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# ADVANCING PLANETARY SUSTAINABILITY THROUGH LITHOLOGICAL MAPPING: ASTER REMOTE SENSING IN ANTARCTICA'S DRY VALLEYS

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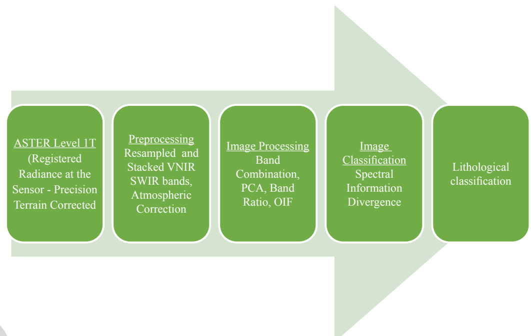
## HIGHLIGHTS

- Dry Valleys mirror Martian and ancient Earth conditions.
- Features Palaeozoic granitoids, Beacon Supergroup, and Jurassic basalts.
- ASTER technology enables precise lithological mapping.
- BR, PCA, and OIF identified key rock types (sandstone, granite, basalt).
- Minimises environmental impact while advancing geological research.

## GRAPHICAL ABSTRACT

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## ABSTRACT

The Dry Valleys of South Victoria Land in Antarctica, one of the most extreme deserts on Earth, offers an unparalleled analogue for Martian landscapes and a vital record of Earth's geological history. Characterised by a cold, arid climate and minimal atmospheric moisture, the region's ancient rock formations, including early Palaeozoic granitoid plutons, Devonian to Triassic sedimentary rocks of the Beacon Supergroup, and Jurassic basalt flows, provide insights into Earth's evolution. The logistical challenges of traditional field-based geological surveys in this remote and fragile environment emphasise the need for sustainable methods of exploration. This study leverages Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) remote sensing technology to achieve high-resolution lithological mapping to minimise the environmental impact of exploring these fragile and remote environments. Image processing techniques such as Band Ratio (BR) analysis, Principal Component Analysis

(PCA), and the Optimal Index Factor (OIF) were employed to enhance the spectral characteristics of the lithologies. These approaches facilitated the identification of key lithological units, including sandstone, granite, gneisses, and basaltic flows, and the production of an accurate lithological map. By integrating remote sensing with sustainable scientific practices, this research paper has the potential to advance planetary sustainability by making critical geological discoveries without regard to extreme environments.





## Introduction

The Dry Valleys of South Victoria Land in Antarctica are among the most extreme deserts on Earth, characterised by a cold, arid, and harsh climate often compared to conditions on Mars. Minimal atmospheric moisture and challenging logistic conditions make this region difficult to explore. From a geological perspective, it represents one of the most ancient and complex landscapes, offering valuable insights into Earth's history (Marchant *et al*., 1993a; Denton *et al*., 1993; Summerfield *et al*., 1999; Schafer *et al*., 1999). The Dry Valleys are part of the Transantarctic Mountains, a natural boundary extending across Antarctica from the Ross Sea to the Weddell Sea. This mountain chain shields the more ancient region of East Antarctica from the much younger folded mountains of West Antarctica. The current topography of the region is attributed to tertiary block faulting, with portions of West Antarctica subsiding below sea level, while sections of East Antarctica have been lifted by more than 4,000 metres.

While contemporary geological studies uses a combination of geological, geophysical, and geochemical methods to infer geological events, direct observation through drilling remains essential. However, drilling in Antarctica poses significant challenges due to the ice, snow, and permafrost, which is exacerbated by the lack of roads and infrastructure. These severe climate conditions complicate operational and logistical matters, resulting in cost overruns, prolonged delays, and a host of unique challenges (Talalay, 2016). Advanced remote sensing technologies provide an effective solution by enabling detailed geological investigations of such inaccessible regions and require only minimal physical intervention. Remote sensing not only facilitates geological research but also aligns with global efforts to reduce the environmental impact of human activity in fragile ecosystems (Nemmour-Zekiri & Oulebsir, 2020).

Remote sensing, particularly multispectral sensors, have proven to be exceptionally effective at identifying and mapping geological features by analysing the spectral responses across visible, shortwave and the thermal infrared regions of the electromagnetic spectrum (Feng *et al*., 2020). High-resolution multispectral datasets such as those provided by the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) remote sensing platform, offer precise spatial information regarding the location and morphology of surface features while capturing essential spectroscopic data (Shao *et al*., 2019). ASTER's enhanced spectral capabilities in the Shortwave Infrared (SWIR) range, compared to the sensors on Landsat-7, make it a powerful tool for understanding geological processes in extreme and, or remote regions (Tommaso & Rubinstein, 2007).

Although no prior remote sensing studies have specifically focused on lithological mapping in the Dry Valleys, ASTER data has proven highly effective for mineral exploration and mapping in other regions. Over the past two decades, ASTER's ability and reliability with regard to geological applications has been amply demonstrated (Islam *et al*., 2024). This study uses ASTER datasets to produce accurate lithological maps and analyse the spectral signatures of various rock formations in the Dry Valleys. These findings not only provide a foundation for understanding the geology of this unique region but also contribute to broader planetary sustainability efforts by demonstrating how advanced technologies can support research in extreme environments.

The harsh environmental conditions of South Victoria Land in Antarctica pose distinct challenges for geological assessments. This research uses ASTER remote sensing technology and integrates image processing methods like Band Ratio (BR), Principal Component Analysis (PCA), and the Optimal Index Factor (OIF) to effectively identify different rock types. The main goal of the research is to determine the feasibility of Multispectral Imaging Remote Sensing (MSI-RS) in extreme conditions for environmentally responsible geological surveys. This method acts as a terrestrial comparison for planetary science, especially with regard to Martian terrain, providing valuable knowledge for upcoming extra-terrestrial exploration.

**Geology of the Study Area**

The Dry Valleys form part of the Transantarctic Mountains, a prominent natural boundary spanning Antarctica from the Ross Sea to the Weddell Sea (Figure 1). This mountain range divides Antarctica into the far older region of East Antarctica and the younger folded mountains of West Antarctica. The region's current topography is shaped by tertiary block faulting, resulting in portions of West Antarctica subsiding below sea level, while areas of East Antarctica have been lifted to elevations exceeding 4,000 m.

The geology of the Dry Valleys includes a basement complex of Lower Palaeozoic igneous and metamorphic rocks, which are overlain by Devonian to Triassic sedimentary rocks of the Beacon Supergroup. These formations are intruded by Jurassic Ferrar dolerites and Cenozoic basaltic flows (Barrett *et al*., 1992; Marchant *et al*., 1993a). Higher elevations feature Sirius Group diamicts, which have played a central role in debates about the formation and timing of the Dry Valleys and the behaviour of the EAIS (Webb *et al*., 1984).

Granitoid plutons of varying compositions intrude the older metasediments of the Koettlitz Group. The lithological units include sandstones, siltstones, granites, granodiorites, gneisses, Jurassic diabase sills, basalt flows, and recent basaltic rocks (Figure 1). These units are crucial to understand the region's geological history.

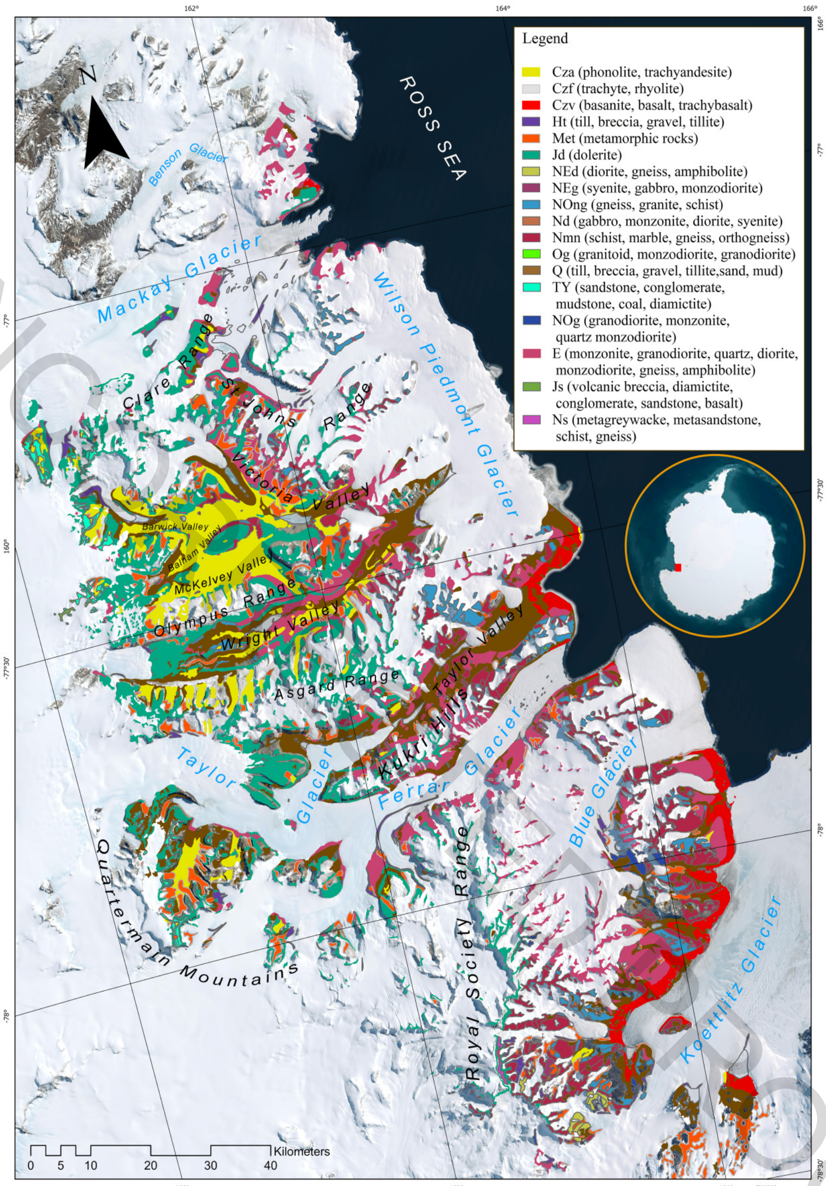


Figure 1: Geographical location and geology map of study area
Source: Authors



## Materials and Methods

This research utilised a single ASTER Level 1T scene covering the southern part of the Dry Valleys. The ASTER is a highly regarded multispectral remote sensing instrument known for its exceptional spatial, spectral, and radiometric resolution. It consists of three subsystems that cover the Visible and Near-infrared (VNIR) ,0.52 to 0.86 µm; 15 m resolution, SWIR, 1.6 to 2.43 µm; 30 m resolution, and Thermal Infrared (TIR) (8.125

to 11.65 µm; 90 m resolution) regions of the electromagnetic spectrum (Figure 2). With a swath width of 60 km and scene coverage of 60 × 60 km², ASTER is particularly suited for regional geological mapping, using its spectral characteristics to support mineral exploration and lithological mapping (Abrams *et al*., 2019).

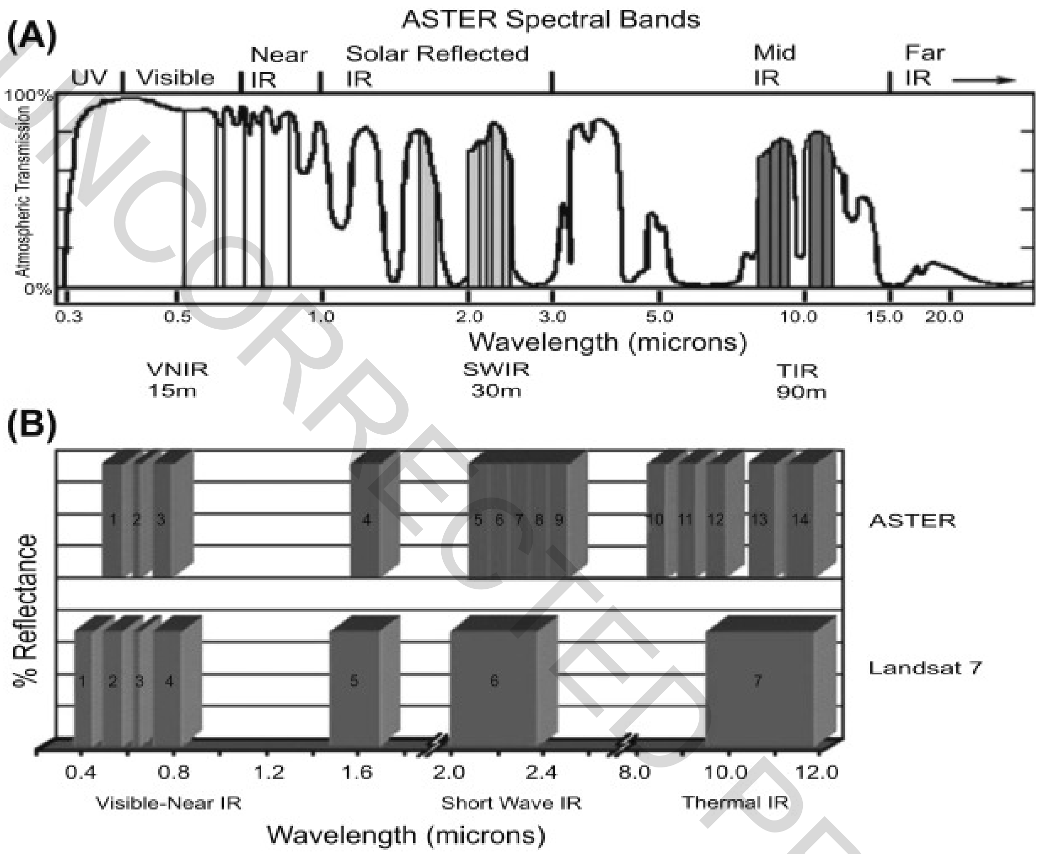


Figure 2: (a) ASTER spectral response channels superimposed over the spectral response of the Earth's atmosphere and (b) comparison of ASTER spectral response channels with those of Landsat 7. Notably, the increased spectral resolution of the SWIR and TIR bands, compared to Landsat TM, gives ASTER greater flexibility in responding to active volcanic features. A low gain state command for the SWIR channels enhances ASTER's dynamic range relative to TM (Wright *et al*., 1999)

Advanced image processing techniques, such as Band Ratios (BR), Principal Component Analysis (PCA), Optimum Index Factor (OIF), and Spectral Information Divergence (SID) classification, further enhance the capabilities of ASTER. BR highlights specific mineralogical features by combining spectral bands, while PCA, applied to multispectral bands can significantly improve image quality by maximising spectral contrast. OIF optimises band combinations for maximum contrast, and SID classification quantitatively assesses spectral similarity by measuring divergence in spectral signatures, making it particularly effective for distinguishing between materials with subtle spectral differences (Chang, 1999).

These methodologies, when combined with ASTER's high-resolution spectral data, make it a powerful tool for understanding the surface composition of the Earth, especially in arid and geologically complex regions.

***Band Ratio (BR)***

The band ratio is one of the most effective and commonly employed image processing techniques, which enhances the distinctions in colour composition of surface materials to detect irregularities while reducing the effect of lighting variations on the entire image (Sabins *et al*., 1999). The band ratio is a quantitative method used to enhance the differences in spectra between several bands. This image processing technique exploits the changes in reflectivity within the spectral signature, involving the division of the Digital Number (DN) from one band by the DN values from another band in a scene consisting of multiple spectral bands (Githenya *et al*., 2019).

***Principal Component Analysis (PCA)***

PCA is a mathematical method used for dimensionality reduction, particularly effective in addressing correlated information common in remote sensing data. It falls under a category of multidimensional descriptive techniques referred to as factorial methods. (El Atillah *et al*., 2019) Furthermore, it is used to collect data on characteristics in order to improve the targeted information within the image. This process involves converting a group of interconnected variables into multiple independent and uncorrelated linear variables by identifying the key axes in the original data that account for the greatest variation. These linear variables carry significant information relating to the spectral characteristics expected from specific bands within the VNIR and SWIR zones. This transformation is achieved through an orthogonal transformation known as Principal Components (PCs) (Singh & Harrison *et al*., 1985; Crosta *et al*., 2003; Gupta *et al*. 2013).

However, while PCA is notably effective at reducing the dimensionality of satellite data by compressing multispectral data sets into principal component bands, it also separates noise components by mitigating irradiance effects, removing data redundancy and calculating a new coordinate system. Additionally, it primarily preserves the vital information contained within the images. The application of PCA in image data involves three principal steps: (1) Assessing variance from the data matrix, (2) deriving eigen-values and eigen-vectors from the variance matrix, and (3) linearly transforming the image data using the coefficients of the eigenvectors. (Khaleghi *et al*., 2020). PCA is commonly used for lithological mapping by leveraging spectral bands from remote sensing devices, as this approach can consistently distinguish 90% geological features and mineral exploration outcomes effectively 90% of the time, as evidenced by numerous studies (Crosta *et al*., 2003; Pour *et al*., 2011; Sheikhrahimi *et al*., 2019; Zoheir *et al*., 2019). As a result, the derived components may provide more reliable interpretations compared to the original images (Tangestani *et al*., 2008; Pour *et al*., 2017a; Pour, 2018).

***Optimum Index Factor (OIF)***

The Optimum Index Factor (OIF) is used to select the best colour composites for analysing satellite images. OIF is a statistical method first introduced by Chavez *et al*., 1982 and later refined to identify the most suitable bands. This method involves a statistical evaluation of all possible combinations of three bands to create a Red, Green and Blue (RGB) image (Equation 1). OIF values are computed to find the most advantageous band combinations (Cengiz *et al*., 2006) and to rank the three bands according to the amount of information each combination provides (Beaudemin & Fung, 2001). The potential for RGB visualisation is determined by the overall variance and the correlation between the various bands (Jensen, 1996).

$$OIF = \frac{Std_i + Std_j + Std_k}{|Corr_{i,j}| + |Corr_{j,k}| + |Corr_{i,k}|} \quad (1)$$

Where $Std_i$ is the standard deviation of band $i$, $Std_j$ is the standard deviation of band $j$, $Std_k$ is the standard deviation of band $k$, $Corr_{i,j}$ is the correlation coefficient between bands $i$ and $j$, $Corr_{j,k}$ is the correlation coefficient between bands $i$ and $j$, $Corr_{i,k}$ is the correlation coefficient between bands $i$ and $j$, Such that:

Standard Deviation (Std): $\sigma_x = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$ (2)

Where $N$ is the number of points and $\bar{x}$ is the mean.

Correlation Coefficient: $Corr_{xy} = \frac{Cov_{(x,y)}}{\sigma_x \sigma_y}$ (3)

Where $\sigma_x$ and $\sigma_y$ represent the standard deviation of $x$ and $y$, respectively.

### *Spectral Information Divergence (SID) Classification*

SID is a probabilistic approach for spectral classification that pairs pixels with reference spectra using a divergence metric (Kumar *et al*., 2020). This method assesses the disparity between probability distributions by employing spectral information from two-pixel vectors, with values calculated from zero to a predefined threshold for its probability.

## Results and Discussion

### *Band Ratios Composite Image*

Image enhancement techniques aim to increase the informational value of an image. Band ratios, a type of spectral enhancement technique, express the ratio of digital numbers across two or more distinct bands. A key challenge is selecting the best combinations of ratios that capture the full range of information within the scene. The Optimum Index Factor (OIF) was used to address this. The OIF evaluates all potential combinations based on the total variance of each band and their level of correlation. High OIF values indicate bands rich in information. This research paper applied the OIF method to determine the optimal R-G-B ratio combination that contains the most spectral information for distinguishing various rocks. This study calculated the normalised reflectance values for all 72 potential ASTER band ratios, comprising four VNIR and five SWIR bands. A standard deviation was used to assess the variance in each band ratio image, while correlation was analysed through a correlation matrix for each image.

The statistical analysis of the various bands revealed that the ASTER band combination ratios of 3/1, 3/2, and 6/1 had the highest OIF values (Table 1), effectively differentiating granitoids and sandstone within the research area (Figure 3).

Table 1: OIF values for band ratios

| OIF Values for Band Ratios | | | | |
|---|---|---|---|---|
| 1. | 3/1 | 3/2 | 6/1 | 139.32 |
| 2. | 3/1 | 3/2 | 6/4 | 137.44 |

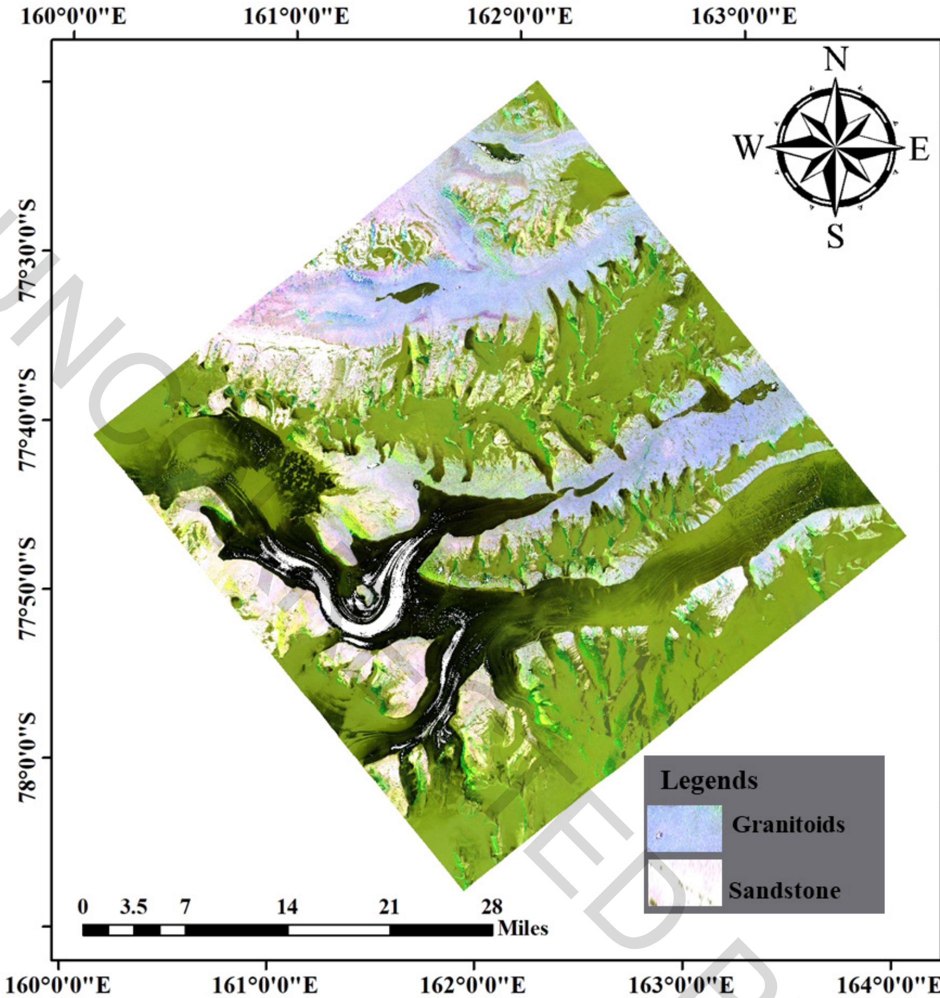


Figure 3: ASTER image map derived from the band ratio combination of 3/1, 3/2, and 6/1 as an RGB colour composite for a selected subset scene covering the southern part of the Dry Valleys Source: Authors.

The Optimum Index Factor (OIF) method was used to identify the most efficient band combination for further analysis. The OIF technique helped select the best bands based on their contributions to the total spectral variance and classification performance. In this case, PCA 1, PCA 2, and PCA 6 were selected based on the OIF assessment (Table 2), which indicated that these components had high OIF values and were well-suited for distinguishing lithological units using spectral data (Figure 4).

Table 2: OIF values for PCA

| OIF Values for PCA | | | | |
|---|---|---|---|---|
| 1. | PCA 1 | PCA 2 | PCA 6 | 19804.35 |
| 2. | PCA 2 | PCA 3 | PCA 7 | 15791.40 |

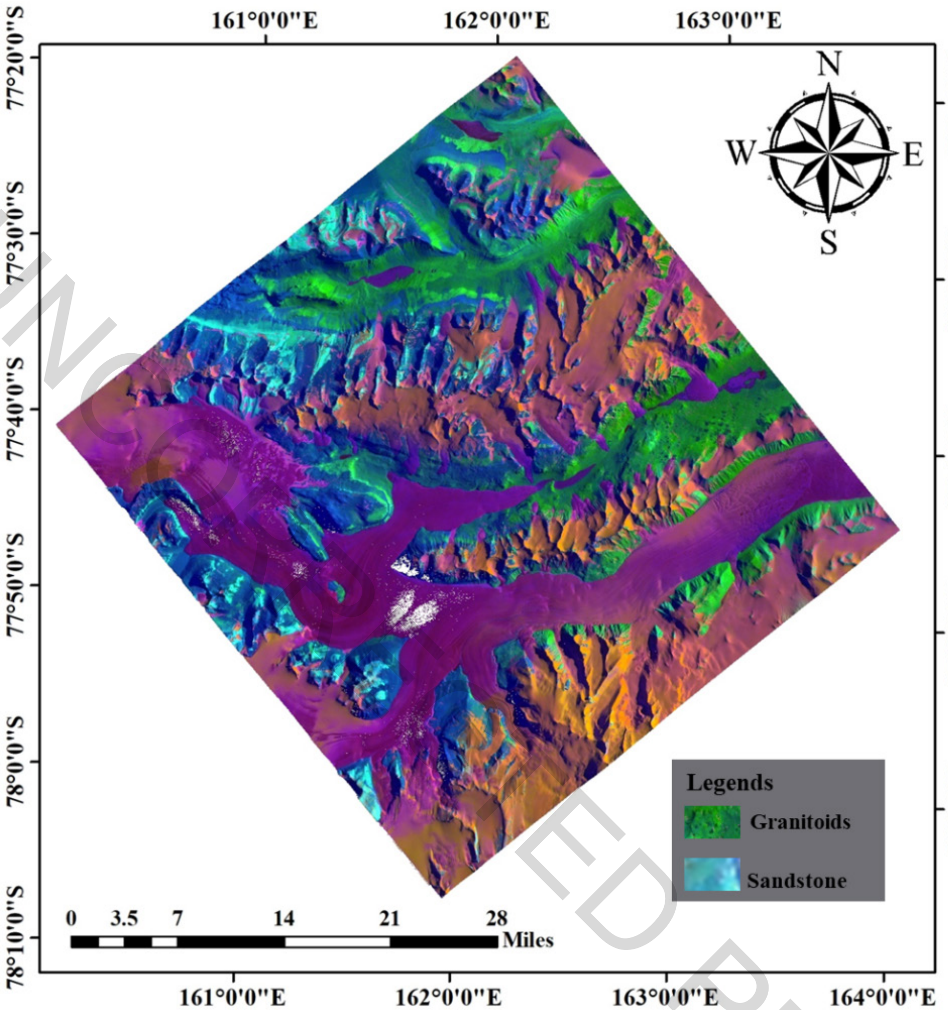


Figure 4: ASTER image map derived from the PCA 1, PCA 2, and PCA 6 components as an RGB colour composite for a selected spatial scene covering the southern part of the Dry Valleys Source: Authors.

A SID classification is a remote sensing method used to assess how distinct different classes (such as lithological units) are based on their spectral signatures. It employs the concept of divergence to measure the variance between spectral classes, which can enhance the effectiveness of classification algorithms by identifying which classes are more or less distinguishable in the spectral domain. SID measures the difference between two spectral signatures using the Kullback-Leibler divergence, which quantifies how one probability distribution diverges from a second, expected probability distribution.

In this study, the reference spectra of granitoids and sandstone endmember minerals for applying SID were selected from spectra resampled to the response functions of ASTER's nine bands, which covered the VNIR and SWIR bands. Granitoid rocks are well discriminated using SID in the ASTER image of the study area (Figure 5).

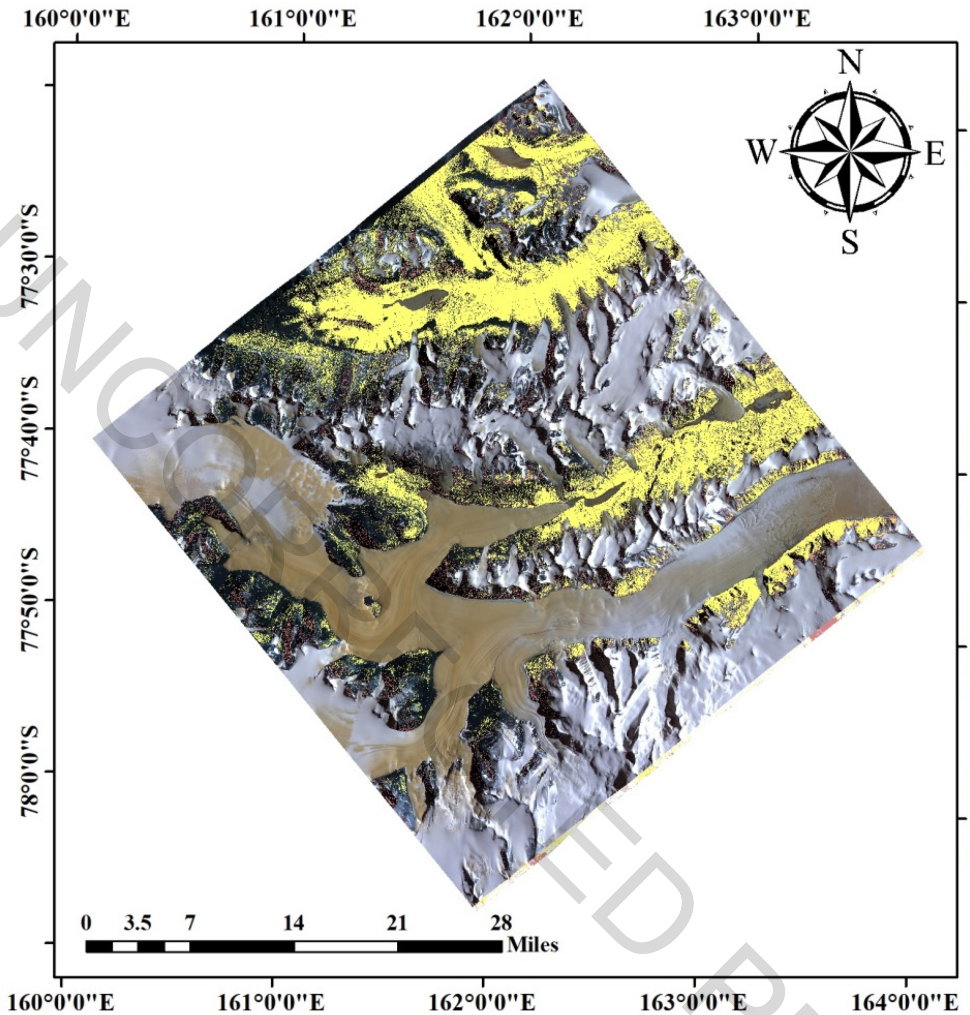


Figure 5: Spectral Information Divergence (SID) classification of the ASTER image (yellow representing granitoids and blue representing sandstone) for a selected spatial scene covering the southern part of the Dry Valleys
Source: Authors.

The combination of methods like Band Ratio (BR) analysis, Principal Component Analysis (PCA), and Optimal Index Factor (OIF) optimisation increases the efficiency and precision of rock type identification, ensuring that the resulting maps meet both scientific and industrial standards for mineral exploration.

From an ecological perspective, such method significantly decreases the necessity for extensive on-site field research, which typically requires considerable logistical support, including transportation and infrastructure. By reducing direct human intervention in delicate ecosystems, this technique limits ecological disruptions and helps preserve the unspoiled nature of locations like Antarctica. Additionally, this approach aligns with global sustainability objectives by decreasing the carbon footprint associated with traditional field surveys such as those arising from vehicle use, fuel consumption, and heavy machinery deployment.

## Conclusions

This research effectively showcases the value of ASTER remote sensing and image processing methods such as Band Ratio (BR), Principal Component Analysis (PCA), and Optimal Index Factor (OIF), the use of Spectral Information Divergence (SID) effectively demonstrated its potential to distinguish between granitoids and sandstone lithological units using ASTER imagery. The SID method, based on Kullback-Leibler divergence, highlighted the distinctiveness of these lithological categories by evaluating their spectral signatures, thereby improving classification accuracy. The integration with the Optimum Index Factor (OIF) technique strengthened the analysis by identifying the most effective band combinations for lithological differentiation. Specifically, the PCA components (PCA 1, PCA 2, and PCA 6) exhibited high OIF values, indicating their importance for spectral analysis. Additionally, the evaluation of band ratios based on OIF identified the most informative combinations such as 3/1, 3/2, and 6/1, which were successful in differentiating between granitoids and sandstone. This study underscores the critical role of advanced spectral enhancement techniques and statistical methods like SID and OIF in improving lithological classification through remote sensing, providing valuable insights for future geological studies and remote sensing applications. Using satellite data, this study successfully addresses the challenges posed by inaccessibility, severe weather conditions, and logistical limitations, facilitating detailed mapping of rock types including sandstone, granite, and basaltic flows. The approach emphasises the capability of remote sensing as a powerful instrument for geological investigations in isolated areas, where traditional field studies are not viable.

The results not only improve our comprehension of the tectonic and mineralogical framework of South Victoria Land but also open opportunities to apply such techniques to other remote and less-explored regions worldwide. Subsequent studies could enhance these methods by incorporating hyperspectral data and advanced machine learning techniques to better lithological classification and adaptability to various geological environments. Additionally, this method offers a dependable model for examining planetary surfaces, like Mars, where remote sensing would be the primary means of exploration.

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## Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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