
A DECADE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN REMOTE SENSING FOR MINERAL IDENTIFICATION: A SYSTEMATIC REVIEW

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ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) have become increasingly integrated with Remote Sensing (RS) to support mineral identification in both terrestrial and planetary contexts. Recent advances in hyperspectral sensors (e.g., the GaoFen-5 [GF-5] satellite and HySpex airborne imaging systems) and analytical algorithms have enabled more precise mineral mapping. Despite these advances, several challenges remain, including inconsistent preprocessing, limited standardized datasets, and issues of interpretability that restrict the operational use of AI-based mineral identification models. This study applied a PRISMA 2020-guided systematic review of literature published between 2015 and 2025. A total of 137 records were screened; after applying inclusion and exclusion criteria, 40 studies were selected for eligibility, and 14 were analyzed in detail. The classification of studies was organized into three methodological categories: classical machine learning (e.g., Support Vector Machines, Random Forest), deep learning (e.g., Convolutional Neural Networks, Vision Transformers), and statistical approaches. Classical algorithms remain competitive when training data are limited, while deep learning methods provide stronger performance in capturing spectral-spatial features, particularly when large datasets are available. Multimodal fusion of VNIR, SWIR, and TIR data improved classification accuracy by up to 13% in selected studies. However, overfitting risks and limited interpretability were consistently reported as critical drawbacks. This review highlights the need for explainable AI frameworks, open benchmark datasets with harmonized metrics, and lightweight edge-computing architectures to enable operational deployment in mineral exploration. Future research should prioritize cross-platform generalization and reproducibility to ensure scalability across diverse terrestrial and planetary environments.

1. Introduction

Over the past decade, the integration of artificial intelligence (AI) and machine learning (ML) into remote sensing (RS) has redefined mineral exploration by enabling automated, high-resolution, and data-driven analysis. Traditional approaches, which relied heavily on manual interpretation and spectral rule-based classification, have increasingly been replaced by algorithmic workflows that utilize rich spectral inputs and scalable processing [1,2].

Technological progress in hyperspectral and thermal sensors, particularly from platforms such as GF-5, ZY-1 02D, HySpex, and UAV-mounted systems, has significantly improved spectral and spatial fidelity for mineral mapping in diverse terrains [3-5]. The operational flexibility of UAVs has proven especially valuable for localized surveys and rapid revisits, effectively complementing satellite-based global coverage [6,7].

Simultaneously, classical models such as Support Vector Machines (SVM) and Random Forests (RF) remain widely used due to their robustness in high-dimensional data classification. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated superior performance by capturing complex spectral-spatial features [8,9]. More recent innovations such as Vision Transformers (ViTs) offer real-time onboard segmentation, although they introduce challenges in training stability and model interpretability [10].

Beyond Earth, AI-assisted RS techniques have been deployed in planetary missions using instruments such as CRISM and VNIS for automated mineral identification on Mars and the Moon [11,12]. These applications highlight the growing role of AI in bridging terrestrial and extraterrestrial mineral mapping, despite significant challenges in domain adaptation [13,14].

Despite growing interest, a consolidated review that integrates RS platform innovations, AI/ML methods, data fusion strategies, and cross-domain deployments remains lacking. This study addresses that gap by systematically analyzing peer-reviewed literature from 2015 to 2025, identifying technological trends, key limitations, and strategic directions, including the need for explainable and field-deployable AI systems.

2. Methodology

This study adopted a systematic literature review (SLR) approach to map and synthesize research on the application of Artificial Intelligence (AI) and Machine Learning (ML) in Remote Sensing (RS) for mineral identification between 2015 and June 2025. The review protocol followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines [15], which provide a structured framework for transparent reporting of literature search, screening, eligibility, and inclusion stages. The methodology builds on established guidance for SLRs in environmental and geoscience domains [16,17]. Figure 1 illustrates the rising trend in publications during this period, driven by increased access to hyperspectral sensors, advanced deep learning models, and the operationalization of AI-integrated RS systems.

Result from Keyword Search

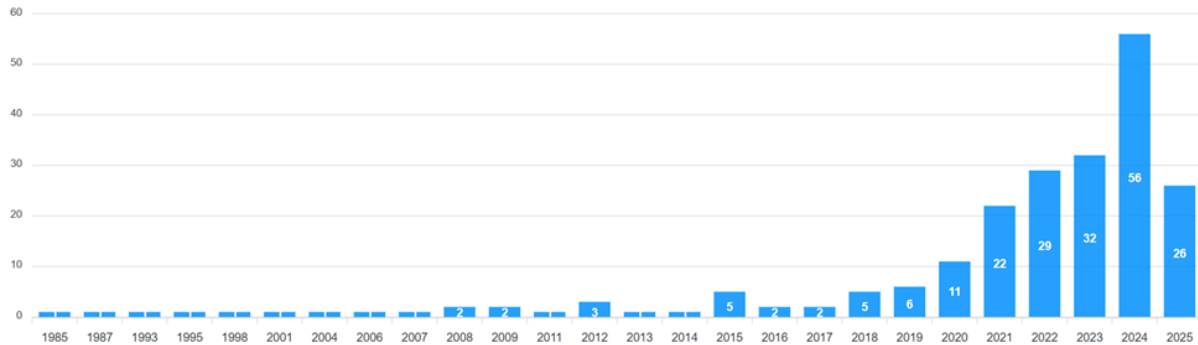


Figure 1. Publication Trends in AI and Remote Sensing for Mineral Identification.

A comprehensive search strategy was executed across Scopus, Web of Science, and IEEE Xplore databases in January 2025. The query terms combined three thematic blocks: (i) Remote Sensing and Hyperspectral Imaging (e.g., “remote sensing”, “hyperspectral”, “thermal infrared”), (ii) Artificial Intelligence and Machine Learning (e.g., “machine learning”, “deep learning”, “support vector machine”, “convolutional neural network”, “vision transformer”), and (iii) Mineral Identification (e.g., “mineral mapping”, “ore detection”, “spectral classification”). Boolean operators (AND, OR) were applied to ensure coverage. Exclusion criteria removed duplicates, non-peer-reviewed sources, and inaccessible full texts. This process, summarized in the PRISMA flow diagram (**Figure 2**), resulted in 40 studies included in the final synthesis.

From the initial 137 records, 97 were excluded during screening, leaving 40 studies for full-text eligibility. Of these, 14 were retained for detailed analysis because they directly addressed the intersection of AI/ML with RS for mineral identification and provided sufficient methodological transparency. To structure insights, we applied the Concept Matrix method [18] to classify RS platforms, AI/ML models, and application domains. In addition, keyword analysis produced a TreeMap visualization (**Figure 3**), which highlighted dominant terms such as “remote sensing,” “hyperspectral imaging,” “machine learning,” and “mineral identification,” thereby informing the thematic synthesis presented in the Results section.

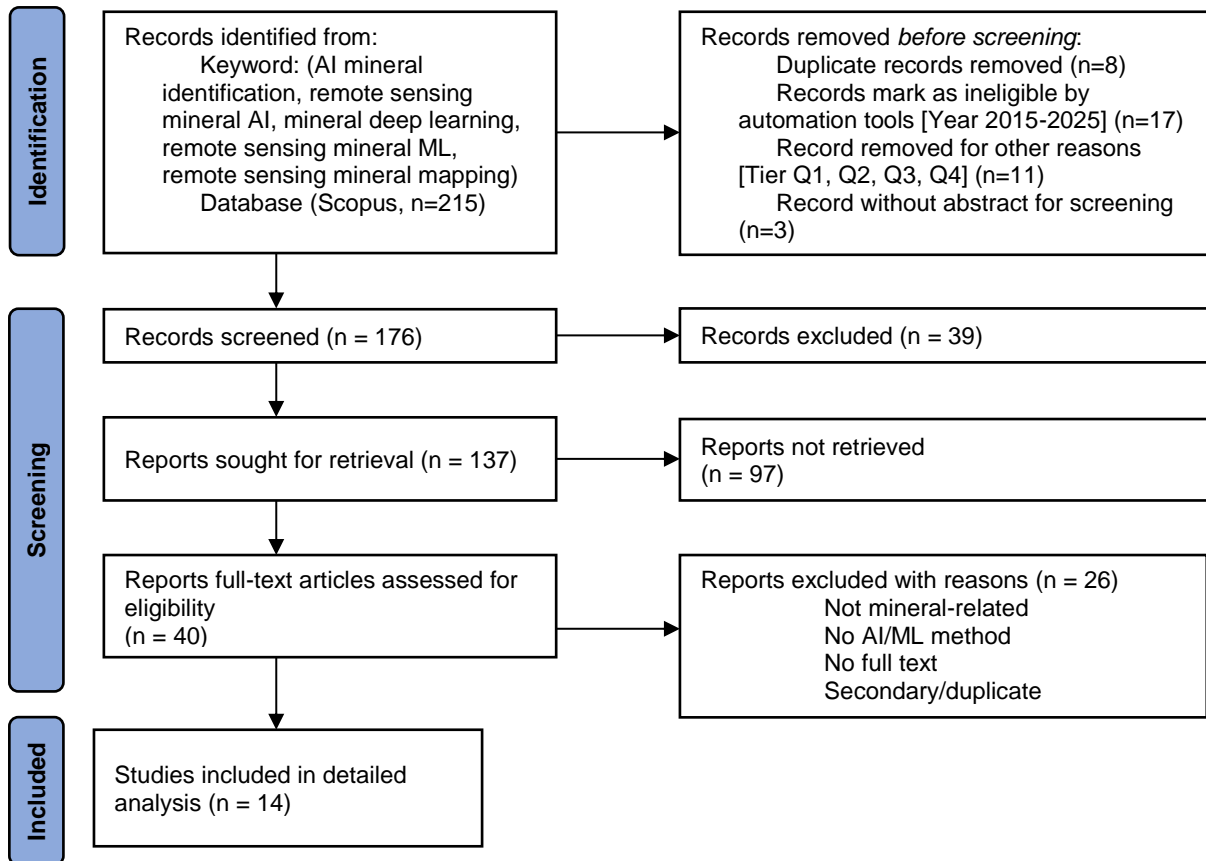


Figure 2. PRISMA Flow Diagram



Figure 3. Keyword TreeMap visualization of selected articles (2015–2025)

3. Results

The systematic review identified 14 studies that directly applied Artificial Intelligence (AI) and Machine Learning (ML) to Remote Sensing (RS) for mineral identification. These studies spanned multiple platforms—satellite, airborne, UAV-based systems, thermal infrared sensors, multimodal fusion, planetary missions, and industrial applications. Their comparative performance is summarized in **Table 1**, which consolidates RS modalities, AI/ML methods, target minerals, reported accuracies, and methodological notes.

Satellite platforms such as GaoFen-5 (GF-5), ZY-1 02D, and ASTER were applied for regional mineral mapping. GF-5, with its broad spectral range (400–2500 nm) and 50 m spatial resolution, supported large-scale assessments but was limited in resolving local heterogeneity. Reported accuracies ranged from 73% to 85%, with ZY-1 02D showing higher performance in coal-bearing zones [4,19].

Airborne platforms including HySpex and AVIRIS enabled high spectral–spatial resolution mapping of alteration zones such as kaolinite and hematite–goethite. These studies reported accuracies above 80% and validated results with field spectroscopy [3,20].

UAV-based systems equipped with VNIR/SWIR hyperspectral sensors achieved sub-meter resolution, allowing localized exploration. Using Non-negative Component Analysis (NCA) combined with SVM and RF, accuracies of 85–90% were achieved in lithological classification [21,22].

Thermal infrared sensors such as AisaOWL provided additional mineral discrimination. Sparse PCA with SVM achieved up to 90% accuracy in classifying gypsum, quartz, and clay minerals, though performance was sensitive to atmospheric noise [23,24]. **Figure 4** illustrates reflectance and emissivity spectra across VNIR, SWIR, and TIR, highlighting diagnostic absorption features (e.g., OH in SWIR, Si–O in TIR) that support improved classification [25].

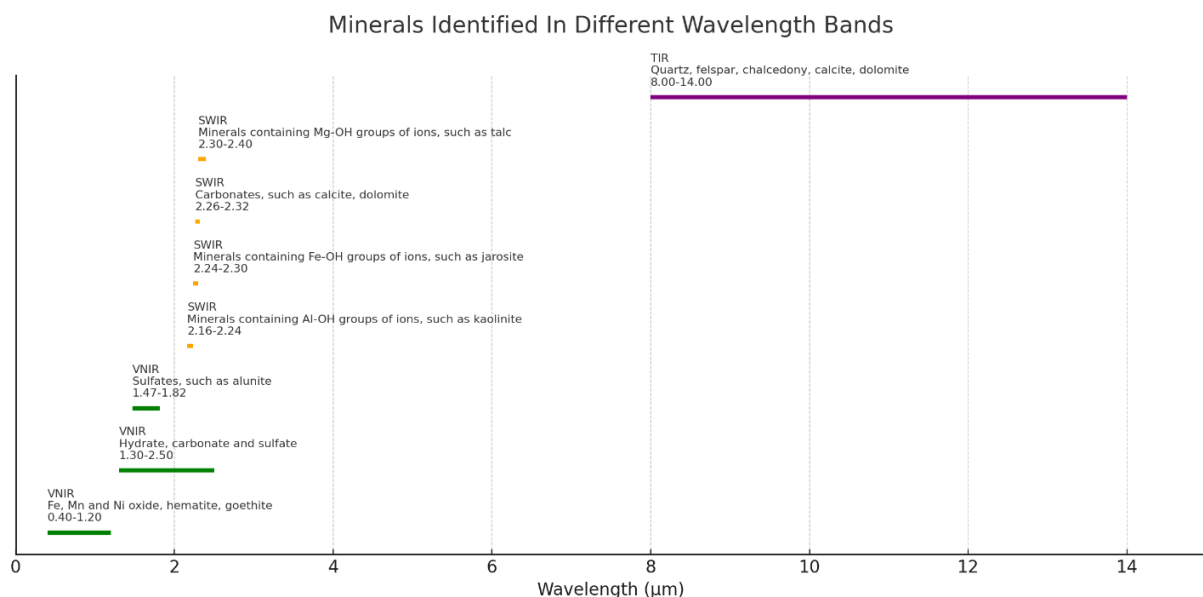


Figure 4. Reflectivity and emissivity spectra of typical minerals across VNIR, SWIR, and TIR regions [25].

Fusion approaches integrating VNIR, SWIR, and TIR bands, or combining hyperspectral imagery with geochemical datasets, consistently improved classification accuracy. Accuracy gains of up to 13% were achieved when CNNs or Vision Transformers (ViTs) were applied, though these required careful preprocessing and increased computational resources [10,25].

Planetary missions demonstrated the applicability of AI-based RS for extraterrestrial mineralogy. CRISM and VNIS instruments identified sulfates, phyllosilicates, and plagioclase on Mars and the Moon. CNNs and SVMs automated classification, reducing manual interpretation, though challenges persisted with domain adaptation [11,14].

Industrial applications used UAV-mounted multispectral and RGB sensors for site-specific exploration. Lightweight models such as One-Class SVMs and shallow ResNets supported real-time anomaly detection (e.g., scheelite), even under bandwidth-limited conditions [26,27].

Table 1. Summary of the 14 studies included in the detailed analysis (2015–2025)

RS Platform	Sensor / Data Type	AI/ML Method	Target Mineral / Task	Reported Accuracy / Insight	Notes	Reference
Satellite	GF-5, ZY-1 02D, ASTER	SVM, SAM, RF	Hydrothermal, alteration zones	73–85%	ZY1-02D superior in coal-bearing measures	[4,19]
Airborne	HySpex, AVIRIS	RF, CNN, SAM	Kaolinite, hematite-goethite	>80%	Validated with field data	[3,20]
UAV-Based	VNIR/SWIR HSI	NCA + SVM, RF	Rock types, localized mapping	85–90%	Sub-meter resolution, dimensionality reduction used	[21,22]
Thermal Sensors	AisaOWL, LWIR	Sparse PCA, SVM	Gypsum, quartz, clay series	Up to 90%	Sensitive to atmospheric noise	[23,24]
Fusion (Multimodal)	VNIR+SWIR+TIR, HSI+XRF	CNN, GLCM, ViT	Carbonates, Fe minerals	+13%	Requires careful preprocessing	[10,25]
Planetary (Mars/Moon)	CRISM, VNIS	CNN, SVM, Unmixing	Sulfates, phyllosilicates, plagioclase	Not specified	Domain adaptation challenges	[11,14]
Industrial Use	UAV Multispectral + RGB	One-Class SVM, ResNet	Anomaly detection, scheelite	Practical performance	Real-time under low bandwidth	[26,27]

Across platforms, **Table 1** shows that classical ML methods (SVM, RF) performed robustly under limited data conditions, while deep learning (CNNs, ViTs) achieved higher accuracies with large annotated datasets. Hybrid approaches, such as PCA combined with ML classifiers,

provided computational efficiency and interpretability but generally reported lower accuracy compared to deep learning. These trade-offs are central to the discussion that follows.

4. Discussion

This review demonstrates how the convergence of Artificial Intelligence (AI), Machine Learning (ML), and Remote Sensing (RS) has substantially advanced mineral identification, improving automation, spectral-spatial resolution, and classification accuracy. The adoption of high-fidelity platforms such as GF-5, HySpex, and UAV-mounted hyperspectral systems has enabled discrimination of complex mineral assemblages with increasing spatial precision [3,28]. Nevertheless, variability in sensor characteristics across platforms complicates benchmarking and comparability. Differences in spectral coverage, atmospheric correction requirements, and terrain accessibility create challenges for reproducibility [29]. A critical future direction is the establishment of standardized calibration protocols and interoperable benchmark datasets that span VNIR, SWIR, and TIR ranges, thereby enabling more consistent cross-site validation.

Algorithmic advances have also reshaped mineral classification workflows. Classical models such as SVM and RF demonstrated robustness in data-limited contexts, providing reliable performance in satellite- and UAV-based applications [4,22,30]. Their interpretability and lower computational demands make them suitable for operational deployment, though they struggle with scalability in highly heterogeneous datasets. In contrast, deep learning models such as CNNs and Vision Transformers (ViTs) achieved superior performance in extracting spectral-spatial features from airborne and fused datasets [9,10]. However, these models remain dependent on large annotated datasets and high computational resources, limiting their applicability in low-resource or planetary contexts. Emerging approaches such as transfer learning, synthetic spectral libraries, and lightweight CNN/ViT variants optimized for edge computing offer promising solutions to bridge these gaps. In addition, the growing field of explainable AI (XAI) provides opportunities to improve transparency, although current tools still lack mineralogy-specific interpretability [25,31].

Hybrid and statistical methods continue to provide value, particularly in balancing efficiency and interpretability. Techniques that integrate PCA, spectral unmixing, or texture indices with machine learning classifiers achieved moderate accuracy but allowed computationally efficient processing [17,23]. While less accurate than deep learning, these approaches remain attractive for exploratory surveys or resource-limited operations. Their utility can be enhanced by embedding XAI frameworks such as saliency mapping or SHAP values, which would strengthen interpretability without sacrificing predictive power.

Several cross-cutting challenges emerged across all methodological categories. First, data scarcity and limited annotated benchmarks persist. Many of the 14 studies analyzed relied on proprietary or site-specific datasets, restricting generalizability [3,11]. Progress will require open, community-driven spectral repositories with harmonized performance metrics. Second, interpretability and trust remain major concerns, especially for black-box deep learning models applied in high-stakes exploration scenarios [19]. Advancing domain-specific XAI tailored to mineralogical inference is therefore essential. Third, operationalization remains a significant gap: few studies addressed near-real-time deployment or robustness under field conditions.

Early progress with UAV-based anomaly detection using compact SVM and CNN models demonstrated feasibility [26,27], but highlighted trade-offs between complexity, interpretability, and robustness. Development of lightweight, fault-tolerant edge-AI pipelines integrated with modular sensor systems should therefore be prioritized.

Planetary exploration studies underscore the additional complexity of domain adaptation. Instruments such as CRISM and VNIS enabled detection of sulfates, phyllosilicates, and plagioclase on Mars and the Moon, with CNNs and SVMs automating classification [11,14]. However, discrepancies in illumination, atmosphere, and surface properties compared to terrestrial conditions limited transferability [13,32,33]. Validation using Earth analogs such as the Atacama Desert has improved confidence, but spectral divergence remains problematic [34]. Incorporating synthetic training datasets and modular transfer learning pipelines may provide a pathway for adapting models to extraterrestrial conditions.

Overall, while deep learning currently dominates in terms of accuracy, classical and hybrid methods continue to play critical roles where data scarcity, interpretability, or computational efficiency are priorities. Moving forward, the advancement of domain-specific XAI, the creation of open benchmark datasets, and the operationalization of lightweight edge-AI architectures will be essential to ensure that AI-enhanced RS systems are robust, interpretable, and scalable across terrestrial exploration and planetary missions.

5. Conclusion

The integration of artificial intelligence (AI) and machine learning (ML) with remote sensing (RS) has profoundly reshaped mineral identification over the past decade. This review synthesized 40 studies (2015–2025), highlighting progress in sensor technologies, algorithmic methods, and multimodal data fusion across terrestrial and planetary settings. Innovations in hyperspectral imaging, combined with models such as SVM, CNN, and Vision Transformers, have improved classification accuracy and operational scalability.

Despite these advancements, challenges persist in model interpretability, cross-platform generalization, and real-time field deployment. The limited availability of standardized datasets and domain-adapted models constrains reproducibility and applicability, especially in resource-limited or extraterrestrial missions.

Future research should prioritize explainable AI frameworks, lightweight edge computing architectures, and open-access spectral repositories. Bridging the gap between high-performance algorithms and field-operational systems will be essential for enabling sustainable, scalable mineral exploration on Earth and beyond.

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Authors Contribution

Adree Octova (Conceptualization; Methodology; Data curation; Formal analysis; Writing – original draft; Visualization)

Mohd Hazizan Mohd Hashim (Supervision; Validation; Writing – review & editing)

Conflict Of Interest

The authors declare no conflicts of interest related to the content, data, or publication of this article. The research and its findings were conducted independently, and the financial support received from the Postgraduate Conference Fund, Institute of Postgraduate Studies, Universiti Sains Malaysia (USM), was provided solely for conference participation and did not influence the study design, analysis, or conclusions.

References

- Ducart, D. F., Silva, A. M., Toledo, C. L. B., & Assis, L. M. D. (2016). Mapping Iron Oxides with Landsat-8/Oli and EO-1/Hyperion Imagery from the Serra Norte Iron Deposits in the Carajás Mineral Province, Brazil. *Brazilian Journal of Geology*, 46(3), 331–349. <https://doi.org/10.1590/2317-4889201620160023>
- Agrawal, N., Gupta, L., & Dixit, J. (2021). Assessment of the Socioeconomic Vulnerability to Seismic Hazards in the National Capital Region of India Using Factor Analysis. *Sustainability*, 13(17), 9652. <https://doi.org/10.3390/su13179652>
- Wang, S., Zhou, K., Wang, J., & Zhao, J. (2022). Identifying and Mapping Alteration Minerals Using HySpex Airborne Hyperspectral Data and Random Forest Algorithm. *Frontiers in Earth Science*, 10. <https://doi.org/10.3389/feart.2022.871529>
- Zhang, X., Zhao, Z., Chen, Q., Chai, W., Li, Z., Zhang, G., Yang, H., & Niu, L. (2023). Mapping Hydrothermal Alteration of the Pulang Porphyry Copper Deposit, SW China, Using ASTER and ZY1-02D Satellite Data. *Ore Geology Reviews*, 161. <https://doi.org/10.1016/j.oregeorev.2023.105605>
- Jakob, S., Zimmermann, R., & Gloaguen, R. (2017). The Need for Accurate Geometric and Radiometric Corrections of Drone-Borne Hyperspectral Data for Mineral

- Exploration: MEPHySTo—A Toolbox for Pre-Processing Drone-Borne Hyperspectral Data. *Remote Sensing*, 9(1), 88. <https://doi.org/10.3390/rs9010088>
- Rakhimov, D., et al. (2023). Application of Hyperspectral and Multispectral Datasets for Mineral Mapping. *E3S Web of Conferences*, 386, 04007. <https://doi.org/10.1051/e3sconf/202338604007>
- Wang, Z., & Zuo, R. (2024). An Evaluation of Convolutional Neural Networks for Lithological Mapping Based on Hyperspectral Images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 17, 6414–6425. <https://doi.org/10.1109/jstars.2024.3372138>
- Deng, K., Zhao, H., Li, N., & Wei, W. (2021). Identification of minerals in hyperspectral imagery based on the attenuation spectral absorption index vector using a multilayer perceptron. *Remote Sensing Letters*, 12(5), 449–458. <https://doi.org/10.1080/2150704x.2021.1903612>
- Zhang, C., Yi, M., Ye, F., Xu, Q., Li, X., & Gan, Q. (2022). Application and Evaluation of Deep Neural Networks for Airborne Hyperspectral Remote Sensing Mineral Mapping: A Case Study of the Baiyanghe Uranium Deposit in Northwestern Xinjiang, China. *Remote Sensing*, 14(20). <https://doi.org/10.3390/rs14205122>
- Ruzicka, V., & Markham, A. (2025). HyperspectralViTs: General Hyperspectral Models for On-Board Remote Sensing. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 18, 10241–10253. <https://doi.org/10.1109/jstars.2025.3557527>
- He, Z., Li, C., Xu, R., Lv, G., Yuan, L., & Wang, J. (2019). Spectrometers Based on Acousto-Optic Tunable Filters for in-Situ Lunar Surface Measurement. *Journal of Applied Remote Sensing*, 13(2), 1. <https://doi.org/10.1117/1.jrs.13.027502>
- Sun, V. Z., & Milliken, R. E. (2015). Ancient and Recent Clay Formation on Mars as Revealed From a Global Survey of Hydrous Minerals in Crater Central Peaks. *Journal of Geophysical Research Planets*, 120(12), 2293–2332. <https://doi.org/10.1002/2015je004918>
- Lin, H., Xu, R., Lin, Y., Xu, X., Wu, B., Gou, S., & Wei, Y. (2023). In-Flight Calibration of Near-Infrared Reflectance Spectra Measured by the Zhurong Mars Rover. *Earth and Space Science*, 10(2). <https://doi.org/10.1029/2022ea002624>
- Liu, Y., Goudge, T. A., Catalano, J. G., & Wang, A. (2018). Spectral and stratigraphic mapping of hydrated minerals associated with interior layered deposits near the

southern wall of Melas Chasma, Mars. *Icarus*, 302, 62–79.
<https://doi.org/10.1016/j.icarus.2017.11.006>

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, n71.
<https://doi.org/10.1136/bmj.n71>

Siddaway, A. P., Wood, A. M., & Hedges, L. V. (2019). How to Do a Systematic Review: A Best Practice Guide for Conducting and Reporting Narrative Reviews, Meta-Analyses, and Meta-Syntheses. *Annual Review of Psychology*, 70(1), 747–770.
<https://doi.org/10.1146/annurev-psych-010418-102803>

Paul, J., Lim, W. M., O’Cass, A., Hao, A. W., & Bresciani, S. (2021). Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). *International Journal of Consumer Studies*, 45(4). <https://doi.org/10.1111/ijcs.12695>

Webster, J., & Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, 26(2), xiii–xxiii.

Guan, Z., Liu, X., Wang, L., Wang, M., Wang, Y., & Cheng, Y. (2025). Extraction and analysis of alteration minerals from GF-5 hyperspectral data: A case study of the quartz-vein type tungsten deposit in Jiaoxi, Tibet. *Geocarto International*, 40(1).
<https://doi.org/10.1080/10106049.2025.2476600>

Kayet, N., Pathak, K., Chakrabarty, A., & Sahoo, S. (2018). Mapping the distribution of iron ore minerals and spatial correlation with environmental variables in hilltop mining areas. *Environmental Earth Sciences*, 77(8). Scopus.
<https://doi.org/10.1007/s12665-018-7482-7>

Sinaice, B. B., Owada, N., Saadat, M., Toriya, H., Inagaki, F., Bagai, Z., & Kawamura, Y. (2021). Coupling NCA Dimensionality Reduction with Machine Learning in Multispectral Rock Classification Problems. *Minerals*, 11(8).
<https://doi.org/10.3390/min11080846>

Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., & Sousa, J. J. (2017). Hyperspectral Imaging: A Review on UAV-Based Sensors, Data Processing and Applications for Agriculture and Forestry. *Remote Sensing*, 9(11), 1110.
<https://doi.org/10.3390/rs9111110>

- Notesco, G., Ogen, Y., & Ben-Dor, E. (2015). Mineral classification of Makhtesh Ramon in Israel using hyperspectral longwave infrared (LWIR) remote-sensing data. *Remote Sensing*, 7(9), 12282–12296. <https://doi.org/10.3390/rs70912282>
- Liu, C., Xu, R., Xie, F., Jin, J., Yuan, L., Lv, G., Wang, Y., Li, C., & Wang, J. (2020). New Airborne Thermal-Infrared Hyperspectral Imager System: Initial Validation. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 4149–4165. <https://doi.org/10.1109/jstars.2020.3010092>
- Ni, L., Xu, H., & Zhou, X. (2020). Mineral Identification and Mapping by Synthesis of Hyperspectral VNIR/SWIR and Multispectral TIR Remotely Sensed Data with Different Classifiers. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 3155–3163. <https://doi.org/10.1109/jstars.2020.2999057>
- Ji, X., Liang, K., Yang, Y., Yang, M., He, M., Zhang, Z., Zeng, S., & Wang, Y. (2024). Identifying Minerals from Image Using Out-of-Distribution Artificial Intelligence-Based Model. *Minerals*, 14(6). <https://doi.org/10.3390/min14060627>
- Tejado-Ramos, J.-J., et al. (2021). Enhancement of the sustainability of wolfram mining using drone remote sensing technology. *Remote Sensing Applications: Society and Environment*, 23. <https://doi.org/10.1016/j.rsase.2021.100542>
- Arroyo-Mora, J. P., Kalačska, M., Inamdar, D., Soffer, R., Lucanus, O., Gorman, J., Naprstek, T., Schaaf, E. S., Ifimov, G., Elmer, K., & Leblanc, G. (2019). Implementation of a UAV-Hyperspectral Pushbroom Imager for Ecological Monitoring. *Drones*, 3(1), 12. <https://doi.org/10.3390/drones3010012>
- Zhang, H., Zhang, B., Wei, Z., Wang, C., & Huang, Q. (2020). Lightweight Integrated Solution for a UAV-Borne Hyperspectral Imaging System. *Remote Sensing*, 12(4), 657. <https://doi.org/10.3390/rs12040657>
- Bahrami, H., Esmaili, P., Homayouni, S., Pour, A. B., Chokmani, K., & Bahroudi, A. (2024). Machine Learning-Based Lithological Mapping from ASTER Remote-Sensing Imagery. *Minerals*, 14(2). <https://doi.org/10.3390/min14020202>
- Xu, W., Wei, L., Cheng, W., Yi, X., & Lin, Y. (2024). Non-Destructive Assessment of Soluble Solids Content in Kiwifruit Using Hyperspectral Imaging Coupled with Feature Engineering. *Frontiers in Plant Science*, 15. <https://doi.org/10.3389/fpls.2024.1292365>
- Yang, Z., & Kang, Z. (2017). Accurate Registration of the Chang'e-1 IIM Data Based on LRO LROC-WAC Mosaic Data. *ISPRS Archives*, XLII-3/W1, 191–198. <https://doi.org/10.5194/isprs-archives-xlii-3-w1-191-2017>



- Rizaldy, A., Afifi, A. J., Ghamisi, P., & Gloaguen, R. (2024). Improving Mineral Classification Using Multimodal Hyperspectral Point Cloud Data and Multi-Stream Neural Network. *Remote Sensing*, 16(13), 2336. <https://doi.org/10.3390/rs16132336>
- Bedini, E., & Chen, J. (2020). Application of PRISMA Satellite Hyperspectral Imagery to Mineral Alteration Mapping at Cuprite, Nevada, USA. *Journal of Hyperspectral Remote Sensing*, 10(2), 87–94. <https://doi.org/10.29150/jhrs.v10.2.p87-94>