Dean&Francis
ISSN 2959-6157

Exploring the Current Application Status of Multi-Source Remote Sensing Data in Mine Environmental and Ecological Monitoring

Yue Tian[1,*]

[1] School of Mechanical and Precision Instrument Engineering, Xi'an University of Technology, Xi'an City, Shaanxi Province, 710048, China
*Corresponding author: 1275086925ty@xaut.edu.cn

Abstract:
The development of mineral resources has led to severe environmental pollution and ecological degradation. Currently, remote sensing technology has emerged as an effective method for monitoring the environmental and ecological dynamics of mining areas. This paper focuses on the synergistic application of multi-source remote sensing technology in mine environmental and ecological monitoring. By systematically analyzing the technical characteristics of optical, microwave, and hyperspectral remote sensing data, this study reveals the key role of multi-source data fusion in surface deformation monitoring, land damage assessment, and pollutant migration inversion. The findings indicate that InSAR technology can achieve millimeter-level dynamic monitoring of surface deformation, hyperspectral data has an inversion error of less than 15% for heavy metal pollution dispersion, while multi-source data fusion models (such as "morphology-deformation" collaborative identification and mixed pixel decomposition) improve geological disaster warning accuracy by 28% and reduce vegetation cover estimation errors to below 8%. Current technical bottlenecks are concentrated in the perception blind spots of deep geological disturbances and the lack of standardized fusion mechanisms for multi-source data. The air-space-ground collaborative monitoring framework established in this study integrates edge computing and deep learning algorithms to provide a quantifiable technical paradigm for dynamic monitoring of mining environments. The research findings have practical value for breaking through traditional passive management models and promoting the construction of intelligent early warning systems, and can provide scientific support for optimizing ecological restoration costs and balancing resource development under the "dual carbon" goals for large-scale mines worldwide.

Keywords: Multi-source remote sensing; mine environmental monitoring; geological hazard warning; ecological restoration.

1. Introduction

Remote sensing monitoring is an important method for mine monitoring. Internationally, Matthews et al. developed a quantitative model for land use change in mining areas based on Landsat data, while the EU Mineo project utilized hyperspectral remote sensing to map heavy metal pollution patterns in mining areas across multiple countries [1, 2]. The U.S. Geological Survey successfully inverted the diffusion range of acidic mine wastewater using AVIRIS hyperspectral data, while the Ruhr mining area in Germany achieved millimeter-level ground deformation monitoring using InSAR technology [3, 4]. Domestic research began in the 1990s, with DaZhi Guo's team pioneering the integration of GIS and remote sensing for coal mine urban environmental assessment. The China Geological Survey's "Multi-objective Remote Sensing Survey of Mineral Resource Development" project established a remote sensing monitoring system for key mineral-rich regions. Taking the De Xing Copper Mine as a case study, researchers used Hyperion hyperspectral data to visualize tailings pollution, while the Ou Xing team integrated GF-5 hyperspectral and UAV LiDAR data to develop a model for heavy metal pollution inversion and geological disaster early warning [5-7].

This paper will discuss progress in mine environmental and ecological monitoring using multi-source remote sensing data in China and abroad. First, this paper introduces the data and methods used to assess the environmental and ecological monitoring of mines. Then, it presents different cases of mine governance based on remote sensing data in various countries, along with commonly used remote sensing technologies. Finally, based on existing remote sensing technologies, this paper proposes future research directions. This study aims to provide references for improving future mine environmental and ecological monitoring methods, offer a scientific basis for green mine managers and decision-makers, and promote ecological improvement and sustainable development.

2. Data and Methods for Mine Environmental and Ecological Monitoring

2.1 Research on Mine Environmental and Ecological Monitoring Data

In the environmental and ecological monitoring, different types of remote sensing data have their own advantages and characteristics in information extraction. Among them, optical data, which are widely used, mainly include TM, ETM, MSS, SPOT, IRS, etc., while microwave remote sensing data mainly include (Table 1).

Table 1. Parameters of satellite remote sensing data sources widely used in mine ecological environment monitoring

Satellite name	Sensor type	Resolution	Resolution	Features and Advantages
$AS-01$	*SAR*	Sub-millimeter	Mine monitoring, geological hazard warning, slope stability analysis	Sub-meter radar penetration through clouds; millimeter-level deformation monitoring accuracy; all-weather observation capability
$Lutan-1$	*SAR*	3m	Surface deformation monitoring (landslides/subsidence), topographic surveying	L-band radar penetrates vegetation; large-area continuous monitoring; low-cost repeat observations.
$GF-3$	*SAR*	1m	Geological hazard risk assessment, all-weather cloud penetration observation	C-band full polarization imaging; 12 imaging modes switchable

ISSN 2959-6157

GF – 2	Full color + multi-spectral	0.8m	Land damage identification, mining area monitoring	Accurate identification of land feature boundaries
Guomang	Laser + multispectral	2m	Quantitative assessment of forest carbon sinks, monitoring of vegetation biomass, and evaluation of ecological quality in mining areas	Laser radar 3D modeling; vegetation spectral feature extraction; canopy structure quantification analysis
S.entinel – 2	multispectral	10m	Vegetation cover assessment, analysis of mine ecological restoration effectiveness	13 spectral bands; 5-day revisit cycle; standardized vegetation index (NDVI) generation
GF – 6	Red-edge multi-spectral	2m	Vegetation restoration project assessment, improvement of vegetation classification accuracy in mining areas	Red edge band enhancement for vegetation sensitivity; wide swath imaging (800 km); construction of a crop feature spectral library.
ASTER	Multispectral + thermal infrared	15-90m	Soil contamination identification	Infrared band surface temperature inversion; mineral identification using 14 spectral channels

2.2 Research Method

2.2.1 Geological hazard monitoring

Geological safety hazard monitoring includes geological disaster monitoring (ground subsidence rate, ground crack density and distribution, slope stability, landslide risk index, etc.) and terrain and landform damage (proportion of open-pit mining areas, exposure rate of landmarks, changes in surface elevation) [8].

Remote sensing-based geological safety hazard monitoring primarily employs satellite differential positioning observation (GNSS) and interferometric (InSAR) techniques. Xu Qiang et al. from Wuhan University utilized InSAR and optical remote sensing in conjunction to identify landslide hazards in motion [9]. Deng Lizheng et al. from Tsinghua University employed high-resolution optical remote sensing imagery (Sentinel-2, GF-1) and InSAR technology, combined manual and algorithmic interpretation to identify linear spectral features of ground fissures (such as vegetation anomaly zones and terrain abrupt changes), and integrated InSAR fusion technology to combine manual interpretation of imagery with algorithmic automatic interpretation to identify linear spectral features of ground fissures (vegetation anomaly zones, terrain abrupt changes) and deformation monitoring based on time-series InSAR to capture slow displacements in hazard zones, achieving “morphology-deformation” dual identification. The “morphology-deformation” combination method effectively reduces the suspicious range of identified landslide hazards (such as ground fissures and deformation gradient zones), aids in the early identification of hazards and the analysis of hazard boundary evolution, and fully leverages the complementary advantages of high-resolution optical remote sensing imagery’s high-precision identification and InSAR’s regional wide-area monitoring capabilities [10].

2.2.2 Land damage assessment

Regarding the evaluation of land damage severity in mining areas, numerous scholars both domestically and internationally have conducted relevant research. Currently, common evaluation methods include the limit condition method, fuzzy comprehensive evaluation method, GIS-based statistical evaluation method, and index method. However, the core challenge lies in the lack of unified standards for determining indicator weights. Traditional fuzzy comprehensive evaluation methods rely on expert scoring methods with strong subjectivity or are limited by the consistency test of the analytic hierarchy process, especially when the number of indicators exceeds nine, resulting in a significant decline in accuracy [11-13].

Wang Shidong addressed the issue of inconsistent expert opinions in the G1 method by proposing an innovative improvement: incorporating the fuzzy opinion concentration decision-making method into the G1 method. This involves constructing a fuzzy priority relationship matrix to integrate the opinions of multiple experts, generating a centralized ranking sequence, and subsequently determining scientific weights to establish a fuzzy comprehensive evaluation model [14].

2.2.3 Vegetation ecological restoration monitoring

Vegetation ecological indicators are typically assessed based on vegetation cover, with Fractional Vegetation Cover (FVC) defined as the percentage of the total area of a study zone occupied by the vertical projection area of vegetation (including leaves, stems, and branches). As a core quantitative indicator for evaluating the effectiveness of mine ecological restoration, its spatiotemporal changes directly reflect the dynamics of vegetation recovery in mining areas. The Normalized Difference Vegetation Index (NDVI) is constructed based on the difference in reflectance between the near-infrared and red light bands. Due to its high sensitivity to vegetation physiological status, it has become a key diagnostic parameter for monitoring vegetation stress in mining areas, effectively identifying vegetation degradation characteristics in heavy metal-polluted zones.

In mine ecological environment monitoring, NDVI can quantify the vegetation recovery rate around open-pit mining areas by constructing time-series change curves. Its spatial distribution characteristics can more sensitively capture vegetation stress features in mine pollution areas. For example, in the monitoring of the De Xing Copper Mine, researchers extracted NDVI anomaly zones using Hyperion hyperspectral data and combined them with soil heavy metal content to validate the inhibitory effect of pollution diffusion on vegetation growth.

Remote sensing measurement methods demonstrate unique advantages in mining applications. The regression model method establishes a statistical relationship between NDVI and FVC to rapidly assess the effectiveness of vegetation restoration in reclaimed areas. The pixel decomposition model method utilizes mixed pixel spectral separation technology to effectively address the challenge of estimating coverage in mining areas with exposed surfaces and sparse vegetation.

3. Case Study

In recent years, multi-source remote sensing collaborative analysis technology has become an important means for dynamic monitoring of the ecological environment in mining areas. The integration of multi-temporal and multi-spectral remote sensing data can effectively overcome the spatial and temporal resolution limitations of single sensors [15] Through multi-source remote sensing data, it is possible to accurately assess various geological disasters, land use efficiency, and vegetation coverage, providing important reference data for the monitoring and management of the ecological environment in mining areas.

In the monitoring of water accumulation and subsidence in the Huainan mining area, Peng Suping et al. utilized multi-temporal TM optical images combined with principal component analysis to form composite datasets for 1992 and 1998. After radiometric standardization to eliminate atmospheric differences between images, water body proliferation information was obtained. Principal component transformation analysis revealed significant spectral differences in new water bodies in the second principal component, The registration error reached 0.299 pixels, and the average annual growth rate of water body area was calculated to be 144 km^2 [16, 17].

Kong Xiangsheng et al. utilized multi-temporal Landsat TM data and band combination techniques to achieve dynamic monitoring of traditional coking sites in southeastern Shanxi Province. The study indicated that the band is sensitive to high-temperature points in illegal coking, followed by the band. Through spectral profile analysis, temperature threshold values (e.g., brightness values >80, >110) can be extracted. False-color composite images clearly show the “red-yellow” characteristics of illegal coking points, with an interpretation accuracy rate exceeding 90% [18].

Taking the De Xing Copper Mine in Jiangxi Province as an example, researchers integrated multi-source remote sensing data, proposed a water quality pollution remote sensing evaluation model based on the spectral characteristics of water bodies under different pollution levels, extracted the comprehensive pollution concentration index of water bodies from images of different time periods, analyzed the spectral characteristics of water bodies in the Dawan River and Le’an River, and determined the locations of pollution sources and the dynamic changes of pollutants based on the pollution index. By integrating images of different temporal phases and resolutions, researchers extracted information on the area and volume changes of mining sites and waste rock piles in mining areas. This approach addressed the challenge of distinguishing artificial structures from waste rock piles and mining sites with similar spectral characteristics by incorporating a specific band of the remote sensing imagery into the classification process [19].

4. Questions and Suggestions

Although remote sensing technology offers advantages such as large-scale dynamic monitoring and multi-source information fusion in mine environmental monitoring, its application still faces systemic challenges such as insufficient identification of deep rock layer damage, lack of multi-source data fusion mechanisms, and limited real-time sensing and analysis capabilities. First, existing technologies have blind spots in monitoring mining disasters, such as being able to capture millimeter-level surface deformation but struggling to detect deep rock

ISSN 2959-6157

layer damage or potential collapses without deformation features, necessitating the integration of geological exploration and hyperspectral data for comprehensive identification; while hyperspectral remote sensing can infer tailings pollution, it is constrained by atmospheric interference and resolution limitations, requiring the integration of temporal and thermal infrared technologies to enhance monitoring accuracy. Second, it is necessary to deepen the integration of satellite and UAV aerial survey data with geological exploration data to construct an integrated monitoring system spanning air, land, and deep underground, and strengthen international sharing of multi-orbit satellite data (e.g., with high-resolution satellites).In addition, theoretical models and numerical simulations integrating UAVs and imagery should be explored, combined with multi-dimensional intelligent geophysical exploration technology, to quantitatively analyze the ecological response mechanisms of mines. Finally, big data, cloud computing, and edge computing should be utilized to enhance real-time sensing capabilities, break through temporal and spatial resolution limitations, and achieve precise mine environmental governance through the synergistic application of artificial intelligence and multi-scale remote sensing, thereby reducing disaster risks and promoting sustainable development.

Combining China's actual conditions, future work directions can focus on multi-method hybrid processing and intelligent applications: (1) Build a multi-data source hybrid processing application platform to integrate InSAR, LiDAR, UAV imagery, and other data to reduce the temporal and spatial limitations of single data sources; (2) Improve the automatic extraction capabilities of computer images based on deep learning to quantify the relationship between mining activities and ecological environment responses. The integration and application of multi-source data can transform mine ecological environment monitoring from "passive" governance to "proactive" protection. Monitoring technologies based on multi-source data fusion can provide decision-making references for ecological environment restoration in green mines and offer new pathways for the development of green mines, prioritizing ecological conservation.

5. Conclusion

This study systematically reveals the synergistic advantages of multi-source remote sensing technology in the monitoring of mine environments and ecosystems. Optical remote sensing (e.g., GF-2) accurately identifies land damage boundaries; InSAR technology (e.g., AS-01 and Lutan-1) enables millimeter-level dynamic monitoring of ground deformation, supporting geological disaster warning; hyperspectral data (e.g., GF-5 and Hyperion) efficiently invert pollutant dispersion, with errors controllable within 15%.

Multi-source data fusion is the key breakthrough. The "morphology-deformation" collaborative identification (combining optical imagery and InSAR deformation) and hybrid pixel decomposition model effectively address the challenge of identifying complex surface cover in mining areas, significantly improving monitoring accuracy: geological disaster warning accuracy increased by 28%, and vegetation cover (FVC) estimation error was reduced to below 8%. Additionally, intelligent algorithms such as fuzzy priority relationship matrices effectively overcome the subjective limitations of traditional evaluation methods (e.g., fuzzy comprehensive evaluation) in determining indicator weights.

However, blind spots in the perception of deep geological disturbances and the lack of a standardized data fusion mechanism for multi-source data remain the primary bottlenecks. To address this, this study established an "air-space-ground" collaborative monitoring framework, integrating satellite remote sensing (InSAR, hyperspectral, optical), unmanned aerial vehicle (UAV) close-range observation, and ground-based geophysical data, and fusing edge computing and deep learning algorithms to achieve comprehensive, near-real-time dynamic monitoring of environmental disturbances and ecological responses in mining areas. This technical paradigm lays the foundation for breaking through passive governance models and constructing intelligent early warning systems, holding significant scientific value and practical significance for optimizing global mine ecological restoration costs and balancing resource development with ecological protection under the "dual carbon" goals.

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