0.16$ to recovery, and intermediate values to no directional change. Because the archived project did not retain alternative-threshold rasters, a retrospective numerical sensitivity curve could not be reconstructed. Inference is therefore most uncertain near the ± 0.16 decision boundary.

$$\text{NDVI}(x) = \frac{\rho_{\text{NIR}}(x) - \rho_{\text{R}}(x)}{\rho_{\text{NIR}}(x) + \rho_{\text{R}}(x)} \quad (1)$$

$$C(x) = \begin{cases} -1 & \text{if } M(x) = 1 \text{ and } \Delta\text{NDVI}(x) < -0.16 \\ +1 & \text{if } M(x) = 1 \text{ and } \Delta\text{NDVI}(x) > +0.16 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

IR-MAD used canonical correlation and iterative weighting to stabilize the unchanged background and identify multispectral anomalies (Nielsen, 2007). Let $M(x)$ equal 1 for an IR-MAD changed pixel and 0 otherwise. Directional class $C(x)$ was assigned as degradation when $M(x) = 1$ and $\Delta\text{NDVI}(x) < -0.16$, recovery when $M(x) = 1$ and $\Delta\text{NDVI}(x) > 0.16$, and stable/undetermined otherwise. Thus, IR-MAD defined where a multispectral change occurred, while ΔNDVI defined its vegetation direction; neither component alone was interpreted as ecological restoration.

UAV interpretation and terrain diagnosis

Satellite change polygons were overlaid on UAV orthophotos and three-dimensional models. Shape, texture, boundary form, and spatial context attributed changes to pits, cut slopes, production platforms, waste-rock dumps, tailings facilities, roads, buildings, or natural bare ground. Terrain metrics were derived from the UAV elevation model. Slope classes were 0–15°, 15–30°, 30–45°, 45–60°, 60–75°, and 75–90°, with 30° used as an operational transition to higher erosion and topsoil-retention concern and 45° used to flag very steep or engineered faces. These thresholds were interpreted with mine-slope restoration evidence rather than as universal ecological boundaries (Li et al., 2018; Yang et al., 2020; López-Marcos et al., 2020). Aspect was grouped into sunny, semi-sunny, shady, and semi-shady categories.

The UAV camera recorded visible bands only. The archived project used a visible-band vegetation-enhancement raster and a threshold of 0.039217 to derive binary cover. Because the complete index formula and calibration record were not retained, the 74.01% estimate was used only as a descriptive surface-cover indicator. It did not enter change classification, accuracy assessment, RPI calculation, or management-zone assignment and should not be interpreted as a physiological vegetation metric.

Accuracy assessment and restoration persistence

Three hundred validation points were selected by stratified random sampling across the eight UAV survey areas. Directional class (degradation, recovery, and stable) and UAV subarea formed the principal strata, and points were dispersed to limit clustering within individual polygons. Centimetre-resolution DOMs were interpreted independently of the satellite labels. Performance was summarized by user's accuracy, producer's accuracy, F1-score, overall accuracy, and Kappa. The archive retained these summary metrics but not the exact point coordinates, slope-stratum allocations, or original contingency-cell counts; consequently, we do not reconstruct a confusion matrix or infer an unsupported sampling balance.

Cross-scale agreement was evaluated at two levels. Overall spatial consistency compared all directional satellite classes with UAV interpretation, whereas recovery-specific consistency measured the proportion of satellite recovery signals corresponding to visible vegetation establishment or surface stabilization. The restoration persistence index (RPI) expressed the share of recovery in all significant directional changes for each interval. It was designed as a transparent trajectory indicator, consistent with the principle that restoration should be evaluated through repeated disturbance–recovery observations rather than a single endpoint (Kennedy et al., 2010; McKenna et al., 2020). RPI does not measure ecological function.

$$RPI_t = \frac{A_{\text{recovery},t}}{A_{\text{degradation},t} + A_{\text{recovery},t}} \quad (3)$$

Management zoning

Management zones were assigned using explicit decision rules. Source-control zones required recent or persistent degradation spatially connected to active pits, dumps, roads, or tailings facilities. Stability-monitoring zones required a recovery signal on slopes >30° or on conspicuous artificial cuts, because apparent greening could coexist with erosion or instability. Low-intervention zones required stable or slowly improving cover on gentler terrain without evidence of renewed disturbance. UAV verification confidence was used to flag ambiguous

polygons for field inspection. The rules constitute a transferable screening framework, not a substitute for statutory site-specific risk assessment.

Results

UAV coverage and product accuracy

The eight UAV surveys covered 93.2826 km². The Boluoshu river corridor and Wolong mining cluster represented 50.7% and 22.5% of the total, respectively. DOM resolution ranged from 0.027 to 0.077 m pixel⁻¹, and reported planar RMSE ranged from 0.038 to 0.118 m. Across the eight sites, positional accuracy did not vary monotonically with image resolution, showing that ground sampling distance alone was not a sufficient proxy for geometric reliability in rugged terrain (Fig. 3; Table 1).

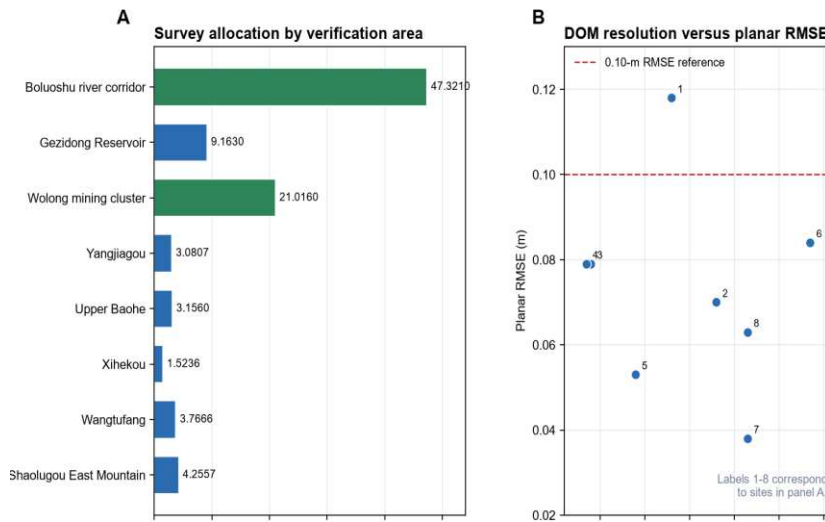


Fig. 3 UAV survey allocation and product accuracy. (A) Surveyed area across the eight verification sites. (B) Relationship between DOM resolution and the independently reported planar RMSE; labels correspond to the sites in panel A.

Temporal change trajectories

Directional trajectories indicated a sustained weakening of vegetation degradation throughout the monitoring period (Fig. 4). Degraded area decreased from 5.3442 km² during 2013–2016 to 3.8187 km² during 2016–2019 and 2.6659 km² during 2019–2022, representing a 50.1% reduction between the first and final intervals. In contrast, vegetation recovery increased gradually from 1.3842 to 1.4764 and 1.5878 km². Consequently, net degradation declined from 3.9600 to 1.0781 km², indicating that vegetation loss progressively weakened over time.

Although recent degradation was substantially reduced, the long-term comparison still revealed a restoration deficit. Across the entire 2013–2022 period, cumulative degradation reached 4.0841 km², whereas cumulative recovery totalled only 2.2372 km², producing a degradation-to-recovery ratio of 1.83 (Fig. 4). These temporal trajectories suggest that mine management has increasingly limited the expansion of new vegetation disturbance, while legacy degradation remains incompletely restored.

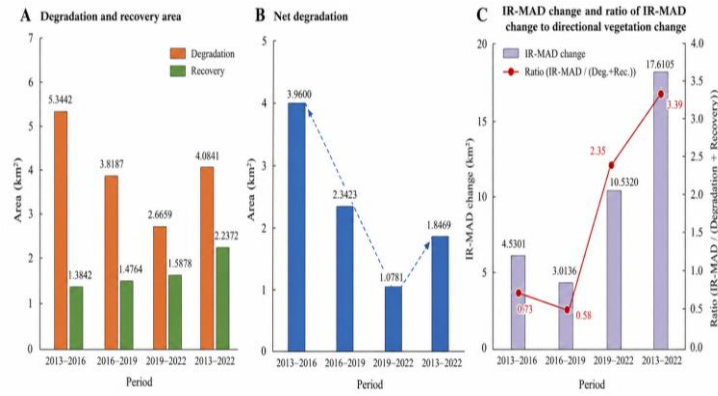


Fig. 4 Directional surface-change trajectories from 2013 to 2022, including degradation and recovery areas, net degradation, and the relationship between IR-MAD change and directional vegetation change.

Mining-related surface reworking

While directional vegetation degradation weakened, multispectral surface disturbance remained active. During 2019–2022, IR-MAD detected 10.5320 km² of surface change, approximately 2.48 times the area exhibiting significant directional NDVI change. UAV observations indicated that this discrepancy mainly resulted from engineering activities including platform grading, haul-road modification, dump expansion, restoration construction, bare-ground boundary adjustment, and fluctuations in tailings ponds. These operations substantially altered surface texture and reflectance before producing measurable vegetation responses.

The mapped spatial distribution further supports this interpretation (Fig. 5). Vegetation degradation remained concentrated around active pit margins, expanding waste dumps, tailings facilities, and transportation corridors, where continuous engineering disturbance inhibited vegetation recovery. In contrast, vegetation recovery was primarily distributed on reclaimed slopes, rehabilitated platforms, and inactive mining areas, reflecting the localized effectiveness of ecological restoration measures. Therefore, increasing IR-MAD change together with declining directional vegetation degradation indicates an ongoing transition from widespread vegetation disturbance towards engineering reworking and gradual ecological rehabilitation, rather than complete ecosystem recovery.

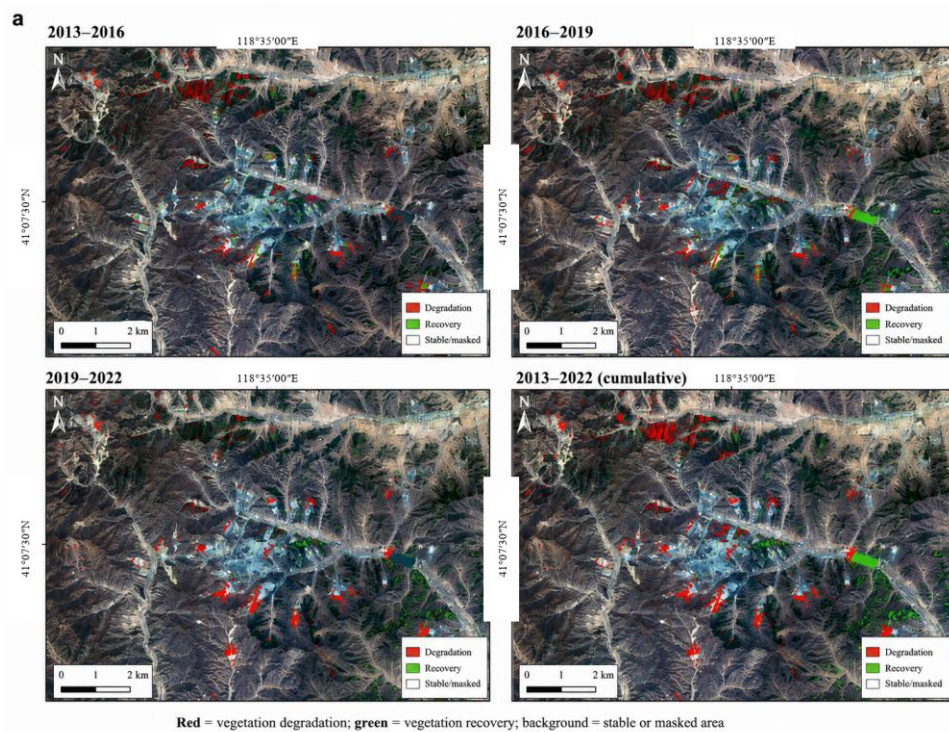


Fig. 5 Spatial distribution of vegetation degradation and recovery during the monitoring periods.

Surface recovery evidence and terrain constraints

Paired imagery from 2013 and 2022 showed that selected bare or sparsely vegetated surfaces developed more continuous cover. These observations provide object-level support for local surface recovery, but they do not demonstrate soil development, community composition, or sustained ecosystem function. This distinction is consistent with mine-rehabilitation frameworks that evaluate present condition against reference states and closure objectives rather than treating greening alone as recovery (Neldner & Ngugi, 2014; Ngugi & Neldner, 2015). Representative evidence is shown in Fig. 6.

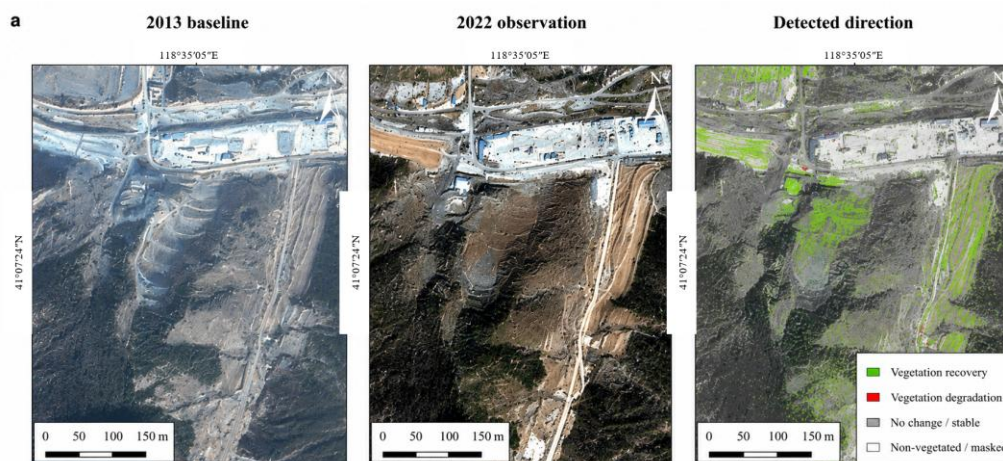


Fig. 6 Image evidence for a representative restoration patch, including the 2013 baseline, 2022 observation, and detected change direction.

In the representative limestone mine, the terrain and visible-cover constraints are summarized in Fig. 7. Elevation ranged from 569.44 to 929.86 m. Slopes of 0-15°, 15-30°, 30-45°, and >45° occupied 19.3%, 25.5%, 22.5%, and 32.6% of the area, respectively. Thus, 55.1% of the site exceeded 30°, where runoff concentration and

topsoil-retention constraints become increasingly important, and nearly one-third exceeded 45°, commonly corresponding to artificial cuts or very steep faces. Sunny and semi-sunny aspects accounted for 52.51%, compared with 47.49% for shady and semi-shady aspects, indicating spatially contrasting radiation and moisture environments. Because the archived dataset did not support class-specific recovery rates by slope or aspect, these results diagnose constraints on stability rather than a statistical causal effect of terrain.

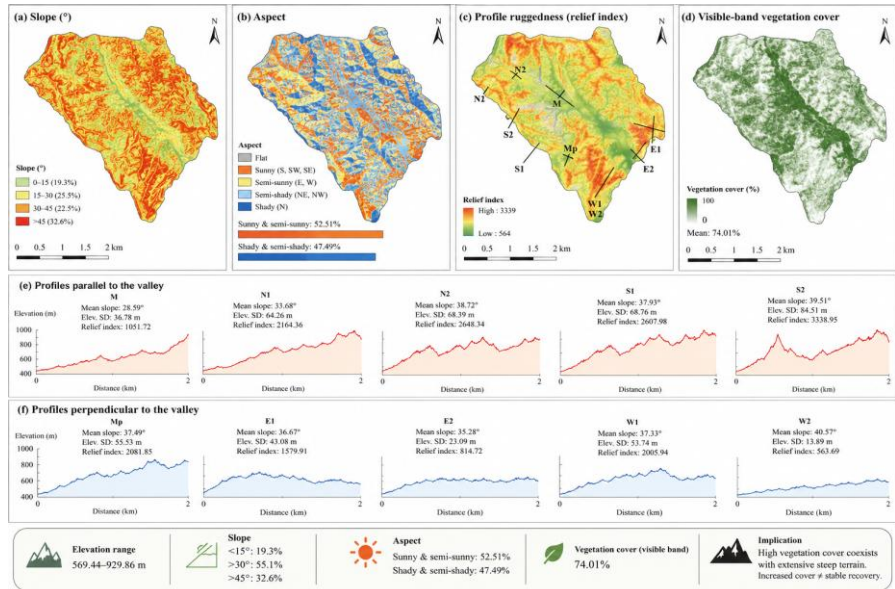


Fig. 7 Terrain and vegetation constraints in the representative limestone mining area, including slope, aspect, profile ruggedness, and visible-band vegetation cover.

These terrain patterns are synthesized in Table 2 as monitoring constraints rather than as independent evidence of ecological recovery. The table links each class to the process most relevant to restoration stability and to an operational response.

Table 2 Terrain and vegetation constraints in the representative limestone mine

Constraint	Class or direction	Share or range	Ecological process	Restoration implication
Slope	0°–15°	19.3%	Lower runoff velocity and greater grading space	Suitable for topsoil placement, enrichment planting, and natural recovery
Slope	15°–30°	25.5%	Increasing erosion risk	Requires drainage and topsoil stabilization
Slope	30°–45°	22.5%	Difficult topsoil retention	Combined engineering and vegetation measures
Slope	>45°	32.6%	Steep slopes or artificial cuts	Stability first; restrict direct revegetation
Aspect	Sunny and semi-sunny	52.51%	Stronger radiation and evapotranspiration	Improve water retention and drought-tolerant planting
Aspect	Shady and semi-shady	47.49%	Lower light and locally cool, wet conditions	Adjust shade-tolerant species and planting density
Vegetation cover	Vegetated	74.01%	High overall surface cover	Assess continuity and community quality

Evidence-based monitoring zones

The evidence chain produced three operational monitoring classes. Source-control zones combined persistent degradation with active mine surfaces and therefore required disturbance cessation, slope stabilization, and drainage reconstruction. Stability-monitoring zones combined apparent recovery with steep or engineered slopes and required repeated checks of erosion, cover continuity, and surface deformation. Low-intervention zones showed stable cover on gentler terrain and were suitable for natural regeneration, topsoil protection, and targeted

enrichment. This prioritization is consistent with regional studies showing that restoration potential depends jointly on current degradation and environmental suitability (Liu et al., 2022; Xiu et al., 2021) (Fig. 8; Table 3).

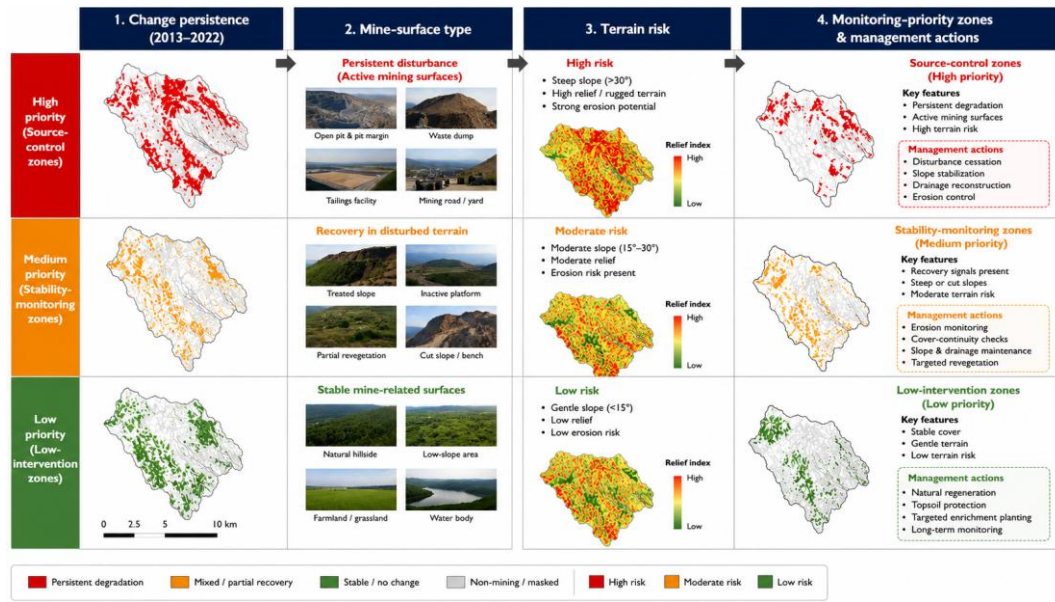


Fig. 8 Monitoring-priority framework linking change persistence, mine-surface type, terrain risk, and differentiated management actions.

The map-based framework is translated into implementable monitoring rules in Table 3. This separation allows Fig. 8 to communicate spatial logic while the table specifies the corresponding objects, risks, actions, and monitoring frequency.

Table 3 Monitoring priorities and differentiated management actions

Zone	Remote-sensing criterion	Typical objects	Main risk	Priority action	Frequency
I Source control	Recent persistent degradation strongly associated with mining facilities	Pit margins, dumps, and tailings facilities	Expansion, instability, and concentrated runoff	Stop expansion; stabilize slopes; reconstruct drainage and topsoil	Quarterly UAV and annual satellite
II Stability monitoring	Improvement on slopes $>30^\circ$ or conspicuous artificial cuts	Revegetated slopes and inactive platforms	Erosion, cover decline, and planting failure	Monitor continuity; control erosion; targeted enrichment	Before and after each growing season
III Low intervention	Long-term stable or slowly improving cover on gentler terrain	Valley slopes and stable-cover areas	Renewed disturbance and local bare patches	Natural recovery; topsoil protection; low-intensity enrichment	Annual satellite and sample checks

Independent validation and cross-scale agreement

Validation against 300 independently interpreted UAV points yielded 89.7% overall accuracy and a Kappa coefficient of 0.84. User's accuracy was 88.5% for degradation, 85.2% for recovery, and 92.3% for stable surfaces; the corresponding producer's accuracies were 87.2%, 87.1%, and 89.8%. F1-scores were 0.88, 0.86, and 0.91, respectively. Recovery was therefore the least separable class, consistent with ambiguity introduced by seasonal vegetation, exposed soil, and temporary engineering surfaces (Fig. 9).

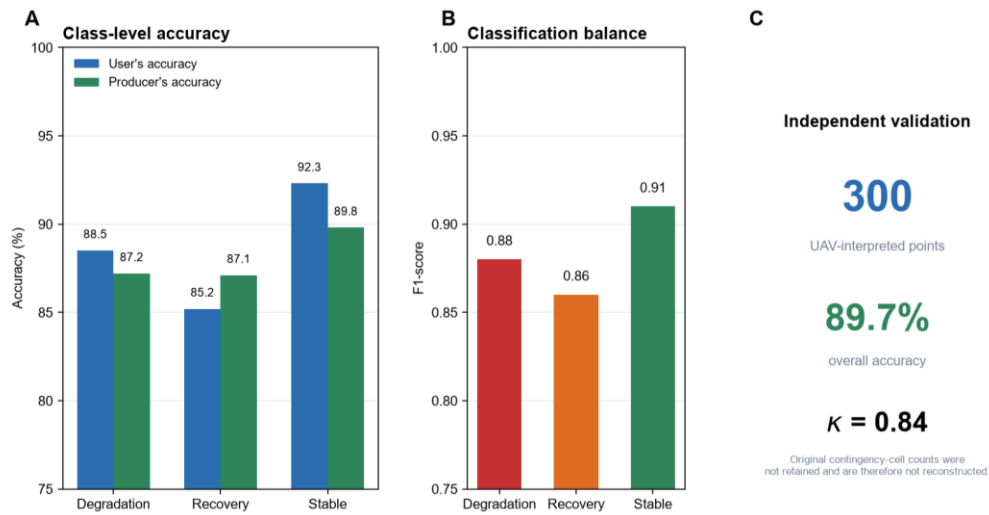


Fig. 9 Independent validation of satellite–UAV directional change detection based on 300 UAV-interpreted points. (A) User's and producer's accuracies. (B) Class-level F1-scores. (C) Overall accuracy and Kappa. Original contingency-cell counts were not retained and are therefore not reconstructed.

Overall satellite–UAV spatial consistency was 87.4%, while 84.6% of satellite-derived recovery signals corresponded to visible vegetation establishment or surface stabilization in UAV imagery. These measures answer different questions: the first evaluates agreement across all directional classes, whereas the second evaluates only the recovery class. Visual review identified seasonal vegetation, exposed soil, temporary engineering surfaces, terrain shadow, and water-level variation as recurrent disagreement mechanisms. Because the archive did not retain a georegistered mismatch layer or cause-coded point table, Fig. 10 presents representative error mechanisms rather than unsupported percentage contributions.

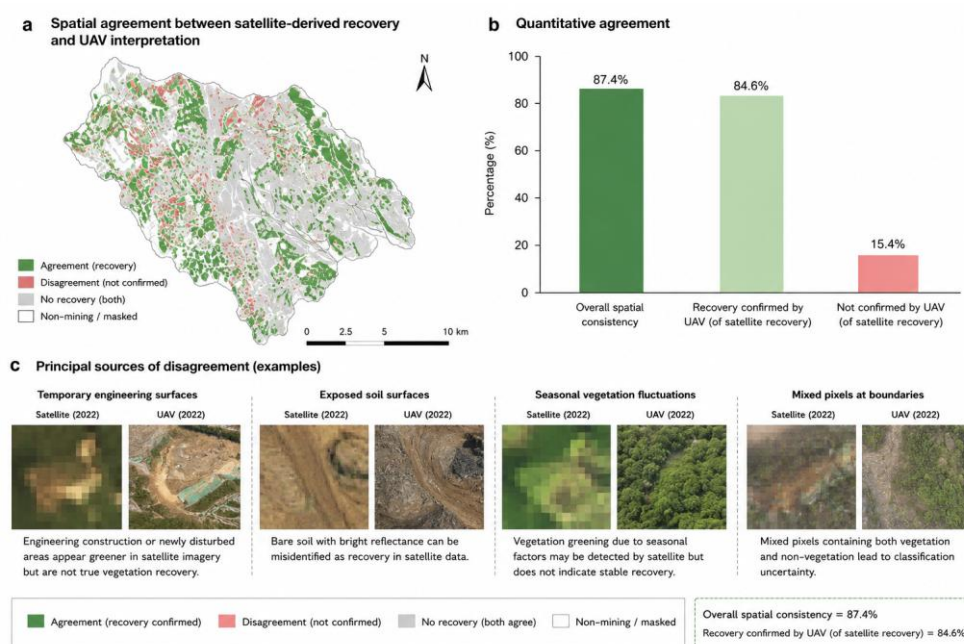


Fig. 10 Cross-scale agreement between satellite-derived recovery signals and UAV interpretation, including principal sources of disagreement.

Restoration persistence

RPI rose from 0.206 in 2013–2016 to 0.279 in 2016–2019 and 0.373 in 2019–2022, confirming that recovery accounted for an increasing share of significant directional change. However, the index remained below 0.5 in the latest interval, and the independent 2013–2022 long-interval comparison still showed more degradation than recovery. The region had therefore not transitioned from net degradation to net surface recovery (Fig. 11).

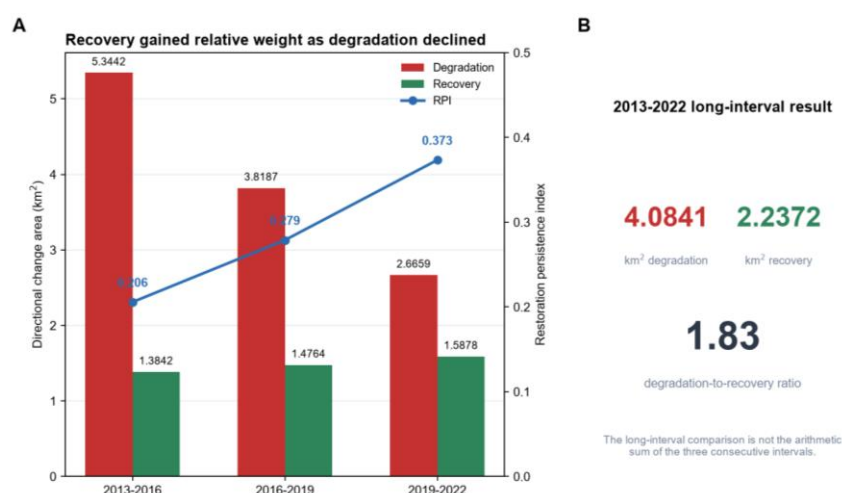


Fig. 11 Restoration persistence through time. (A) Interval degradation, recovery, and the restoration persistence index. (B) Independent long-interval comparison for 2013–2022; this result is not the arithmetic sum of the three consecutive intervals.

Discussion

Contribution of the multi-scale evidence chain

The main contribution of this study is an auditable evidence chain that connects regional trajectories to mine-surface objects, terrain constraints, independent validation, and management action. Reviews of mine rehabilitation have shown that increases in vegetation indices are often presented as restoration outcomes without sufficient attention to landform, reference condition, or persistence (McKenna et al., 2020). By assigning distinct inferential roles to IR-MAD, NDVI, UAV imagery, and terrain models, our framework reduces the risk that an isolated spectral response is mistaken for complete ecological recovery. This logic is consistent with recent Environmental Monitoring and Assessment studies that combine remote sensing with explicit environmental interpretation and verification (Wasehun et al., 2024; Safo Kantanka et al., 2025).

The framework also resolves the apparent contradiction between the large IR-MAD footprint in 2019–2022 and the continued decline in directional vegetation degradation. IR-MAD captured active surface reworking, whereas NDVI identified the direction of vegetation response. Applied alone, IR-MAD could misclassify restoration construction as degradation; applied alone, NDVI could overlook engineering changes with weak vegetation contrast. Their combination therefore improves process interpretation without extending the evidence beyond observable surface change.

Transition towards management of legacy degradation

The 50.1% decline in interval degradation and the increase in RPI indicate that pressure from new disturbance weakened, but the 1.83 degradation-to-recovery ratio shows that accumulated damage remained dominant. Similar spatially uneven trajectories have been reported from the Antaibao and Inner Mongolian mining regions, where localized greening coexists with active extraction and legacy disturbance (Wang et al., 2021; Hu et al., 2022). Pingquan is further constrained by narrow valleys, dense mine clusters, and steep engineered slopes that place active disturbance, river corridors, and restored patches in close proximity. Its trajectory is therefore best interpreted as a transition from expansion control to legacy-damage management.

Terrain separates increased cover from stable recovery

The coexistence of extensive visible cover and a 55.1% share of terrain steeper than 30° demonstrates why greening alone is an inadequate endpoint. On steep mine slopes, thin or heterogeneous substrates reduce water storage and root anchorage; concentrated runoff removes fine material; and freeze–thaw cycling can reopen cracks or detach surface layers. Aspect further modifies radiation and evapotranspiration, while excavation changes slope geometry and drainage connectivity. These processes reinforce one another: weak substrates and rapid runoff limit establishment, discontinuous cover increases exposure to erosion, and erosion further degrades substrate quality. Comparable terrain–soil controls have been reported for restored rock-cut and mine slopes (Li et al., 2018; Yang et al., 2020; López-Marcos et al., 2020).

Value and limits of independent validation

The high overall accuracy, Kappa, and class-level F1-scores support the reliability of the principal surface-change categories, but recovery remained the least certain class. Overall spatial consistency (87.4%) and recovery-

specific UAV support (84.6%) have different denominators and should not be used interchangeably. Considered together, they support the mapped surface-restoration trajectories while leaving ecosystem-level recovery untested.

Method applicability and uncertainty

Five limitations define the next methodological steps. First, inconsistent acquisition seasons leave residual phenological, illumination, and terrain-shadow effects; future monitoring should prioritize same-season annual imagery and dense trajectories that identify disturbance onset and persistence (Kennedy et al., 2010; Zhu & Woodcock, 2014). Second, a single recent UAV campaign cannot verify historical states, requiring repeat surveys over fixed benchmark plots. Third, the visible-band index formula and calibration record were not retained, so future campaigns should archive calibrated index definitions, multispectral targets, and field cover measurements. Fourth, exact validation coordinates, contingency counts, and cause-coded disagreement records should be preserved to permit spatial error modelling and reproducible confusion matrices. Fifth, remotely sensed surface evidence should be paired with erosion or runoff measurements, soil physicochemical sampling, water-quality monitoring, and vegetation-community surveys before claims are extended to ecological function.

Transferability and limitations

Transfer to other mining regions requires local calibration rather than direct reuse of every threshold. Semi-arid coalfields have lower vegetation baselines and stronger soil-background effects, favouring locally derived NDVI thresholds and moisture-sensitive indices. Humid metal-mining mountains require denser optical or radar observations and closer integration with soil and water chemistry because cloud cover, rapid succession, and contamination pathways alter the evidence base. Limestone and other rocky mines place greater emphasis on high-resolution terrain models and slope-stability inspection. Across these settings, the transferable element is the sequence of inference: regional screening, object-level verification, terrain and process diagnosis, independent validation, and management prioritization.

Figure 12 defines this inference boundary explicitly. Level 1 supports statements about observable surface-cover change and vegetation trajectories. Level 2, complete ecological recovery, additionally requires evidence of soil development and contamination, water and sediment quality, species composition, habitat quality, ecosystem processes, and long-term resilience. Mine-soil studies in Environmental Monitoring and Assessment likewise show that restoration claims depend on physicochemical and biological measurements that optical imagery cannot replace (Ameh et al., 2021). The proposed framework should therefore operate within a broader environmental assessment programme, not as stand-alone certification of ecosystem recovery.

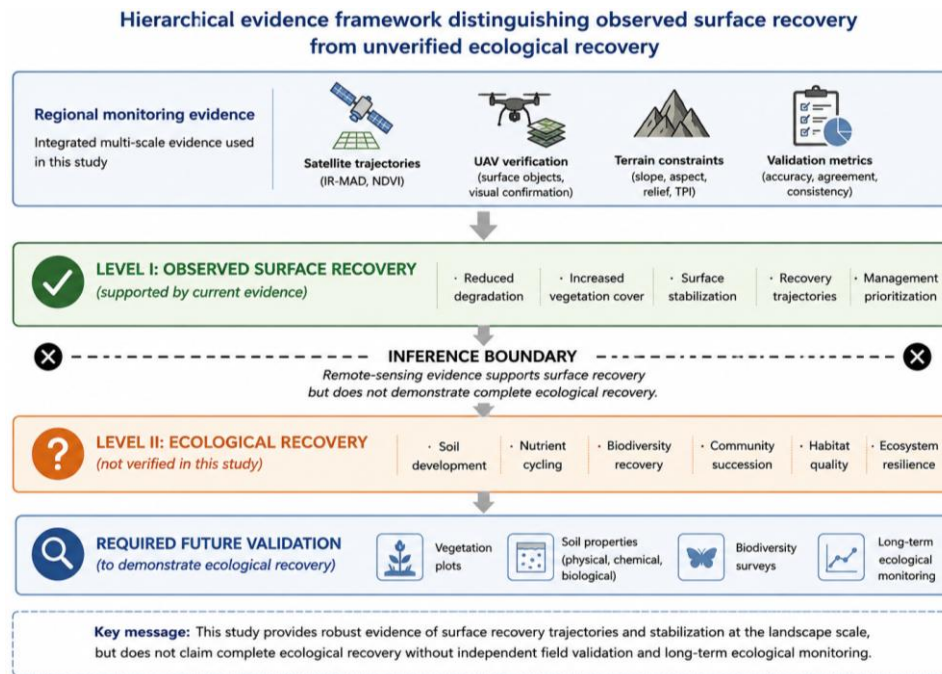


Fig. 12 Hierarchical evidence framework distinguishing observed surface recovery from unverified ecological recovery.

Management implications

Implementation requires differentiated responsibility. Mining enterprises should maintain annual disturbance maps, submit UAV evidence for newly rehabilitated slopes, stabilize active cuts and dumps, reconstruct drainage, and preserve auditable monitoring records. Natural-resource regulators can use annual satellite screening to detect expansion and verify reclamation commitments, while ecological-environment authorities target soil, sediment, surface-water, and heavy-metal sampling to source-control zones. Joint inspections should prioritize recovery signals on slopes $>30^\circ$, tailings facilities, river-adjacent disturbance, and locations where satellite and UAV evidence disagree. Monitoring intensity can be reduced in stable, low-risk areas so that resources remain focused on persistent sources and potentially unstable restored slopes.

Conclusions

Multi-temporal monitoring revealed a sustained reduction in interval degradation and an increasing contribution of recovery between 2013 and 2022. Yet degradation in the long-interval comparison remained 1.83 times the recovery area, demonstrating that Pingquan is entering a phase of legacy-damage management rather than approaching completion of regional restoration.

Topography separated apparent greening from potentially durable recovery. Because 55.1% of the representative limestone mine exceeded 30° slope, steep engineered slopes and artificial cuts remain priorities for erosion control, stability inspection, and repeated vegetation monitoring.

By integrating satellite trajectories, UAV-based object attribution, terrain diagnosis, and independent validation, the framework provides a reproducible basis for screening and prioritizing restoration in mountainous mining clusters. Its conclusions apply to observable surface recovery; ecosystem recovery must still be demonstrated with soil, water, biodiversity, and process-based measurements.

Statements and declarations

Funding

This work was supported by the China Geological Survey Program (Grant No. DD202607101905).

Competing interests

The authors declare that they have no competing interests.

Author contributions

Conceptualization, M.W. and N.Z.; methodology, M.W. and B.X.; investigation, M.W., W.T., and C.L.; data curation, M.W. and C.L.; formal analysis, M.W. and B.X.; validation, B.X. and C.L.; visualization, M.W.; writing—original draft preparation, M.W.; writing—review and editing, B.X., W.T., C.L., and N.Z.; supervision, N.Z.; project administration, N.Z. All authors have read and approved the final manuscript.

Data availability

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. Non-confidential derived tables and analysis outputs may be shared for academic research with appropriate attribution. Access to original high-resolution satellite imagery, UAV orthomosaics, and terrain products is subject to project requirements, licensing conditions, and institutional data-management regulations.

Ethical responsibilities

All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

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