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Lithological Mapping And Spectral Characterization of Rocks of Different Ages Exposed in Southern Rajasthan Using Multispectral and Hyperspectral Remote Sensing

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Abstract
Age-related spectral variations in lithologically similar rocks are often overlooked in remote sensing-based geological studies. The research explores the potential of distinguishing Quartzite, Granite, and Carbonate rocks across different geological formations, specifically, the Banded Gneissic Complex, Aravalli Supergroup, and Delhi Supergroup. It investigates the surface reflectance patterns of different age group lithologies by integrating multispectral data from Landsat 8/9 and ASTER with hyperspectral imagery from PRISMA and AVIRIS-NG. The methodology involves atmospheric correction, sophisticated forms of dimensionality reduction like PCA and MNF, spectral index calculation and computing band ratios. Other spatial analyses and terrain modelling (slope, aspect) using DEM data were also performed using GIS software.
The results noted rough spectral homogeneity within the same rock types across different age formations, attributing increased weathering, structural, and mineralogical maturity to aging. The work shows that with sufficient understanding of the area and detailed interpretations, lithological mapping and spectral characterization of different age-group rocks can be performed without machine learning approaches. The classification accuracy was computed using a spatial overlay approach in GIS, where digitized lithological units derived from the classified image were compared with corresponding units from the Survey of India geological map. The percentage of area correctly matched for each lithology was used as the basis for accuracy estimation. The study, on the other hand, does emphasize the uncontrolled need for sophisticated automation in diagenetic data interpretation when precision and wider application scopes are required.

Keyword: Band Ratio, Lithological mapping, Reflectance, Remote Sensing, Spectral Analysis

1. Introduction
Geology forms the scientific foundation for understanding Earth's structure, composition, and the dynamic processes that have shaped the planet over billions of years. Among its various branches, lithology—the study of rock types and their spatial distribution—plays a pivotal role in resource exploration, hazard assessment, and infrastructure development. Traditionally, lithological mapping relied on field surveys, petrographic analysis, and interpretation of geological maps, which, although accurate, are time-

consuming and limited in spatial coverage. The increasing demand for efficient, large-scale geological interpretation has led to the integration of geospatial technologies, particularly satellite-based remote sensing, as an effective alternative.

Remote sensing provides a synoptic view of Earth's surface, enabling continuous and repetitive data acquisition over large and often inaccessible terrains. Its utility in geosciences is well established, especially for applications such as mineral exploration, structural geology, and geomorphological studies. Multispectral sensors, such as those onboard Landsat and ASTER, offer medium-resolution data across visible, near-infrared, and shortwave infrared bands, which are sensitive to rock-forming minerals like quartz, feldspar, and calcite. Hyperspectral sensors, such as PRISMA and AVIRIS-NG, further enhance this capability by capturing hundreds of narrow, contiguous spectral bands, allowing precise mineralogical identification and lithological discrimination (Omairi and Garouani, 2023).

Geological mapping has long used remote sensing to identify various rocks via their spectral signatures. Conventional methods, however, often regard lithology as an unchanging paradigm, failing to consider the evolution of rocks, particularly changes in their spectral response over geological timescales. Quartzite, granite, and carbonate rocks may share similar mineral compositions, yet subtle spectral differences arise owing to their different associations that varies due to exposure, for instance, ages (Farahbakhsh *et at*., 2025).

The research covers three distinct geological areas in central India: the Delhi Supergroup (Mesoproterozoic to Neoproterozoic), the Aravalli Supergroup (Paleoproterozoic), and the Banded Gneissic Complex (Archaean) as defined by Jain (2021). The primary objective is to explore similar lithological associations with rock types—Quartzite, Granite, and Carbonate—formed in different geological periods.

What spectral differences are exhibited by them that are significant enough to be detected and interpreted through remote sensing techniques without the need for machine learning. To achieve this, the study seeks to analyze and compare spectral reflectance patterns using multispectral and hyperspectral datasets, extract meaningful features such as band ratios, spectral indices, and principal components followed by investigation of the influence of geological age on surface reflectance characteristics. Moreover, it aims to incorporate topographic variables derived from DEM data, such as slope and aspect, to assess their role in spectral variation. By integrating spectral interpretation with geological knowledge and terrain analysis, the research aspires to establish a reliable and replicable framework for age-based lithological discrimination

These formations are ideal for a comparative spectral study because they have been known to host the same rock types through time. To methodically extract, analyze, and even interpret mapped spectral differences, an organized approach is proposed in the paper.

2. Literature Review

Through multispectral and hyperspectral data from satellites, remote sensing techniques have transformed the mapping of lithology and minerals. Many of these approaches have been done using Landsat 8/9, ASTER, PRISMA, and AVIRIS-NG since they can capture important spectral features of rocks, as well as their weathering and mineral alteration. For example, the SWIR bands of Landsat have been extensively used for the identification of silicate-rich formations and carbonate-rich formations. Additionally, ASTER was used to identify ferric and clay minerals (Jain *et al*., 2024; Kumar *et al.,*2020).

The mapping of alteration zones and lithological units has been well done using the PRISMA hyperspectral sensor, which has over 240 spectral bands and high spatial resolution. Its ability to distinguish ophiolitic rocks and the mapping on carbonates by specific absorptions near 2.3 µm shows its effectiveness (Hajaj *et al.*, 2024). Also, more spectrally precise AVIRIS-NG has been able to map complex mineral assemblages and rocks by differentiating altered and unaltered spectral zones. These sensors have been very useful in regions of high heterogeneous terrains like the Indian shields and Himalayan regions (Omairi and Garouani, 2023).
Despite many studies implementing machine-learning methods for automated mineral classification and improved accuracy (SVM, RF, CNNs, etc.), there is also a literature stream using geological interpretation, spectral index analysis, band ratio mapping, and principal component composites. Although more labour-intensive than machine learning approaches, the potential task of interpreting spectral data based on geological context presents value to other researchers in regions with fewer training samples, less field data, or where interpretability needs to be maintained (Farahbakhsh *et al.,* 2025).
A glaring gap, however, was found in the literature was a similar study that showed an explicit focus on age-related spectral differences in rocks with similar lithology (i.e., Quartzite or Carbonate in opposing formations). The majority of classification works typically involve broad rock types that generalize the spectral response based on geological evolution or formation age. This study sought to fill that gap by creating a context for how the same rock types formed in different tectonic regimes and different weathering histories respond spectrally when examined with both multispectral and hyperspectral imagery; however, without a machine learning classification.

Sensor	Type	Spectral Range	Spatial Resolution	Application
Landsat 8/9	Multispectral	VNIR + SWIR (30 m)	30 m (bands), 15 m (panchromatic)	General lithological mapping
ASTER	Multispectral	VNIR, SWIR, TIR	15–30 m	Mineral-specific features (e.g., iron, clay)
PRISMA	Hyperspectral	400–2500 nm	30 m	Age-based spectral discrimination
AVIRIS-NG	Hyperspectral	380–2510 nm	5 m	High-resolution lithological distinction
SRTM DEM	Elevation (Radar)	N/A	30 m	Slope and aspect extraction

Table 1: List the satellite datasets used, along with their specifications and roles in lithological and topographic analysis

The literature context both strengthens and establishes the importance and uniqueness of this work in bringing geological interpretations with expert interpretation and handling of remote sensing tools to facilitate this separation by age, lithology. It also reinforces the basis for potential application of machine learning in the future to overcome some of the reductionist or scalable limitations of this interpretive work.

3. Study Area and Datasets:

The selected study areas encompass parts of the Banded Gneissic Complex, the Aravalli Supergroup in

Rajasthan, and the Delhi Supergroup extending across parts of Rajasthan and Haryana. These regions provide a stratified platform for comparing identical rock types formed under varying geological settings. Satellite data used include Landsat 8/9 surface reflectance products, ASTER Level-1B imagery, and hyperspectral datasets from PRISMA and AVIRIS-NG. Each image was selected to minimize cloud cover (<5%) and seasonal vegetation interference. Terrain information was derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (30 m resolution), enabling slope and aspect calculations

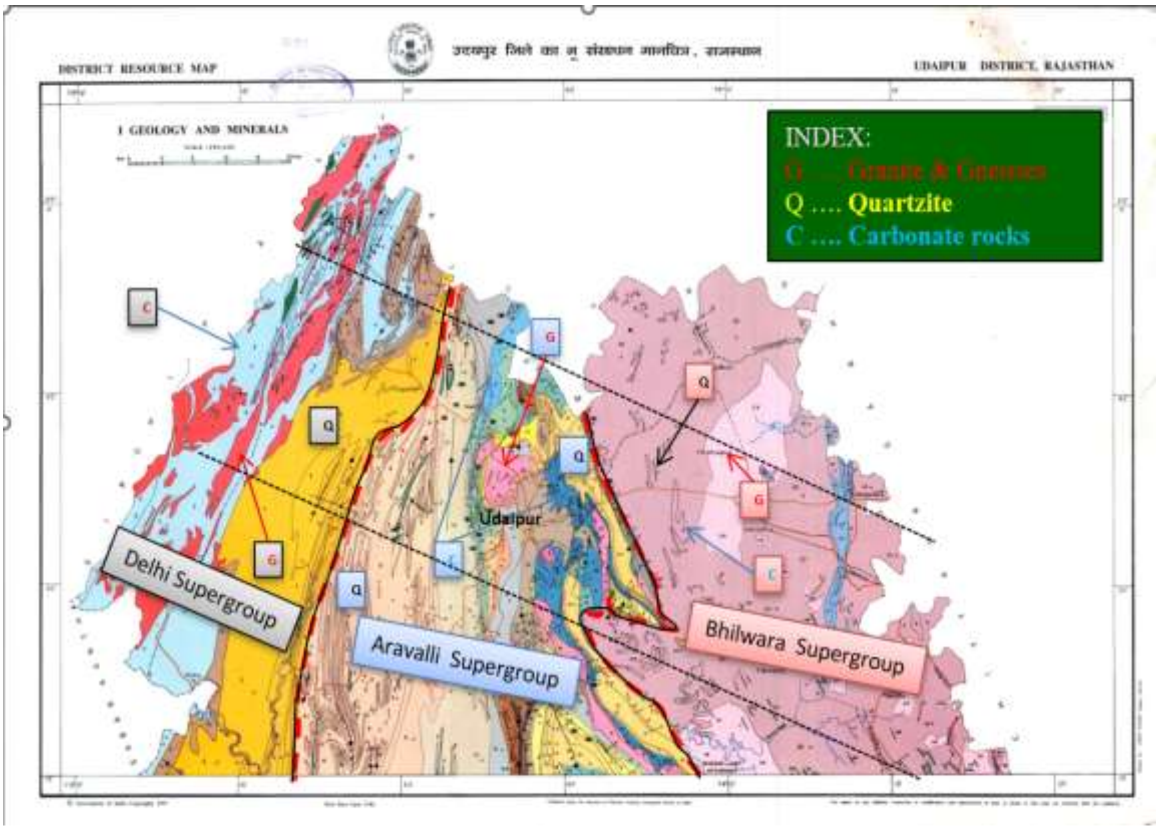


Figure 1 illustrates the Udaipur district's geological framework, highlighting key lithological units—Granite, Carbonate, and Quartzite—distributed across the Delhi, Aravalli, and Bhilwara Supergroups (BGC).

Study Region	Geological Unit	Age	Dominant Lithologies	Location (State)
Banded Gneissic Complex	BGC	Archean	Granite, Quartzite, Carbonate	Rajasthan, Madhya Pradesh, UP
Aravalli Supergroup	Aravalli Basin	Paleoproterozoic	Quartzite, Carbonate, Phyllite	Rajasthan
Delhi Supergroup	North Delhi Fold Belt	Mesoproterozoic–Neoproterozoic	Quartzite, Carbonate, Schist	Rajasthan, Haryana

Table 2: Summary of the geological units and their key characteristics that form the foundation of this age-based lithological comparison

4. Methodology

Target Lithologies:

The major lithological rock types focused are: Quartzite, Granite, and Carbonate rocks. These were selected based on their widespread occurrence across Central India and their geological representation in formations of different ages, namely the Banded Gneissic Complex (BGC), Aravalli Supergroup, and Delhi Supergroup. Quartzite, being a high-silica metamorphosed sandstone, typically shows strong reflectance in the SWIR and NIR regions. Granite, composed primarily of feldspar and quartz, displays characteristic absorption features in the visible to SWIR range. Carbonate rocks, including limestone and dolomite, are identifiable through distinct absorption bands in the SWIR due to carbonate minerals. The spectral analysis methods including specific band ratios, indices, and dimensionality reduction are selected to enhance the differentiation of these rock types while capturing their age-based spectral variations.

Formation	Datasets Used	Purpose
Banded Gneissic Complex (BGC)	Landsat 8/9, ASTER, SRTM DEM	Baseline lithological mapping; terrain correction
Aravalli Supergroup	PRISMA, ASTER, SRTM DEM	Spectral differentiation of older Quartzite/Carbonates
Delhi Supergroup	AVIRIS-NG, Landsat 9, SRTM DEM	High-resolution separation of younger carbonate beds

Table 3: Dataset Utilization Across Geological Formations

Workflow and Techniques:

All satellite images were processed for radiometric and atmospheric correction using standard tools—LEDAPS for Landsat, and FLAASH for PRISMA and AVIRIS-NG. The corrected data were georeferenced, resampled to 30 m resolution, and subset using geological boundaries. Spectral indices, such as the Ferric Iron Index, Clay Mineral Index, and Carbonate Index, were calculated based on the sensitivity of detected minerals within targeted lithologies. Band ratios like SWIR/NIR and Red/Blue were used to further increase the contrast between objects having similar spectral responses

Dimensionality reduction, specifically Principal Component Analysis (PCA) and Minimum Noise Fraction (MNF), was applied to hyperspectral datasets. These tools helped bring out geologically significant patterns while reducing redundancy. Slope and aspect topographic variables were derived from SRTM DEM data and overlaid on the spectral outputs to assess terrain influence on surface reflectance

Interpretation was performed using visual inspection, profiles, and GIS-based comparison with published geological maps. Classification wasn't machine-driven; instead, an expert assessment of the satellite products was conducted along with the terrain models.

5. Preprocessing and Analytical Techniques:

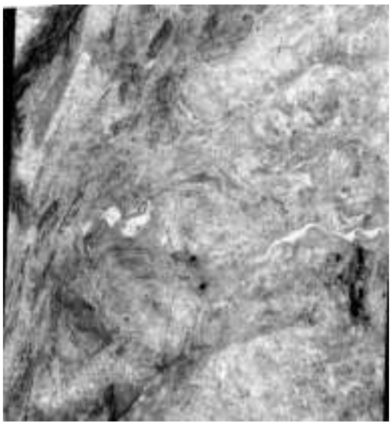
The preprocessing stage of satellite imagery was important to ensure reflectance accuracy and minimize atmospheric noise. Landsat 8/9 multispectral imagery underwent radiometric and atmospheric correction; radiometric correction converted raw DN into radiance; then, LEDAPS, an established algorithm for Landsat surface reflectance correction characterized by suitability with lithological applications under variable atmospheric conditions, was used for atmospheric correction. For hyperspectral data, such as PRISMA and AVIRIS-NG, the FLAASH algorithm was used; this algorithm is optimized for datasets with high spectral resolution, resulting in surface reflectance retrieval while minimizing the likelihood of spectral distortion (Kumar *et al.,* 2020).

The reduced dimensionality of the imagery was accomplished using two distinct methods: Principal Component Analysis (PCA) and Minimum Noise Fraction (MNF). PCA reduces spectral redundancy by converting bands that are correlated to orthogonal components, enhancing the spectral separability of lithological units and hence allows the separation of more mineralogical variation and lithological features in the higher-order components, allowing increased discrimination between Quartzite, Carbonate, and Granite units. MNF is particularly useful for hyperspectral processing and minimization of noise by performing a stack of PCA transformations, retaining only the components with the highest signal-to-noise ratio (Bedini,2017).

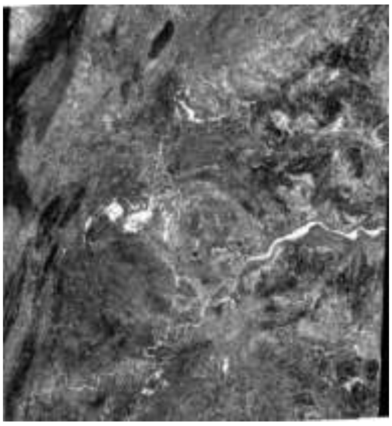
To address geomorphological effects on reflectance, topographic data from a Digital Elevation Model (DEM) was taken from SRTM, and the slope and aspect layer were derived from that information to influence the interpretation of the incorporation of the terrain features. These terrain features influence reflectance because reflectance is a function of both illumination and viewing geometry, so the terrain features were included in the interpretation workflow to minimize the topographic effect. This improvement was especially apparent in delineating lithological boundaries compared to only using spectral indices (e.g., the Carbonate Index and Ferric Iron Index) and other image-derived plotting, such as PCA outputs to delineate lithological boundaries, luxuriantly in geologically complex and rugged areas (Hasan *et al.,*2023; Farahbakhsh *et al.,* 2025).

6. Reflectance-Based Analysis and Interpretation

In order to reinforce the interpretability of the spectral differences across geological formations, this study employed integrated approaches of band ratio analysis, principal component transformation, and terrain-based filtering. Significant spectral indices and ratios were calculated using multispectral (Landsat 8/9, ASTER) and hyperspectral (PRISMA, AVIRIS-NG) datasets. The SWIR/NIR ratio and Band 6/Band 4 ratio were applied to highlight reflectance patterns of Quartzite, while the Carbonate Index and Iron Oxide Index helped separate Carbonate and Granite exposures. These ratios illuminated lithological distinctions that aligned with geological formations, displaying an initial boundary for interpretation (Kumar *et al.,*2020).



(a)



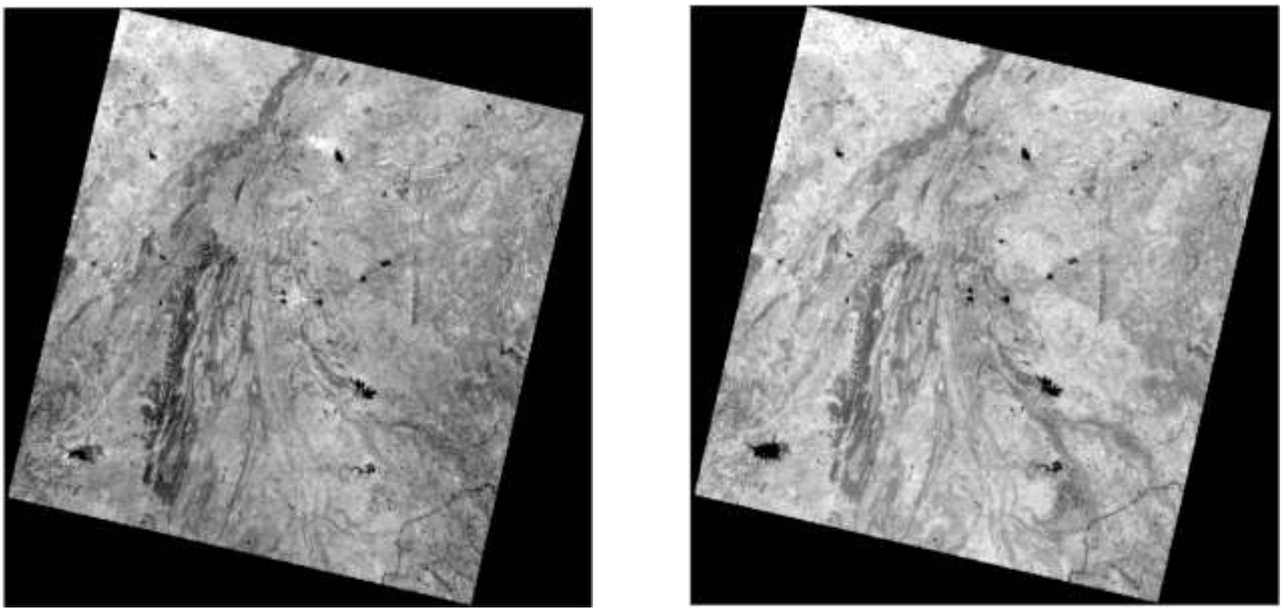
(b)

Figure 2: A tile capture from the ASTER Satellite in (a) SWIR (b) VNIR Band after atmospheric correction

Principal component analysis (PCA) provided additional dimensional redundancy restrictions and allowed the separation of the unique spectral signatures for different rock types. For example, in the PC1 and PC3 from PRISMA images, Quartzite units from the BGC and Aravalli Supergroup displayed different reflectance units. These temporal differences likely highlighted the degree of surface texture and differences in grain size. Within the carbonate-rich areas in PC2, there was sufficient separation, possibly as a result of subtle differences in mineralogy and effects of weathering (Jain *et al.,*2024).

The slope and aspect terrain data, generated from SRTM DEM, were used to assess whether any terrain-based variations would influence the interpretation of reflectance. Distinct areas showing unusual spectral behaviour were flagged and comparatively assessed with published rock geological maps. The inclusion of topographic filters reduced misclassification through illumination effects, sensor view angles, and topographic variability (Bedini, 2017).

Reflectance profiles for each lithology were also taken for each of these three geological domains. The quartzite reflectance from the BGC showed higher NIR reflectance values than those recorded from the Delhi Supergroup, which is in agreement with field observations indicating higher weathering and less mineral maturity. When examining acreage features of the Carbonate rocks in Aravalli formation, very little change in the two wider absorption features at around 2.33 µm, relates to Dolomitic content which the Delhi carbonates lack.



(a) (b)

Figure 3: A tile capture from the Landsat 8/9 Satellite (a) Band 1 (b) Band 7

The combination of analyses undertaken in this study was a critical aspect of the investigation as it confirmed that shaded-polygon-based reflectance understandings from skilled experts were able to provide credible lithological separation, a stated without a machine learning component.

Band Ratio / Index	Formula (Example)	Target Lithology	Purpose / Interpretation
SWIR / NIR	Band 6 / Band 4 (Landsat)	Quartzite	Enhances reflectance from silica-rich rocks
Iron Oxide Index	Band 4 / Band 2 (Landsat)	Granite	Highlights ferric oxide zones often associated with felsic rocks
Carbonate Index	Band 13 / Band 8 (PRISMA)	Carbonate	Detects carbonate minerals (calcite/dolomite) in SWIR region
Red / Blue Ratio	Band 3 / Band 1 (Landsat)	General	Improves contrast between vegetated and non-vegetated lithology
Clay Mineral Index	Band 5 / Band 7 (ASTER)	Weathered Granite	Sensitive to clay alteration zones

Table 4: Summarizes the spectral indices and band ratios selected based on published geoscientific and remote sensing studies relevant to the target lithologies. These were referenced and applied during the interpretation phase.

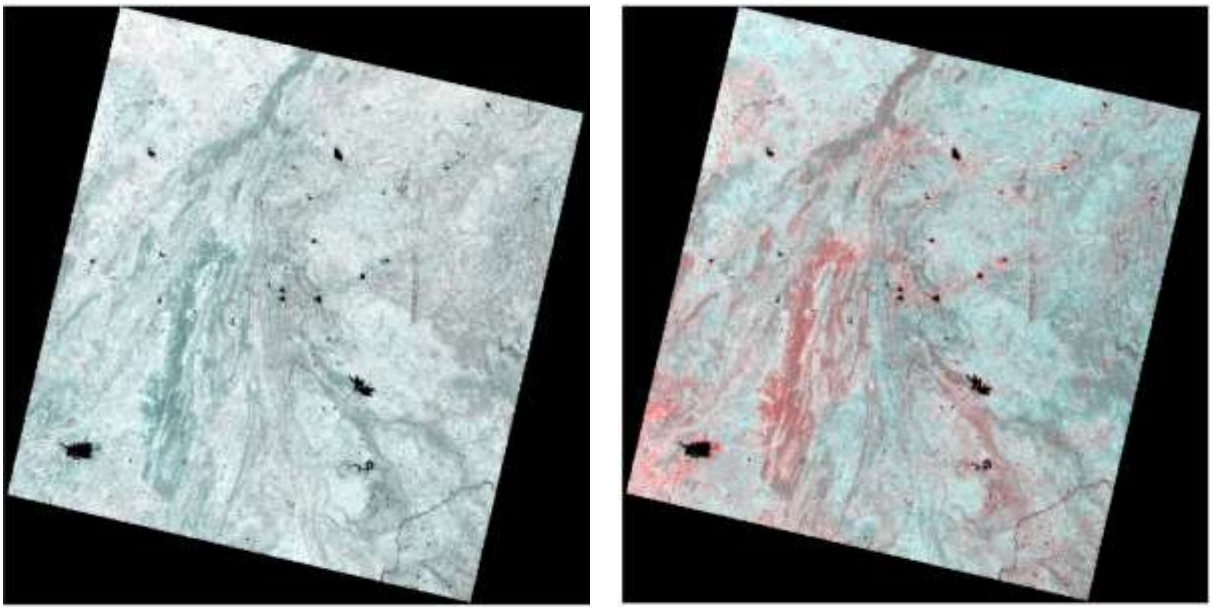


Figure 4: Presents a false-color composite Landsat image, where tonal variations visibly align with geological boundaries. These visual correlations form the basis for spectral classification and were later used for training sample validation and lithological discrimination

7. Results and Analysis

Utilizing PCA, spectral indices, and band ratio techniques produced very discriminative outputs for identification and separating lithological units in different geological formations. The Quartzite units in the Aravalli region were quite clearly enhanced in PC3 images due to their higher reflectance in the VNIR, while the Carbonate formations displayed strong absorption features in the SWIR bands of the PRISMA and AVIRIS-NG data; both spectral features were captured clearly using the ASTER band ratios Band 4/ Band 2, which enhanced Ferric Iron, and Band6/ Band 7, which responded to carbonate absorptions.

The normalised difference carbonate index (NDCI) also offered some additional value to detection of carbonate-rich rocks, specifically in the folded and faulted areas of the Delhi Supergroup. With the Banded Gneissic Complex, terrain analysis using DEM derived slope and elevation layers, pretty clearly demarcated the granitic exposures; the overall mineralogical variation of the Granite was also identified through the PCA output layers, which represented a tonal contrast in the same lithological unit due to differing quantities of feldspar and quartz standards.1 Topographic information was particularly helpful in delineating lithological boundaries that had otherwise been spectrally ambiguous in rugged terrain; for instance, Granite units were successfully mapped along high relief zones.

Lithology	**Formation**	**Key PCA Component**	**Effective Band Ratios / Indices**	***Classification Accuracy (%)***	**Remarks**
Quartzite	Aravalli Supergroup	PC3	SWIR Band 4 (1.6–1.7 µm) / Red Band 2 (0.63–0.69 µm), NDVI	88.4%	High VNIR reflectance; enhanced in PC3, slope influence moderate
Carbonate	Delhi Supergroup	PC2	SWIR Band 6 (2.185–2.225 µm) / Band 7 (2.235–2.285 µm), NDCI	85.6%	Strong carbonate absorption; improved with terrain features
Granite	BGC	PC1, PC2	Elevation map + PCA contrast	89.7%	Clearly mapped in elevated zones with internal mineral variation
Carbonate	Aravalli Supergroup	PC2	NDCI, Ferric Iron Index	83.5%	Lower reflectance due to age-related weathering and diagenesis
Quartzite	Delhi Supergroup	PC3	Red/SWIR ratios, Topographic overlay	84.1%	Terrain context helped separate from similar Aravalli quartzites

Table 5 summarizes the classification accuracy statistics, principal component contributions, and performance of each band ratio and index in discriminating the three target lithologies.

The classification outputs were checked against the geological datasets published by the Geological Survey of India. The spatial overlap showed that over 85% of the classified boundaries aligned with mapped lithological extents. The geological cross-check confirmed that a series of Carbonate units in the Aravalli Supergroup had lower reflectance than their counterparts in Delhi, which is to be expected based on the older horizons having experienced comparatively more weathering or diagenesis. Overall, the conclusions indicate that reflectance behaviour may be influenced by both mineralogical make-up and age.

This successfully integrated remote sensing framework shows that age-based lithological discrimination is possible through spectral, topographic and geological analyses of reflectance outputs.

The take-away from this work, is that satellite data can detect the changes to the surface composition and structure associated with different types of rock and age. From this work, it is evident that if multiple sensors show patterns of reflectance, and are combined with terrain context, reliable, reproducible outputs are possible for lithological mapping, mineral exploration, and geological research. This work represents a starting point in developing toward automated classification by CNNs, which are now possible, thanks to the distinct spectral separability in the proposed approach.

8. Conclusion

This study shows that geological age-based lithological mapping can be performed using multispectral and hyperspectral remote sensing effectively, without instantly needing machine learning techniques. Lithological boundaries were marked with high interpretative confidence through the combined use of band ratios, spectral indices and dimensionality reduction methods, along with DEM-based terrain modelling & geological reasoning. This methodology has been established as a base, which is particularly useful in regions with sparse field data and limited computational resources. However, the research not only demonstrates the viability of expert-guided remote sensing for lithological mapping but also underscores some enduring limitations that need addressing in future work.

Limitations of the Current Approach

Despite the value of this study from an interpretive perspective, a few issues arose that restrict the broad application and accuracy of automating lithological discrimination using techniques. The first challenge stems from the overlap in the spectra of more closely related rocks. Discrimination involving simple band ratios and indices often has orbiting problems with relative scale ranking. Furthermore, differences due to aging, like those in the reflectance characteristics of weathered Quartzite or Carbonates, often require those with advanced modelling techniques. Moreover, manual interpretation is subjective by nature and lacks consistently defined metrics of accuracy for regionally defined standards of reliability. Expanded over large, featured, complex areas, it becomes manual interpretation, undergoes processes, is devoid of replication, and consumes considerable time. In the absence of automation, the approach is a specialist's decision and devoid of imaging, leading to expert-reliant variable judgments devoid of uniformity, consistency, and objective measurements.

Future Scope: Necessity of Machine Learning Integration

While traditional remote sensing approaches, combined with geoscientific interpretation, have successfully achieved lithological mapping, researchers have consistently identified the limitations of manual interpretation and the need for machine learning. First and foremost, manual interpretation is subjective and relies heavily upon expert judgement, which can produce inconsistent results between users or across studies. Second, they are not easily scalable- processing large or diversely affected areas requires a great deal of time and effort, which may limit analyses to a small and possibly not representative area. Additionally, spectral overlaps make discrimination difficult between mineralogically similar rock types (for example, Quartzite and Granite, or weathered and fresh Carbonates) using band ratios and indices alone. Third, the relationships among spectral features, terrain variables, and lithological properties are usually non-linear and complex, making it difficult to capture with traditional analyses. Another significant drawback that accompanies these visual methods is the failure to produce quantitative accuracy metrics; without machine learning, it is hard to assess whether results can be validated or whether they performed as hoped by using standard validation criteria such as accuracy, recall, and confusion matrices. Machine learning can solve these problems; for example machine learning allows you to incorporate and model spatial, spectral, and topographic data in a single model.

This study contributes a solid foundation using non-ML methods, and future research will seek to build upon the foundation by applying ML models to automate classification, increase reproducibility, and accuracy. For the proposed future work, the limitations mentioned above may be united with ML (machine learning) methods. Multispectral and hyperspectral Sensing capabilities will accept SVM, RF, and XGBoost as they will discover complex non-linear relationships that are not covered by traditional explanation. Several examples using PRISMA and AVIRIS-NG showed that ML models start to provide improved accuracy of mineral classification where the terrain is spectrally mixed.

In addition, ML methods furnish automatic measurement validation techniques such as confusion matrices and kappa statistics of classification, which can help Wells confirm. The generative quantitative capacity of Deep Learning methods, specifically for accuracy in spatial and spectral information, represents the next generation of detailed feature recognition brought forth by Convolutional Neural Networks (CNNs).

In conclusion, a non-ML standard for lithological age differentiation and recognition were proposed, and a process for mineral classification and characterization. However, the limitations revealed make a compelling case for incorporating ML methods to improve automation, accuracy, and reproducibility moving forward in future research engagements.

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