

EVALUATING THE IMPACT OF SPECTRAL BAND INTEGRATION ON 3D-CNN PERFORMANCE FOR MINERAL IDENTIFICATION

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Abstract

Remote sensing plays a vital role in mineral exploration by offering cost-effective, large-scale, and non-invasive mapping solutions. However, many advanced mineral classification approaches rely heavily on hyperspectral data, which are costly, computationally demanding, and often lack global availability. This study evaluates the performance of extended spectral input combinations using ASTER multispectral imagery for mineral classification in skarn-type iron deposits of the Western Tianshan Mountains, China. While the earlier study demonstrated the potential of integrating selected band ratio (BR) images and principal component (PC) bands with ASTER data, the present research expands this by systematically assessing six additional configurations, including: (1) all 9 bands, (2) all 15 BR images, (3) a combined input of all PCs and BRs, (4) ASTER original bands with all PCs, (5) ASTER bands with all BRs, and (6) ASTER bands combined with both all PCs and all BRs. A 3D Convolutional Neural Network (3D-CNN) model was used to evaluate how spectral feature selection impacts mineral classification accuracy and model behavior. The results revealed significant variability in performance across configurations. Using all PCs alone achieved an overall accuracy (OA) of 89.31%, outperforming all BRs (OA = 84.73%), while the combined use of all PCs and BRs yielded the lowest accuracy (OA = 79.39%), likely due to spectral redundancy. In contrast, the best classification results were obtained using a targeted integration of ASTER bands, selected PCs, and selected BRs, achieving an OA of 98.64% and Kappa coefficient of 98.27%. The study also identified persistent misclassification challenges, with over 50% of skarn samples misidentified as wall rocks or intrusions and approximately 35% of intrusions misclassified as skarn or wall rock in certain setups. These issues were mitigated through optimized spectral integration, which enhanced class separability without the need for hyperspectral inputs. The findings demonstrate that a systematically optimized, sensor-flexible spectral strategy using ASTER data can deliver high classification performance while reducing the complexity, cost, and processing burden associated with hyperspectral approaches.

Keywords: 3D-CNN, Bands integration, Mineral classification, Principal Component Analysis, Skarn-type iron deposits

INTRODUCTION

Remote sensing has emerged as a rapid and effective method for mineral exploration, particularly in regions with exposed bedrock. Its ability to detect and classify surface mineralogy makes it especially valuable in regions with extensive rock exposure and limited vegetation, such as the arid and semi-arid zones of Central Asia. Among the various

applications, mineral classification remains a core challenge, particularly when dealing with lithologically complex systems like skarn-hosted deposits, where spatial variability and spectral overlap are common (Song, Wang & Yu 2019). Numerous studies have leveraged multispectral and hyperspectral remote sensing for mineral mapping, with increasing adoption of machine learning techniques to enhance classification accuracy (Rigol-Sanchez, Chica-Olmo & Abarca-Hernandez 2003; Magendran & Sanjeevi 2014; Salem & El Gammal 2015; Pour et al. 2018; Soltaninejad et al. 2018; Son et al. 2019; Traore, Çan & Tekin 2020; Ghoneim et al. 2022; Xiao et al. 2023). Notably, convolutional neural networks (CNNs) have gained more attention in recent years due to their strong pattern recognition capabilities (Li, Zhang & Shen 2017; Zhao et al. 2019; Tomita et al. 2020; Xiao, Le & Ha 2021; Zhang 2023). However, 2D CNNs are inherently limited by their inability to process spatial and spectral dimensions simultaneously. To address this, 3D CNNs have been proposed and applied successfully in hyperspectral image analysis however hyperspectral data is often expensive, computationally intensive, and not globally available (Li et al. 2017; Xiao et al. 2021).

To mitigate this limitation, Abubakar et al. (2024) introduced a novel framework that integrates 3D CNNs with ASTER multispectral imagery, coupled with band ratio (BR) and principal component analysis (PCA) techniques. This approach leverages ASTER's global availability and well-positioned VNIR/SWIR bands to simulate hyperspectral-like classification performance while maintaining manageable data dimensionality. Their method employed five selected band combinations and demonstrated competitive accuracy, supporting the use of ASTER as a viable alternative to hyperspectral sensors in mineral exploration. However, the earlier work did not explore the effect of incorporating all available spectral derivatives, such as the complete set of 9 PC bands and 15 BRs. This raised an open question: does increasing spectral input diversity enhance or hinder model performance in complex mineralogical settings? The current study addresses this gap by evaluating the classification accuracy of 3D CNN models trained with six extended band configurations (individually and jointly combining all PCs, all BRs, and ASTER original bands).

The study area focuses on iron-bearing skarn deposits in the Western Tianshan Mountains, Xinjiang, China, which is an ideal setting due to the spectral similarity of skarn minerals (e.g., diopside, garnet, chlorite) to surrounding volcanic and intrusive rocks. This overlap, particularly in the SWIR region, often leads to misclassification in lower-resolution spectral datasets. By testing how expanded band integration affects separability in such geologically complex terrain, the study offers a deeper understanding of spectral feature optimization. ASTER's moderate spatial resolution (15 m for VNIR and 30 m for SWIR) and nine spectral bands are strategically positioned to capture diagnostic mineral features. When supplemented with BRs and PCs, the spectral richness of ASTER data can be enhanced to support 3D CNN models effectively. BRs improve class separability by amplifying spectral differences between classes (e.g., iron ore vs skarn) through arithmetic band enhancements, while PCA reduces redundancy and correlation in the input data as well as computational load, thus helping to streamline the model and mitigate overfitting during CNN training.

Therefore, this study extends the work of Abubakar et al. (2024) by assessing whether broader spectral integration improves classification performance or introduces diminishing returns due to noise and redundancy with a focus on skarn iron minerals in the Western Tianshan Mountains of Xinjiang, China. The findings contribute to developing efficient, scalable models for mineral identification using globally available sensors. The structure of this paper is as follows: Section 2 describes the study area, data sources, and methodology. Section 3 presents the results, including performance comparisons of the different input combinations. Section 4 discusses the classification outcomes, model behavior, and implications. Finally, Section 5 summarizes the conclusions and potential directions for future research.

MATERIALS AND METHODS

This study adopts the same methodology developed in Abubakar et al. (2024), which combines multispectral image derivatives with a 3D convolutional neural network (3D-CNN) for mineral classification. However, to ensure reproducibility and clarity for readers unfamiliar with the previous publication, a concise methodological outline is provided here. The primary dataset comprises ASTER Level 1T imagery, captured on September 14, 2002, covering the Western Tianshan region. The imagery includes VNIR bands at 15-meter spatial resolution and SWIR bands at 30-meter resolution, enabling adequate spatial granularity for mineral classification tasks. The VNIR and SWIR regions are especially sensitive to iron oxide and skarn alteration minerals, making ASTER suitable for lithological discrimination in complex terrains.

Preprocessing included atmospheric correction using the FLAASH algorithm, radiometric calibration, and geometric alignment to UTM Zone 45N, with nearest-neighbor resampling to preserve spectral integrity. Subsequently, 15 band ratio (BR) images were generated by algebraically combining ASTER bands based on known mineral absorption and reflectance features. In parallel, nine principal component (PC) bands were computed through PCA, with components selected based on eigenvalues greater than one to retain most of the spectral variance while reducing redundancy. To investigate the impact of spectral band integration on classification accuracy, 11 band combinations were tested. These included not only the configurations evaluated in Abubakar et al. (2024), which focused on selected BR and PC bands, but also new configurations that involved all computed BRs and PCs, either alone or in combination with the original ASTER bands. The goal was to evaluate whether broader spectral inclusion enhances or hinders model performance.

Geological Characteristics of the Study Area

The investigation focuses on iron deposits within the Awulale Metallogenic Belt (AMB) located in the western Tianshan Mountains in China. The AMB lies within the geographic extent spanning approximately 82°E to 86°E in longitude and 42°20'N to 44°N in latitude (Figure 1a). The study specifically examines three major iron deposits (Zhibo (ZID), Dundu

(DID), and Beizhan (BID) iron deposits) which are part of a well-known submarine volcanic-hosted iron oxide deposit belt. This belt, marked by a history of intense volcanic activity, is crucial for understanding the processes of iron mineralization (Hou et al. 2014). The specified geographical coordinates of the Dundee deposit extend approximately from longitude 85°18'37" to 85°21'34" E and latitude 43°15'15" to 43°16'34" N, covering an overall area of approximately 570 hectares (Figure 1b). For Zhibo deposit, the delineated study area spans specific geographical coordinates, ranging from longitude 84°59'45" to 85°04'15" E and latitude 43°18'29" to 43°20'43" N, encompassing an extensive area of approximately 7300 hectares (Figure 1c). Geographically, Beizhan deposit spans from longitude 85°32'49" to 85°34'18" E and latitude 43°14'43" to 43°15'15" N, positioned at the eastern extremity of the metallogenic belt (Figure 1d).

Situated in the western Tianshan Mountains, the AMB forms part of the Central Asian Orogenic Belt (CAOB). The belt can be subdivided based on geological history and structural characteristics. The Northern and Southern sections of the AMB feature Silurian-Devonian volcanoclastic rocks that represent an ancient volcanic arc system. In contrast, the Eastern AMB is dominated by Carboniferous volcanic and volcanoclastic rocks indicative of intense late Paleozoic activity, while the Western AMB consists of Permian terrestrial clastic and volcanic rocks, reflecting a shift to a post-collisional tectonic regime (Wang et al. 2007; Zhang et al. 2012).

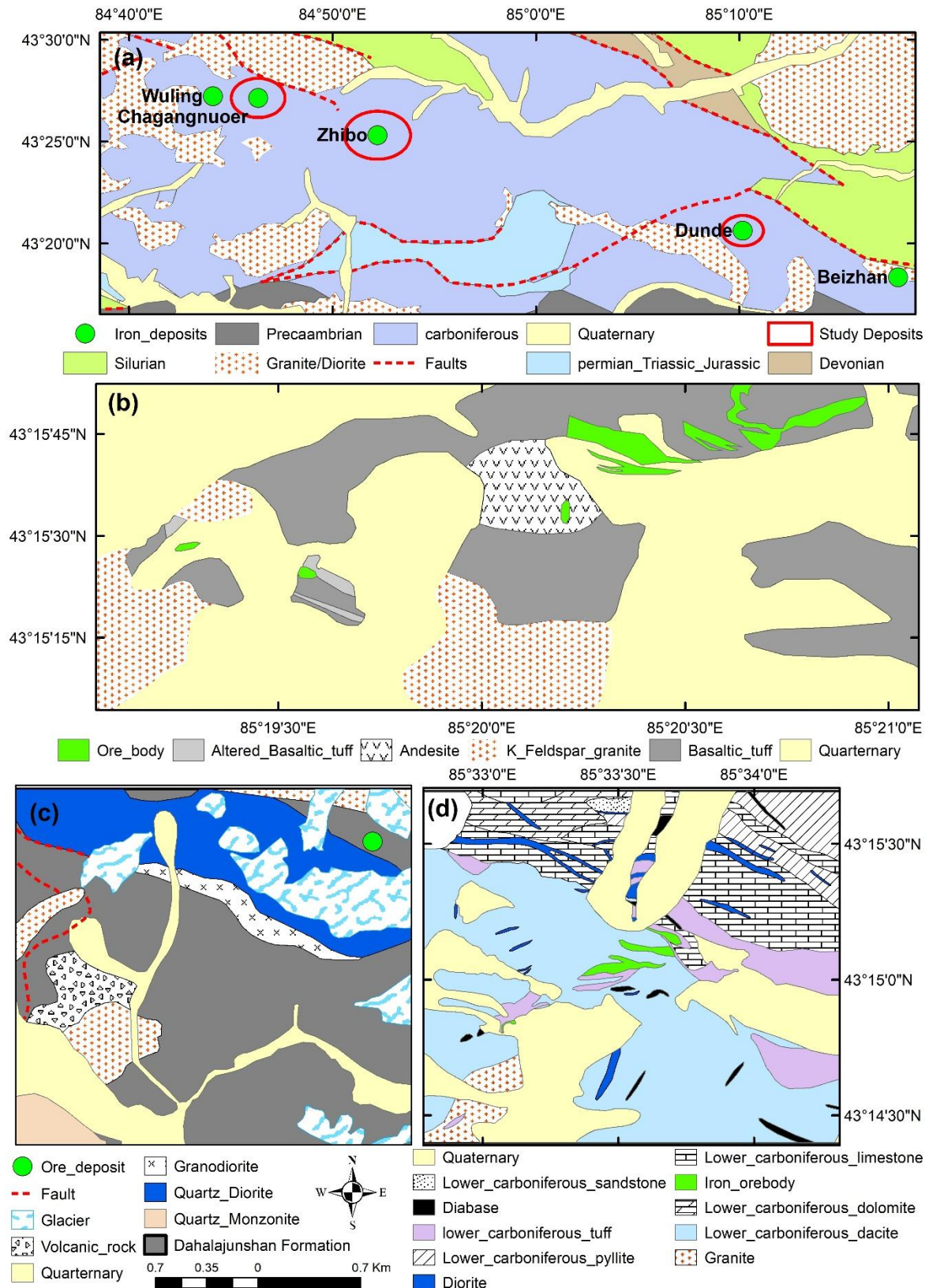


Figure 1: Geological Map of the Study Area: (a) Western Tianshan Mountains; (b) Dundee Iron Deposit; (c) Zhibo Iron Deposit; and (d) Beizhan Iron Deposit.

Source: Adapted from Abubakar et al. (2024)

The Zhibo, Dundee, and Beizhan iron deposits in the AMB exhibit distinct geological settings and mineralization processes. The ZID is hosted in Carboniferous volcanic and volcanoclastic rocks, with the ore primarily consisting of massive, disseminated, and banded magnetite, along with minor hematite, pyrites, and gangue minerals (Luo et al. 2018). The DID is unique for its mineralogical diversity, featuring iron ores such as magnetite, sphalerite, chalcopyrite, and pyrite, alongside skarn minerals like diopside and garnet, associated with volcanic rocks and limestone (Yan et al. 2018). The BID is characterized by magnetite ore in various forms, including massive, brecciated, and disseminated, hosted within volcanic rocks and skarn formations (Zhang et al. 2012). Skarnization at the contact between volcanic rocks and limestone plays a key role in ore distribution, with notable mineral assemblages like calcite, garnet, and diopside. Together, these deposits highlight a variety of ore-forming processes, including magmatic, hydrothermal, and skarn mineralization, contributing to the region's rich mineral diversity.

The selection of these deposits is based on several criteria: (1) extensive documentation in the geological literature (e.g., Luo et al., 2018; Yan et al., 2018; Zhang et al., 2012); (2) mineralogical diversity, including magnetite, pyrite, sphalerite, diopside, and garnet; and (3) their occurrence in distinct lithological settings that span Carboniferous to Permian volcanic and sedimentary units. These characteristics provide a geologically robust and spectrally complex testbed for evaluating mineral classification using multispectral imagery and deep learning. The spatial complexity and mineral assemblage variability of these sites, particularly the overlapping spectral features between skarn, wall rocks, and intrusions, make them ideal for assessing the effectiveness of different band integration strategies in resolving classification ambiguities.

Research Method

The application of optical satellite remote sensing for mineral detection and classification requires integrating rock and mineral spectral data with satellite imagery that captures the full spatial extent of the study area. To prepare the satellite images for analysis, a systematic preprocessing routine was applied to correct for atmospheric, radiometric, and geometric distortions, ensuring that the data were optimized for model training, testing, and validation. Concurrently, the spectral data from rocks, minerals, and surrounding features were carefully processed to enable the creation of diverse indices that effectively distinguish between host and alteration minerals.

Atmospheric correction was performed using the FLAASH module in ENVI 5.3, which applies physics-based radiative transfer to convert radiance to surface reflectance, accounting for water vapor, aerosol, and adjacency effects. Radiometric calibration ensured conversion to at-sensor reflectance, standardizing the pixel values. Geometric correction aligned the image to the UTM Zone 45N coordinate system using a first-order polynomial transformation and nearest-neighbor resampling to preserve spectral integrity.

Following preprocessing, 15 band ratio (BR) images were generated based on established mineral indices to enhance spectral separability of features like iron oxides, carbonates, and

silicates. Additionally, PCA was applied to the original ASTER bands. The first nine PCs, representing eigenvalues above 1, were retained to capture most of the spectral variance while minimizing dimensional redundancy. Ground truth labels for classes such as iron ore, skarn, intrusion, wall rocks, vegetation, and glacier were derived from the image cross-referenced with field observation records to generate input patches. In generating the ground truth image, sample points are buffered to include the immediately surrounding pixels in every direction. This technique serves as a data augmentation method to increase the number of training pixels used for input patch generation. Notably, this approach does not degrade the training data quality, as field samples are carefully collected from areas where the target class is clearly dominant within a 30-meter radius. The patches (7×7 pixels) were extracted using a fixed sampling window, and class balance was maintained during sampling.

The materials, procedures, and data collection protocols followed in this study are comprehensively detailed in Abubakar et al. (2024). That work also outlines the rationale behind the selection of specific band ratios and principal components for integration with the original ASTER bands, which serve as input for the model. Although this study builds upon the framework of Abubakar et al. (2024), a new set of 949 training patches, 50 validation patches, and 333 testing patches were generated using the same field control points and digitized outlines to ensure consistency while enabling performance assessment across the eleven spectral band configurations evaluated. All data were normalized between 0 and 1 before input into the network.

The 3D CNN model used here mirrors the design implemented by (Abubakar et al. 2024) and includes three convolutional layers and one residual layer to enhance model stability and mitigate overfitting. Standard convolutional layers employ a 3×3×3 kernel, while the residual layer uses a 7×7×7 kernel, with batch normalization and ReLU activation applied after each convolution. A SoftMax classifier was used at the final output layer to assign class probabilities. Due to the small input size, no pooling layers were used.

For this study, the impact of incorporating BRs and PCs was evaluated using 11 different band combinations which is an expansion from the five combinations examined in (Abubakar et al. 2024). This additional set of combinations offers a more comprehensive view of the influence of these spectral derivatives on classification performance. Detailed lists of the band ratios and the 11 band combinations can be found in (Abubakar et al. 2024) and Table 1, respectively. The performance of each combination was assessed using overall accuracy, average accuracy, and the kappa coefficient.

Table 1: List of the Band Combinations Evaluated

Input Bands Configuration	Input patch size
All nine (9) computed PC bands	$7 \times 7 \times 9$
All 15 computed BR images (Abubakar et al., 2024)	$7 \times 7 \times 15$
All PCs + All BRs	$7 \times 7 \times 24$
ASTER bands + All BRs	$7 \times 7 \times 24$
ASTER bands + All PCs	$7 \times 7 \times 18$
ASTER bands + All PCs + All BR	$7 \times 7 \times 33$
Only ASTER bands	$7 \times 7 \times 9$
4 Selected PCs + 6 Selected BRs (Abubakar et al. 2024)	$7 \times 7 \times 10$
ASTER bands + Selected BRs	$7 \times 7 \times 15$
ASTER bands + Selected PCs	$7 \times 7 \times 13$
ASTER bands + Selected PCs + Selected BRs	$7 \times 7 \times 19$

Source: Adapted from Abubakar et al. (2024)

RESULTS

The classification experiments were conducted on a system equipped with an 11th Gen Intel Core i7 processor and 16GB RAM. While GPU acceleration was not used, model efficiency was assessed by tracking training duration for each of the eleven band configurations. Input dimensionality significantly influenced training time with the models using selected BRs and PCs completed training in 121 seconds, whereas configurations with all PCs and BRs required over 550 seconds. Higher-dimensional inputs (e.g., ASTER + all BRs + all PCs) approached the system's RAM limit, indicating increased computational demand as spectral input expands. Each model was trained for 100 epochs using a batch size of 32, a learning rate of 0.001, dropout rate of 35%, and an L2 regularization parameter of 0.001. The SoftMax classifier predicted six classes.

To train the models, 949 training patches, 50 validation patches, and 333 testing patches were prepared (detailed in Tables 2). To mitigate the class imbalance between the various classes, during model learning, a class-weighted cross-entropy loss function was used during training to penalize misclassifications more heavily in underrepresented categories; and input patches were normalized, and class sampling was stratified during mini-batch formation to maintain balanced gradient flow. This approach ensured that the model learned a representative decision boundary across all six classes despite inherent sample distribution disparities and improved the robustness of the classification outputs.

Table 2: Ground-truth Image Training, Testing, and Validation Patches Summary

Class	Iron Ore	Skarn	Volcanic Wall rock	Intrusions	Vegetation	Glaciers	Total
Class Id	1	2	3	4	5	6	-
Number of patches	306	306	126	189	180	225	1332

Source: Authors Research work (2026)

Detailed performance metrics for each configuration are provided in tables 3 and 4 (in subsequent sections). Among all tested configurations, the ASTER + selected PCs + selected

BRs setup consistently delivered the highest classification performance with an overall accuracy of 98.64%, average accuracy of 97.08%, and Kappa coefficient of 98.27%.

Impact of Bands Combinations Involving Selected PCs and BRs

The configurations involving selected principal components (PCs) and band ratios (BRs) consisted of four main setups: selected PCs + selected BRs, ASTER bands + selected BRs, ASTER bands + selected PCs, and ASTER bands + selected PCs + selected BRs. Additionally, the performance of ASTER bands alone was also assessed to understand the effect of integrating selected bands.

The results indicated that combining selected BRs with ASTER bands achieved an overall accuracy (OA) of 91.16%, with an average accuracy (AA) of 80.79% (Table 3). While this combination improved classification accuracy for iron ores and surrounding wall rocks, it led to significant confusion in distinguishing skarn minerals from intrusions and volcanic wall rocks, with over 70% of skarns misclassified as wall rocks or intrusions and about 35% of intrusions misclassified as skarns or wall rocks (Figure 2, Table 3). Despite this, integrating selected BRs with ASTER bands reduced misclassification of glaciers and wall rock pixels, improving overall accuracy.

In contrast, using only ASTER bands resulted in higher classification accuracy (OA = 94.56%, AA = 92.44%, Kappa coefficient = 93.03%), outperforming the combination of ASTER bands with BRs or PCs. This unexpected result highlighted that while band ratios typically enhance classification by improving spectral sensitivity, the image derived from ASTER bands alone contained more misclassified pixels, particularly in regions with glaciers.

The inclusion of selected PC bands alongside ASTER bands resulted in a significant improvement, with OA rising to 95.92%, AA to 93.01%, and Kappa coefficient to 94.46%. This enhancement, about a 2% increase in OA, was expected, as PCs help reduce confusion by clarifying spectral features. The inclusion of PC bands improved classification accuracy for intrusions and wall rocks by over 5% and 10%, respectively, though skarn accuracy decreased by over 10%. This suggests that while PC bands positively impacted overall accuracy, they may compromise skarn classification.

The best results were achieved by combining ASTER bands, selected PCs, and selected BRs. This configuration significantly improved the classification of both intrusions and skarns, resulting in OA of 98.64%, AA of 97.08%, and Kappa coefficient of 98.27%, a substantial improvement from the other configurations. This combination consistently produced the highest classification accuracy across all classes, demonstrating the effectiveness of integrating these data types.

While the differences in overall accuracy, such as 94.56% versus 98.64%, are considerable and follow consistent trends across combinations, no formal statistical significance testing (e.g., McNemar's or ANOVA) was conducted in this study. The observed results reflect performance under uniform training and validation conditions. Given the controlled data preparation and consistent model architecture, the trends are considered robust. Nonetheless,

future research could incorporate statistical tests to rigorously assess the significance of accuracy improvements across input configurations.

Table 3: Mineral Classification Accuracy Assessment when using Selected PCs and BRs

Image used	Accuracy (%)								
	Iron Ore	Skarn	Intrusion	Wall rock	Vegetation	Glacier	OA (%)	AA (%)	Kappa (%)
Only ASTER bands	100	87.50	94.12	75.00	100	98.04	94.56	92.44	93.03
Selected (PCs + BR)	100	62.50	64.71	75.00	100	96.08	89.12	83.05	85.81
ASTER bands + Selected BR	100	25.00	64.71	95.00	100	100	91.16	80.79	84.60
ASTER bands + Selected PCs	100	75.00	100	85.00	100	98.04	95.92	93.01	94.46
ASTER bands + Selected (PCs + BR)	100	87.50	100	95.00	100	100	98.64	97.08	98.27

Source: Authors Lab work (2026)

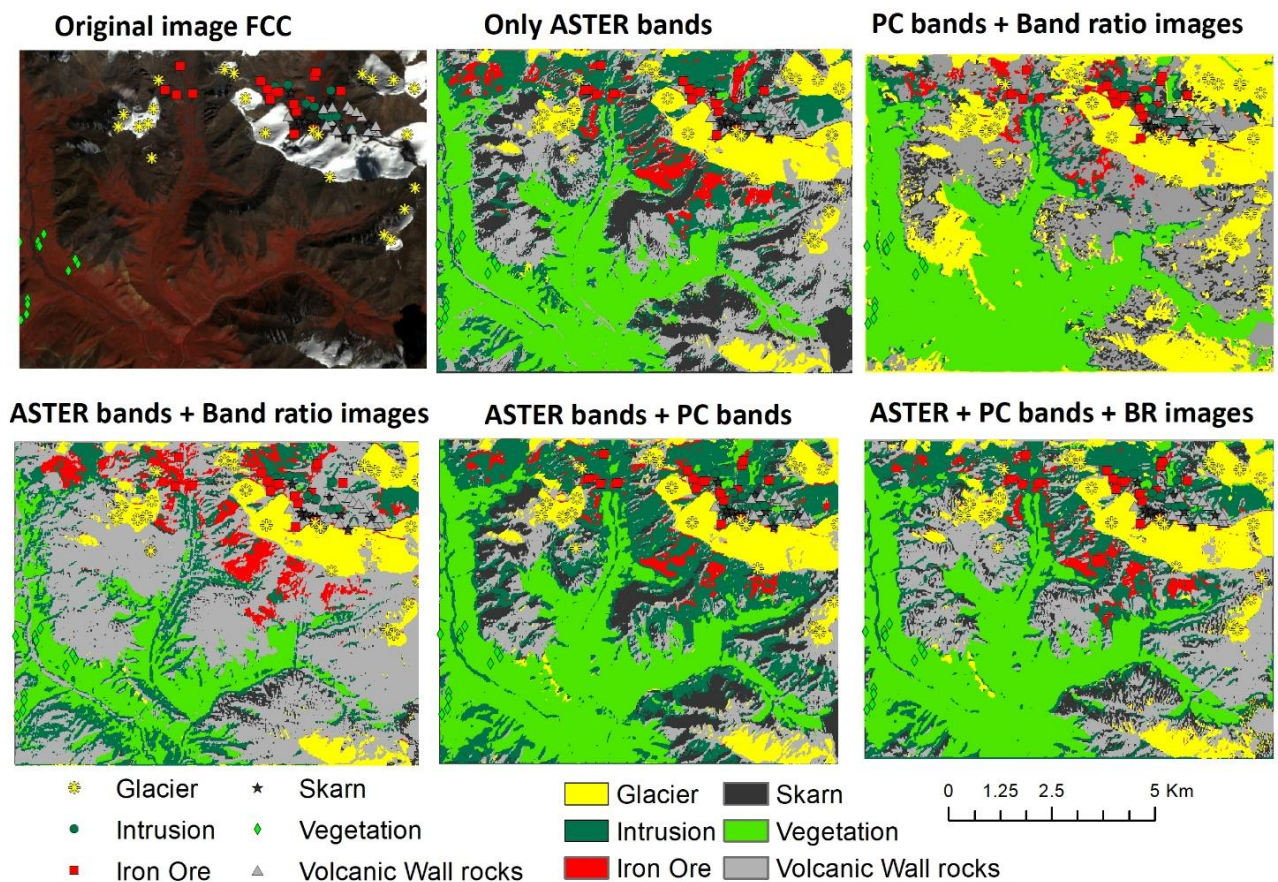


Figure 2: Classified Images with Selected Bands Configurations

Source: Authors Lab work (2026)

Impact of Bands Combinations Involving All PCs and BRs

Further analysis was conducted to evaluate the effect of integrating all PCs and BRs on classification performance. This additional analysis extended the configurations from (Abubakar et al. 2024) to include all PCs and/or BRs, such as all PCs, all BRs, and their combinations with ASTER bands.

The results (Figure 3 and Table 4) showed significant variation depending on the input data used. Using only all PC bands resulted in an OA of 89.31% and a Kappa of 85.74%, indicating strong classification performance. However, using only all BRs resulted in a lower OA of 84.73% and a Kappa of 79.98%, suggesting that BRs alone do not provide sufficient information for accurate classification (Table 4). The combination of all PCs and BRs produced the lowest performance (OA = 79.39%, Kappa = 72.80%), worse than using either all PCs or BRs alone. This outcome highlights the drawbacks of using too many spectral bands, leading to redundancy and noise, which negatively impacts classification accuracy.

Combining ASTER bands with all BR images improved the accuracy to OA = 88.55%, Kappa = 84.92%, but still performed below the results from the combination of selected BRs (OA = 91.16%, Kappa = 84.60%). Similar trends were observed when combining ASTER bands with all PCs or with both all PCs and BRs, both of which underperformed compared to combinations using selected BRs and PCs.

The best performance among combinations that included all data sets was observed with ASTER bands and all PCs, which outperformed the combination of ASTER bands, all PCs, and all BRs. This reinforces the importance of carefully selecting BRs to ensure that only those that enhance classification accuracy are included. However, none of these combinations surpassed the performance achieved by the ASTER bands + selected PCs + selected BRs configuration.

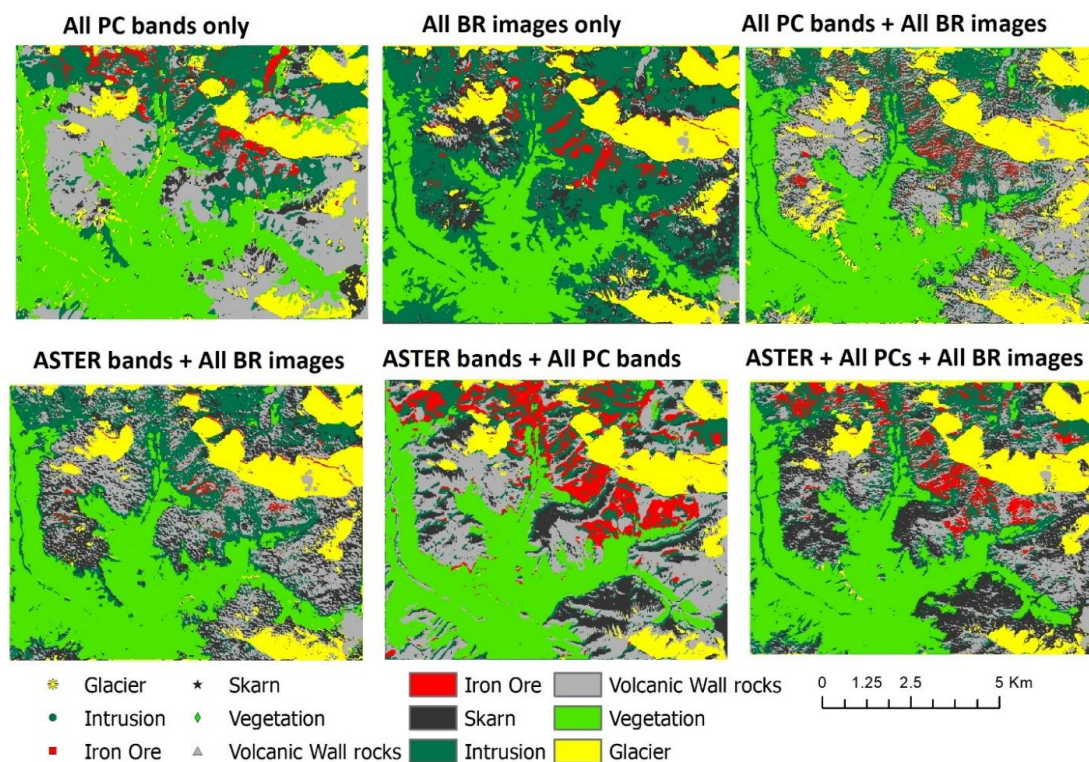


Figure 3: Classified Images using all PCs and BRs in the Input Combination

Source: Authors Lab work (2026)

Table 4: Mineral Classification Accuracy Assessment for All PCs and BRs

Image used	Accuracy (%)						OA (%)	AA (%)	Kappa (%)
	Iron Ore	Skarn	Intrusion	Wall rock	Vegetation	Glacier			
All PC bands	75.00	53.85	92.86	71.43	100.00	100.00	89.31	82.19	85.74
All BR images	100.00	92.31	57.14	47.62	100.00	96.15	84.73	82.20	79.98
All PCs + All BRs	50.00	38.46	71.43	47.62	100.00	96.15	79.39	67.28	72.80
ASTER bands + All BRs	100.00	100.00	78.57	47.62	100.00	98.08	88.55	87.38	84.92
ASTER bands + All PCs	100.00	61.54	100.00	100.0	100.00	100.00	96.18	93.59	94.92
ASTER bands + All PCs + All BR	75.00	100.00	92.86	71.43	100.00	100.00	93.89	89.88	91.88
ASTER bands + Selected PCs + Selected BRs	100	87.50	100	95.00	100.00	100.00	98.64	97.08	98.27

Source: Authors Lab work (2026)

The processing time further demonstrated the trade-offs between data complexity and computational efficiency. Using all PCs took 532 seconds for training, while using all BRs took 569 seconds. Combining both resulted in a training time of 552 seconds. Despite this increased complexity, testing times remained fast, typically under 0.08 seconds. The most efficient configuration, in terms of both training time and accuracy, was the ASTER bands + selected PCs + selected BRs, which reduced training time to just 121 seconds, indicating the benefits of selecting relevant spectral data without sacrificing classification performance. Although loss curves are not presented here, convergence behavior was carefully monitored during model training. All configurations reached training stability well before the 100th epoch, and no signs of overfitting or instability were observed. Models with selected PCs and BRs showed the fastest and most stable convergence, while configurations involving all PCs and BRs converged more slowly but remained stable throughout the training process.

The accuracy for individual classes (Table 4) varied based on the input data combination. Using all PC bands resulted in strong performance for Intrusion (92.86%), Vegetation, and Glacier (100%), but poor accuracy for Skarn (53.85%) and Wall Rock (71.43%). All BR images alone performed well for Iron Ore (100%) and Skarn (92.31%) but poorly for Intrusion (57.14%) and Wall Rock (47.62%). ASTER bands with all PCs showed strong results across most classes, with 100% accuracy for Iron Ore, Intrusion, Vegetation, and Glacier. However, Skarn classification accuracy was lower (61.54%). The best results were obtained using ASTER bands + selected PCs + selected BRs, achieving 100% accuracy for Iron Ore, Intrusion, Vegetation, and Glacier, with significant improvements in Skarn (87.50%) and Wall Rock (95.00%).

These findings highlight the importance of carefully selecting spectral bands and their combinations to optimize classification accuracy. While integrating too many bands can lead to redundancy and noise, the strategic selection of ASTER bands, selected PCs, and selected BRs provides superior classification performance and computational efficiency, confirming the robustness of the proposed approach.

DISCUSSION

This study explored the impact of integrating different band types—such as Principal Component (PC) bands, Band Ratio (BR) images, and the original ASTER bands—on the classification performance of a 3D Convolutional Neural Network (3D-CNN) for mineral mapping and identification. The model was configured with a batch size of 32 patches, a learning rate of 0.001, a dropout rate of 35%, and an L2 regularization parameter of 0.001. Kernel and filter sizes were selected based on the specifications provided in (Abubakar et al. 2024). For each category, the dataset included 949 training patches, 50 validation patches, and 333 testing patches.

The integration of various band types, including PC bands, BR images, and original ASTER bands, had a significant impact on classification accuracy. The inclusion of BR images with ASTER bands notably reduced misclassifications, particularly when identifying glaciers and wall rocks. This supports previous studies, which have shown that band ratios improve the

spectral signatures of key features (Kalinowski & Oliver 2004; Gabr, Ghulam & Kusky 2010; Zoheir & Emam 2012; Rajendran & Nasir 2014; Son et al. 2022). For instance, the ASTER + selected BRs configuration achieved an OA of 91.16% and Kappa of 84.60%, improving upon the OA of 84.73% observed when using all BRs alone. However, contrary to expectations, using only ASTER bands produced similar or even better results than when combined with BRs or PC bands. Specifically, the use of ASTER bands alone yielded an OA of 94.56% and Kappa of 93.03%, which exceeded the performance of some BR and PC combinations. This unexpected result challenges the common belief that band ratios always enhance classification accuracy, suggesting that more nuanced analysis is required when considering band integration strategies.

When PC bands were combined with ASTER bands, improvements were observed, both visually and statistically, especially in reducing misclassification of wall rocks and glaciers. For example, ASTER + selected PCs reached an OA of 95.92% and Kappa of 94.46%. However, this integration introduced challenges in distinguishing skarn minerals from other features such as intrusions and volcanic wall rocks, leading to some misclassifications. Nonetheless, the combination of ASTER bands, selected BRs, and selected PC bands consistently produced the highest classification accuracy across various configurations. This result highlights the importance of input diversity and the need to carefully select the most relevant spectral bands and combinations, enabling the model to capture complex relationships between spectral bands and improving classification performance (Xiang et al. 2022). The degradation of performance when using all PCs and BRs (OA = 79.39%) suggests that overloading the model with spectral inputs introduced both redundancy and spectral noise. This is likely due to high correlation among lower-order PCs and between certain BRs, particularly those involving non-diagnostic bands or overlapping ratios. Including such redundant features may have weakened the effect of more informative bands, leading to confusion between spectrally similar classes such as skarn, intrusion, and wall rocks. Additionally, it is plausible that some individual BRs were poorly discriminative for specific lithological classes. For instance, BRs designed for ferric-iron detection may not effectively distinguish silicate-dominated skarn zones from volcanic wall rocks, contributing to misclassification patterns observed in confusion matrices. This reinforces the benefit of selective BR integration based on mineralogical relevance.

The improved accuracy with the inclusion of all three band types indicates that the 3D-CNN model benefited from the added diversity in the input data. This enhanced the model's ability to differentiate between mineral classes with subtle spectral differences, such as skarn and wall rocks. Interestingly, models relying solely on PC bands showed lower accuracy when classifying glaciers and wall rocks, compared to those incorporating BR images. This reinforces the importance of integrating a range of spectral data to improve classification outcomes.

CONCLUSION

This study highlights the significant influence of integrating various spectral band combinations, such as ASTER bands, Principal Component (PC) bands, and Band Ratio (BR) images, on the classification performance of a 3D Convolutional Neural Network (3D-CNN) for mapping iron-bearing skarn deposits in the Western Tianshan Mountains, China. The findings demonstrate that the combination of ASTER bands with selected PC bands and selected BR images yielded the highest classification accuracy, achieving an overall accuracy (OA) of 98.64% and a Kappa coefficient of 98.27%, making it the benchmark configuration of the study. In contrast, using all PCs and all BRs simultaneously resulted in performance degradation, with OA dropping to 79.39%, due to increased spectral redundancy and noise. Models using only all PC bands or all BRs achieved OA values of 89.31% and 84.73%, respectively, indicating that unfiltered spectral combinations may affect classification precision. Furthermore, persistent confusion was observed between skarn and surrounding lithologies, where over 50% of skarn samples were misclassified as wall rocks or intrusions in some configurations, and approximately 35% of intrusions were confused with either skarn or wall rock. These findings underscore the importance of systematic and selective spectral integration, rather than indiscriminate inclusion of all available derivatives, in achieving accurate and computationally efficient classification outcomes. Beyond its performance implications, this study also highlights the value of leveraging widely available multispectral data, such as ASTER, as a cost-effective alternative to hyperspectral imagery, making advanced mineral mapping accessible for regions with limited data infrastructure. The approach is applicable to broader geological applications and may be adapted to other sensors such as Landsat 8/9 or Sentinel-2, provided that BR and PCA strategies are tailored to the sensor-specific spectral profiles. Future research should further investigate feature selection techniques and real-time deployment options to enhance mineral exploration workflows in diverse terrain settings.

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