

Article

Machine Learning- and Remote Sensing-Based Lithological Mapping Using VNIR + SWIR PRISMA Hyperspectral and ASTER Multispectral Datasets in Northwest of Queensland

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Abstract

Lithological mapping is essential for geological studies, mineral exploration, and environmental assessment. Satellite remote sensing combined with machine learning provides a scalable, cost-effective approach for regional lithological discrimination. This study evaluates hyperspectral and multispectral satellite imagery for lithological mapping in a geologically complex region of northwestern Queensland, Australia. The study area, within the Mount Isa Inlier, comprises diverse sedimentary, volcanic, intrusive, and metamorphic lithologies. PRISMA hyperspectral and ASTER multispectral imagery were analyzed using supervised classification algorithms, including Support Vector Machine (SVM), Mahalanobis Distance (MaDC), Minimum Distance (MDC), and Maximum Likelihood (MLC). Image-derived endmembers from representative lithologies were used as training data. Classification accuracy was assessed using confusion matrices, Overall Accuracy (OA), and the Kappa coefficient. PRISMA imagery outperformed ASTER data. SVM achieved the highest performance for PRISMA (OA = 82.03%, Kappa = 0.81), whereas MLC achieved the highest performance for ASTER (OA = 33.29%, Kappa = 0.30). Classification accuracy was evaluated using an independent set of validation ROIs that were spatially separated from the training samples, providing a more reliable estimate of model performance. These results highlight the benefits of hyperspectral remote sensing with machine learning for lithological discrimination in complex terrain and emphasise the importance of spatially independent validation. The approach demonstrates strong potential for regional-scale applications and may support more efficient mineral exploration and geological mapping workflows.



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Keywords: lithological mapping; hyperspectral remote sensing; multispectral imagery; PRISMA; ASTER; machine learning; Support Vector Machine; Mount Isa Inlier; VNIR-SWIR spectroscopy

1. Introduction

Lithological mapping is essential for understanding the spatial distribution of rock units, tectonic evolution, and mineral resource potential, and also supports groundwater

assessment and environmental management [1–10]. Traditional field-based mapping methods provide reliable data but are time-consuming, labor-intensive, and difficult to apply over large or inaccessible areas [6,11,12].

Remote sensing offers a practical means of acquiring spatially continuous geological information [8,13–15]. Satellite remote sensing enables lithological discrimination based on diagnostic mineral absorption features in the Visible and Near-Infrared–Shortwave Infrared (VNIR–SWIR) regions [16–23]. Multispectral sensors such as ASTER have been widely used due to their Visible and Near-Infrared–Shortwave Infrared–Thermal Infrared (VNIR–SWIR–TIR) coverage, particularly for mapping alteration minerals [1,2,14,15,18,24], although their limited spectral resolution (14 bands) restricts discrimination of spectrally similar lithologies.

Hyperspectral data provide a major improvement by offering hundreds of narrow spectral bands (e.g., 200+ bands), enabling precise mineral identification and enhanced lithological discrimination [9,13,25–27]. Sensors such as PRecursores IperEspectrales de la Misión Aplicativa (PRISMA) can resolve subtle diagnostic absorption features, improving classification accuracy in complex geological settings [10,17,18,27–32].

Several studies have demonstrated the value of remote sensing for geological mapping and mineral exploration in the Mount Isa region and comparable Proterozoic terrains. For example, Jakob et al. (2016) [33] applied remote sensing datasets to investigate structurally controlled mineralization around the Mount Isa Inlier and highlighted the importance of satellite-based geological interpretation in this complex metallogenic province. In parallel, multispectral remote sensing data, particularly ASTER imagery, have been widely used for lithological mapping, mineral exploration, and alteration mineral detection because of their VNIR–SWIR spectral coverage [1,2,14,34]. ASTER-based studies have successfully discriminated lithological units and hydrothermal alteration zones in a variety of geological settings, including the Mountain Pass region, California, the Cuprite mining district, Nevada, and the Neyriz ophiolite complex, Iran [1,2,5,35]. More recently, machine learning approaches have been increasingly adopted for lithological classification using multispectral and hyperspectral remote sensing datasets [6,21,31]. Previous studies have demonstrated that machine learning classifiers, particularly Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANNs), generally outperform conventional statistical classifiers in complex geological environments [6,36,37]. The effectiveness of SVMs for geological remote sensing applications has also been demonstrated through lithological classification of ASTER imagery in the Mawat Ophiolite Complex, northeastern Iraq, where SVM achieved improved discrimination compared with conventional statistical approaches [6]. For example, Tangestani et al. (2011) [5] successfully applied ASTER data for lithological mapping of the Neyriz ophiolite complex in southwestern Iran, while Rowan and Mars (2003) [2] demonstrated the effectiveness of ASTER imagery for lithological discrimination in the Mountain Pass region, California. More recently, Bahrami et al. (2024) [31] employed machine learning algorithms with ASTER imagery and reported improved lithological classification performance compared with conventional image analysis approaches.

Recent studies have also demonstrated the effectiveness of hyperspectral remote sensing for lithological and mineral mapping [9,13,18]. PRISMA hyperspectral imagery has shown strong potential for geological applications owing to its high spectral resolution and ability to resolve subtle diagnostic absorption features. For example, Ali-Bik et al. (2025) [38] successfully applied PRISMA data for lithological mapping of Neoproterozoic rocks in the South Sinai region of Egypt using machine learning classifiers, achieving high classification accuracy across multiple lithological units. Similarly, Shirkhani et al. (2025) [39] compared ASTER and PRISMA datasets for mineral mapping in the Bafq

mining district, Iran, and demonstrated that PRISMA provided superior discrimination of spectrally similar geological materials due to its enhanced spectral resolution. Table 1 summarizes representative studies that have applied multispectral and hyperspectral remote sensing data to lithological mapping and mineral exploration.

Table 1. Summary of previous remote sensing studies on lithological mapping and mineral exploration using multispectral and hyperspectral datasets.

Study	Study Area	Dataset	Classification/Analysis Method	Main Findings
Rowan and Mars (2003) [2]	Mountain Pass, California, USA	ASTER	Spectral analysis and lithological mapping	Demonstrated the capability of ASTER data to discriminate major lithological units and map geological boundaries.
Rowan et al. (2003) [1]	Cuprite, Nevada, USA	ASTER	Spectral analysis and mineral mapping	Successfully mapped hydrothermal alteration minerals and highlighted the utility of ASTER SWIR bands.
Tangestani et al. (2011) [5]	Neyriz Ophiolite Complex, Iran	ASTER	Spectral feature fitting (SFF)	Effectively discriminated ophiolitic lithological units using ASTER spectral information.
Othman and Gloaguen (2014) [6]	Mawat Ophiolite Complex, Iraq	ASTER	Support Vector Machine (SVM)	SVM improved lithological discrimination compared with conventional statistical classifiers.
Jakob et al. (2016) [33]	Mount Isa Inlier, Australia	Multi-source remote sensing datasets	Structural and mineral exploration analysis	Demonstrated the value of remote sensing for identifying structurally controlled mineralization in the Mount Isa region.
Bahrami et al. (2024) [31]	Sar-Cheshmeh copper mining region, Iran	ASTER	RF, SVM, GB, XGB, and ANN ML algorithms	Machine learning approaches improved lithological classification performance relative to conventional image analysis methods.
Ali-Bik et al. (2025) [38]	South Sinai, Egypt	PRISMA	Machine learning classifiers	Achieved high lithological classification accuracy and demonstrated the effectiveness of PRISMA hyperspectral imagery.
Shirkhani et al. (2025) [39]	Bafq Mining District, Iran	ASTER and PRISMA	Comparative spectral analysis and mineral mapping	PRISMA outperformed ASTER in discriminating spectrally similar geological materials owing to its higher spectral resolution.
This Study	Mount Isa Inlier, Australia	ASTER and PRISMA	SVM, MaDC, MDC, and MLC	First systematic comparison of multispectral and hyperspectral satellite datasets for lithological mapping in the Mount Isa Inlier.

Despite these advances, direct comparisons between multispectral and hyperspectral satellite datasets for lithological mapping remain relatively limited, particularly in geologically complex Proterozoic terrains. Although previous studies have demonstrated the utility of ASTER imagery for lithological discrimination and the growing potential of PRISMA hyperspectral data for geological applications, no study has directly compared the performance of ASTER and PRISMA imagery for lithological mapping within the Mount Isa Inlier. Consequently, the extent to which hyperspectral data improve the discrimination of spectrally similar lithological units in this region remains insufficiently quantified. Addressing this gap is important for evaluating the practical benefits of next-

generation hyperspectral sensors for regional geological mapping and mineral exploration in complex terrains.

Understanding the spectral characteristics of rock-forming minerals is essential for interpreting satellite remote sensing data in geological applications, as lithological units exhibit diagnostic absorption features in the VNIR–SWIR regions controlled by their mineralogical composition [16–18,23,40,41]. Mafic rocks, composed mainly of pyroxene, amphibole, and plagioclase, typically show low reflectance and broad absorption features around 1 μm due to iron-related electronic transitions [40,42–44]. Ultramafic rocks exhibit diagnostic absorption features near 1–2 μm [16,23,40,45].

Metamorphic rocks display variable spectral signatures depending on their mineral assemblages, with minerals such as chlorite, mica, and amphibole producing absorption features in the SWIR region related to hydroxyl (OH) groups [13,46,47]. Carbonate minerals such as calcite and dolomite show diagnostic absorption features near 2.33–2.35 μm due to carbonate bonds [16,23,48,49], while clay minerals, including illite, kaolinite, and montmorillonite, exhibit strong absorption features near 2.2 μm associated with hydroxyl-bearing minerals [42,50]. These spectral properties are particularly useful for identifying lithological units and mapping hydrothermal alteration zones.

In parallel, machine learning techniques have improved the analysis of remote sensing data. Traditional classifiers (e.g., Minimum Distance, Maximum Likelihood) rely on statistical assumptions that may not hold for complex datasets [51–55], whereas algorithms such as Support Vector Machine (SVM) effectively model nonlinear relationships in high-dimensional data, leading to improved classification performance [20,21,56–60].

To address this gap, the present study provides the first systematic comparison of ASTER multispectral and PRISMA hyperspectral imagery within the Mount Isa Inlier using four supervised classification algorithms across 22 lithological classes. The study aims to evaluate the relative performance of multispectral and hyperspectral datasets for lithological discrimination and to assess the influence of spectral resolution on classification accuracy in a geologically complex Proterozoic terrain. The principal novelty of this work lies in the direct side-by-side evaluation of ASTER and PRISMA imagery within the same geological setting, enabling quantitative assessment of the benefits and limitations of each sensor for regional lithological mapping.

2. Materials and Methods

2.1. Study Area

The study area is in northwestern Queensland, Australia, within a geologically complex region characterised by diverse lithological units and structural features (Figure 1). This area forms part of the Mount Isa Inlier, one of Australia’s most important metallogenic provinces, hosting significant deposits of copper, lead, zinc, and gold [61]. Its geological evolution reflects Proterozoic tectonic events that produced sedimentary basins, volcanic sequences, and intrusive bodies [62–65]. As a result, a wide range of sedimentary, volcanic, intrusive, and metamorphic rocks are exposed across the region, shaped by long-term tectonic, magmatic, and metamorphic processes. Structural elements such as faults, folds, and deformation zones strongly control the spatial distribution of lithological units and mineralization [33,66]. Given the geological complexity of the study area, field-based mapping alone cannot fully capture lithological variability; remote sensing provides a complementary, large-scale view of surface materials. Spectral information derived from satellite imagery can reveal mineralogical variations associated with different rock types and hydrothermal alteration zones [1,56]. In addition, the arid-to-semiarid climate of northwestern Queensland results in sparse vegetation cover, thereby enhancing bedrock exposure and improving the effectiveness of remote sensing methods for geological mapping [18].

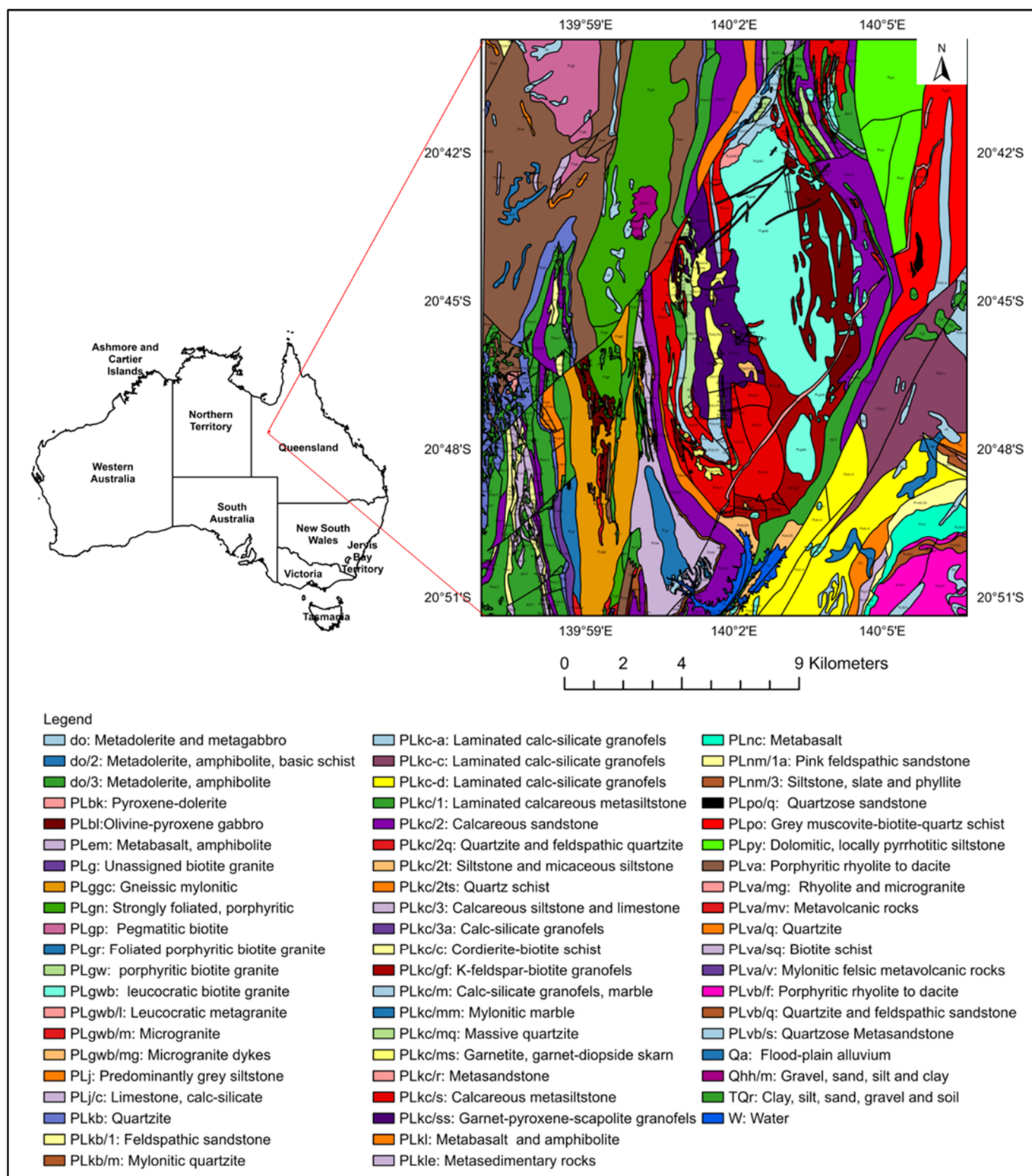


Figure 1. Location of the study area in northwestern Queensland, Australia, and geological map of the investigated region showing the distribution of major lithological units. The geological map was generated using a GIS from geological mapping datasets provided by the Geological Survey of Queensland (GSQ) and adapted for this study.

Sedimentary rocks form a major component of the study area and are described in detail in Table 2. These include sandstone, siltstone, shale, and carbonate units deposited in a variety of environments. Sandstones are typically medium- to coarse-grained and formed in fluvial, deltaic, or shallow marine settings, while siltstones and shales represent

fine-grained deposits formed in low-energy environments such as offshore basins and floodplains. Carbonate rocks, including limestone and dolomite, indicate periods of marine platform development. Volcanic rocks are also widely distributed, ranging from mafic to intermediate compositions such as basalt and andesite, reflecting ancient volcanic activity linked to extensional or subduction-related tectonic regimes.

Table 2. Detailed descriptions of lithological units in the study area. Lithological descriptions compiled from the Geological Survey of Queensland geological mapping dataset.

Unit Code	Dominant Rock	Rock Unit Name	Lithology Description
do	Gabbroid	do-MI	Metadolerite and metagabbro of various ages passing into amphibolite and local biotite or chlorite schist; rare pyroxene-bearing dolerite
do/2	Gabbroid	do/2-MI	Metadolerite, amphibolite, basic schist
do/3	Gabbroid	do/3-MI	Metadolerite, amphibolite; minor schistose amphibolite, biotite or chlorite schist;
PLbk	Gabbroid	Lakeview Dolerite	Relatively unmetamorphosed pyroxene-bearing dolerite: Relatively unmetamorphosed pyroxene-bearing dolerite
PLbl	Gabbroid	Lunch Creek Gabbro	Olivine-pyroxene gabbro, biotite diorite, hybrid diorite, and tonalite;
PLem	Magna Lynn Metabasalt	Magna Lynn Metabasalt	Metabasalt, amphibolite; minor quartzite, meta-arenite, mafic schist, and quartz-feldspar porphyry
PLg	Gabbroid	PLg-6956	Unassigned biotite granite
PLggc	Granitoid	Greens Creek Quartz Monzonite	Strongly foliated to gneissic and locally mylonitic, extensively recrystallised, fine- to medium-grained, porphyritic amphibole-biotite quartz monzonite
PLgn	Granitoid	Natalie Granite	Strongly foliated, porphyritic, biotite amphibole monzogranite to syenogranite; local pegmatite; local mafic igneous bodies
PLgp	Granitoid	Playboy Granite	Foliated, coarse-grained to pegmatitic biotite syenogranite; mingled coarse and fine-grained foliated biotite syenogranite with local mafic domains
PLgr	Granitoid	Rosebud Granite	Foliated, fine- to medium-grained, slightly porphyritic biotite granite with local traces of amphibole
PLgw	Granitoid	Wonga Granite	Strongly foliated to gneissic porphyritic biotite granite and biotite amphibole metagranite
PLgwb	Granitoid	Burstall Granite	Pink, foliated, medium to coarse-grained, leucocratic biotite granite
PLgwb/L	Granitoid	Burstall Granite/L	Leucocratic metagranite
PLgwb/m	Granitoid	Burstall Granite/m	Microgranite with garnet, diopside, and albite
PLgwb/mg	Granitoid	Burstall Granite/mg	Microgranite dykes
PLj	Mixed siliciclastic rocks/carbonate rocks	Overhang Jaspilite	Predominantly grey siltstone with local jaspilitic layers and common limestone (locally stromatolitic and silicified with jaspilitic layers); local ironstone, banded in places
PLj/c	Mixed siliciclastic rocks/carbonate rocks	Overhang Jaspilite/c	Structurally interlayered, isoclinally folded and transposed, sparry limestone, calc-silicate, carbonate breccia, carbonatised metadolerite, quartzite, schist and metasiltstone
PLkb	Quartzite	Ballara Quartzite	Quartzite, locally micaceous; minor conglomerate
PLkb/1	Arenite-rudite	Ballara Quartzite/1	Very coarse-grained, feldspathic sandstone to granule conglomerate; local pebble to boulder conglomerate

Table 2. Cont.

Unit Code	Dominant Rock	Rock Unit Name	Lithology Description
PLkb/m	Quartzite	Ballara Quartzite/m	Strongly lineated mylonitic quartzite
PLkc-a	Mixed siliciclastic rocks/carbonate rocks	Corella Formation-a	Laminated calc–silicate granofels; common to pervasive redrock-style alteration and locally extensive calc–silicate breccia; moderate to strong magnetic response; low in all radiometric channels
PLkc-c	Mixed siliciclastic rocks/carbonate rocks	Corella Formation-c	Laminated calc–silicate granofels, some mica schist; moderate to high magnetic response, moderate potassium response and low in other radiometric channels
PLkc-d	Mixed siliciclastic rocks/carbonate rocks	Corella Formation-d	Laminated calc–silicate granofels; topographically resistant, mostly low magnetic response (some more highly magnetic linear features), high potassium radiometric response
PLkc/1	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/1	Laminated calcareous metasiltstone and fine-grained feldspathic sandstone, limestone and siltstone; pass into calcareous scapolitic granofels, calc–silicate (hornblende–diopside) granofels and quartzo-feldspathic gneiss
PLkc/2	Arenite-mudrock	Corella Formation/2	Calcareous sandstone, slate grading into pelitic (andalusite–sillimanite) schist, quartzite, micaceous quartzite and meta-arenite (locally scapolitic), metasiltstone, limestone and marble, and calc–silicate granofels
PLkc/2q	Quartzite	Corella Formation/2q	Quartzite and feldspathic quartzite; locally calcareous
PLkc/2t	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/2t	Siltstone and micaceous siltstone grading into mica schist; local laminated calcareous siltstone and sandstone grading into calc–silicate rocks; some impure marble
PLkc/2ts	Pelite	Corella Formation/2ts-MK	Quartz–muscovite–biotite–sillimanite schist
PLkc/3	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/3	Laminated calcareous siltstone and limestone; pass into calcareous scapolitic granofels and laminated feldspathic quartzite; minor metabasalt at top
PLkc/3a	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/3a	Calc–silicate granofels and impure marble with common metasiltstone interbeds
PLkc/c	Metamorphosed sedimentary rocks	Corella Formation/c	Cordierite–biotite schist, mica schist, and cordierite–anthophyllite–talc rocks
PLkc/gf	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/gf-MK	K–feldspar–quartz–pyroxene–amphibole–biotite granofels
PLkc/m	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/m-MK	Thickly bedded, calc–silicate granofels, marble
PLkc/mm	Carbonates (limestone or dolomite)	Corella Formation/mm-MK	Mylonitic marble, calcareous breccia, and massive calcite
PLkc/mq	Quartzite	Corella Formation/mq-MK	Massive quartzite and amphibole–diopside quartzite
PLkc/ms	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/ms-MK	Garnetite, garnet–diopside skarn
PLkc/r	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/r	Breccia of angular–subangular metasandstone, siltstone, and locally limestone clasts in a calcareous sandy matrix; mostly matrix-supported but locally grades into coherent bedded rocks; passes into calc–silicate breccia with increasing metamorphic grade
PLkc/s	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/s-MK	Thinly bedded, calcareous metasiltstone

Table 2. Cont.

Unit Code	Dominant Rock	Rock Unit Name	Lithology Description
PLkc/ss	Mixed siliciclastic rocks/carbonate rocks	Corella Formation/ss-MK	Garnet–pyroxene–scapolite granofels
PLkl	Mafites (lava, clastics & high-level intrusive)	Lime Creek Metabasalt Member	Metabasalt (locally pillowed) and amphibolite
PLkle	Metamorphic rocks	Undaunted Metamorphics	Strongly deformed metasedimentary rocks, with minor metavolcanic, amphibolite, and metagranitoid lenses
PLnc	Mafites (lavas, clastics & high-level intrusive)	Cone Creek Metabasalt Member	Metabasalt
PLnm/1a	Quartzite	Mitakoodi Quartzite/1a	Pink feldspathic sandstone and subordinate quartzose sandstone, minor siltstone; local porphyritic rhyolite (southeast of Malbon)
PLnm/3	Mudrock	Mitakoodi Quartzite/3	Siltstone, slate, and phyllite
PLpo/q	Quartzite	Mount Roseby Schist/q	Grey to pink, fine-grained, thick to very thick-bedded, massive feldspathic to quartzose sandstone
PLpo	Metamorphosed sedimentary rocks	Mount Roseby Schist	Grey muscovite–biotite–quartz schist (psammopelite) and minor quartzite, calc–silicate granofels and limestone; commonly thin-bedded with abundant poikiloblastic scapolite porphyroblasts, particularly in the north
PLpy	Mixed siliciclastic rocks/carbonate rocks	Lady Clayre Formation	Dolomitic, locally pyrrhotitic siltstone, silty to sandy dolostone and fine-grained, variably dolomitic sandstone
PLva	Mixed metamorphosed felsites & sedimentary rocks	Argylla Formation	Porphyritic rhyolite to dacite (flows and volcanoclastic rocks including ignimbrite), quartzose to feldspathic sandstone and minor siltstone; grade into mica schist and quartzo-feldspathic gneiss; minor conglomerate and metabasalt
PLva/mg	Felsites (lavas, clastics & high-level intrusives)	Argylla Formation/mg	Intrusive, magnetic, coarsely feldspar-phyric rhyolite and microgranite
PLva/mv	Felsites (lavas, clastics & high-level intrusives)	Argylla Formation/mv	Gneissic to mylonitic felsic metavolcanic rocks with minor metasedimentary rocks, amphibolite, and metagranitoid (mylonitic granitic gneiss) lenses
PLva/q	Quartzite	Argylla Formation/q	Quartzite; some feldspathic and micaceous sandstone, and minor siltstone
PLva/sq	Metamorphosed sedimentary rocks	Argylla Formation/sq	Biotite schist, metasiltstone, calcareous quartzite
PLva/v	Felsites (lavas, clastics & high-level intrusives)	Argylla Formation/v	Mylonitic felsic metavolcanic rocks with minor metasedimentary rocks, amphibolite, and metagranitoid lenses
PLvb/f	Felsites (lavas, clastics & high-level intrusives)	Bulonga Volcanics/f	Porphyritic or crystal-rich rhyolite to dacite (including ignimbrite), commonly magnetite-bearing
PLvb/q	Quartzite	Bulonga Volcanics/q	Medium to coarse-grained quartzite and feldspathic sandstone; some micaceous sandstone and siltstone
PLvb/s	Quartzite	Bulonga Volcanics/s	Feldspathic to quartzose, locally micaceous metasandstone, siltstone, tuffaceous, and epidote-rich sandstone
Qa	Alluvium	Qa-QLD	Clay, silt, sand, and gravel; floodplain alluvium
Qhh/m	Man-made deposits (tailings, landfills, mine dumps, etc.)	Qhh/m-QLD	Gravel, sand, silt, and clay: man-made deposits associated with mining; waste-rock dumps, tailings, and rehabilitated mining areas

Table 2. *Cont.*

Unit Code	Dominant Rock	Rock Unit Name	Lithology Description
TQr	Stratified unit (including volcanic and metamorphic)	TQr-QLD	Clay, silt, sand, gravel, and soil; colluvial and residual deposits (generally on older land surfaces)
W			Water

Intrusive igneous and metamorphic rocks further contribute to the geological complexity of the study area. Granitic and granodioritic intrusions represent felsic magmatism associated with crustal melting, while mafic bodies such as gabbro and dolerite reflect mantle-derived processes. Metamorphic rocks, including schists, gneisses, and amphibolites, record regional metamorphism related to Proterozoic tectonic events, indicating significant burial, deformation, and thermal alteration [62,64]. Overall, the coexistence of these lithological units highlights a complex geological history involving sedimentation, magmatism, deformation, and metamorphism, which together shaped the present-day geological architecture of the study area, as summarized in Figure 1 and Table 2. For clarity in the subsequent analysis, classification was conducted using 22 selected lithological units (Table 3). These units were chosen based on (i) their geological significance within the Mount Isa Inlier, (ii) their spectral separability in the ASTER and PRISMA imagery, (iii) their clear representation in the Geological Survey of Queensland (GSQ) geological mapping dataset, and (iv) their sufficient spatial extent to provide representative training and validation samples. The selected classes encompass the major sedimentary, metamorphic, volcanic, and intrusive lithologies present in the study area and allow a detailed assessment of classification performance across spectrally diverse geological units.

Table 3. List of the 22 lithological units used for supervised classification and accuracy assessment. Units were selected from the Geological Survey of Queensland geological mapping dataset and grouped for the purposes of this study.

Lithological Unit	Rock Unit Name	Lithology Description
PLpo	Mount Roseby Schist	Grey muscovite–biotite–quartz schist
PLpy	Lady Clayre Formation	Dolomitic, locally pyrrhotitic siltstone
PLkc-c	Corella Formation-c	Laminated calc–silicate granofels
PLkc-d	Corella Formation-d	Laminated calc–silicate granofels (low magnetic response)
PLnc	Metabasalt	Metabasalt, locally amphibolitic
PLvb/f	Bulunga Volcanics	Porphyritic rhyolite to dacite
PLkc/s	Corella Formation-s	Siliciclastic unit (Corella subunit)
do/3	Mafic unit (do/3-MI)	Metadolerite, amphibolite
PLkc/2	Corella Formation-2	Calcareous sandstone to metasiltstone
PLpo/q	Mount Roseby Schist (quartz-rich)	Quartz-rich schist
PLgwb	Burstall Granite	Leucocratic biotite granite
PLva	Argylla Formation	Porphyritic rhyolite
PLgp	Playboy Granite	Coarse-grained foliated granite
PLgn	Natalie Granite	Porphyritic biotite amphibole monzogranite
Qhh/m	Qa-QLD	Alluvial deposits (clay, sand, gravel)

Table 3. *Cont.*

Lithological Unit	Rock Unit Name	Lithology Description
PLkc/gf	Corella Formation-gf	K-feldspar-quartz-pyroxene-amphibole granofels
PLbl	Ballara Quartzite	Quartzite, locally micaceous
PLggc	Greens Creek Quartz Monzonite	Foliated to gneissic quartz monzonite
Water	Water	Water bodies
PLkc/ms	Corella Formation-ms	Mixed siliciclastic unit
PLkc/ss	Corella Formation-ss	Siliciclastic subunit
PLkb	Quartzite	Quartzite

2.2. Data Description

Two types of satellite dataset were utilized in this study: multispectral ASTER imagery and hyperspectral PRISMA imagery. These datasets provide complementary spectral information that is useful for identifying and discriminating lithological units (Table 4) [30,38,39].

Table 4. Comparison of key characteristics of ASTER and PRISMA satellite sensors used in this study. Information compiled from the official ASTER and PRISMA mission specifications.

Feature	ASTER	PRISMA
Sensor type	Multispectral	Hyperspectral
Spectral coverage	Visible and Near Infrared, Shortwave Infrared, Thermal Infrared	Visible and Near-Infrared, Shortwave Infrared
Number of bands	14 bands (3VNIR+6SWIR+5TIR)	~240 bands 66VNIR+173SWIR
Spectral resolution	Moderate	Very high
Spatial resolution	15 m (VNIR), 30 m (SWIR), 90 m (TIR)	~30 m
Main advantage	Good for regional lithological mapping and alteration detection	Precise mineral identification using detailed spectral signatures
Typical application	Lithological mapping, alteration zones	Mineral identification, detailed lithological discrimination

2.2.1. ASTER Data

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is a multispectral imaging sensor onboard NASA's Terra satellite [16,67–69]. ASTER provides a total of 14 spectral bands covering the Visible, Near-Infrared, Shortwave Infrared, and Thermal Infrared regions of the electromagnetic spectrum (Figure 2) [68,69].

The ASTER sensor includes:

- Three VNIR bands with 15 m spatial resolution.
- Six SWIR bands with 30 m spatial resolution.
- Five TIR bands with 90 m spatial resolution.

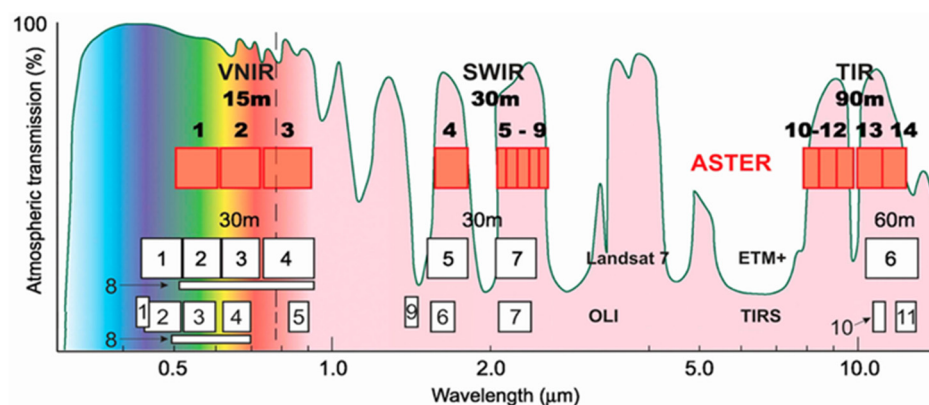


Figure 2. Spectral coverage of ASTER and Landsat ETM+ sensors across the VNIR, SWIR, and TIR regions of the electromagnetic spectrum. The blue line represents atmospheric transmission, while the pink shaded regions indicate atmospheric absorption features. Spatial resolution (pixel size) for each band is shown in meters above the corresponding bands. The figure was adapted and redrawn by the authors based on information reported in [70–73]. The figure is reprinted from [71].

The SWIR spectral region is particularly important for geological applications because many rock-forming minerals exhibit diagnostic absorption features in this wavelength range [1,74]. Minerals such as clays, carbonates, and hydroxyl-bearing minerals display distinctive spectral signatures that can be detected using ASTER SWIR bands. For this reason, ASTER data have been widely used in hydrothermal alteration mapping and lithological discrimination studies [1,2,14,75,76].

It should be noted that the SWIR subsystem of the ASTER sensor ceased operation in 2008 due to an instrument malfunction. Therefore, in this study, the available SWIR bands acquired prior to the sensor failure were combined with the corresponding VNIR imagery to construct a consistent multispectral dataset. The ASTER scene used in this study (AST_L1T_00305152005005253_20150509120314_81959.hdf_001) was acquired on 25 May 2005 and processed on 09 May 2015. Despite this limitation, ASTER remains valuable because of its relatively long temporal archive, which enables access to historical imagery and supports long-term geological investigations [68].

2.2.2. PRISMA Data

PRISMA is a hyperspectral satellite mission developed by the Italian Space Agency (ASI) [28,29]. The PRISMA sensor provides hyperspectral imagery with approximately 240 contiguous spectral bands covering the Visible and Shortwave Infrared spectral regions [29]. The hyperspectral sensor records spectral information with high spectral resolution, enabling the detection of subtle absorption features associated with specific minerals [17,27,77]. These detailed spectral signatures make hyperspectral data particularly suitable for mineral identification and lithological mapping [9,13].

PRISMA hyperspectral imagery has a spatial resolution of approximately 30 m for hyperspectral bands. In addition, PRISMA also includes a panchromatic band with higher spatial resolution that can be used for image sharpening and spatial analysis [29].

The scene used in this study (PRS_L2C_STD_20220807005245_20220807005250_0001) was acquired on 7 August 2022. The PRISMA L2C product (surface reflectance) was used as delivered, and no additional atmospheric correction was applied. The large number of spectral bands provided by PRISMA enables detailed characterization of mineralogical composition and improves the ability to distinguish spectrally similar lithological units. Consequently, hyperspectral data offers significant advantages compared to multispectral sensors for geological applications [18,30].

It should be noted that the datasets used in this study were acquired at different times, with ASTER data acquired in 2005 and PRISMA data acquired in 2022. This temporal gap of approximately 17 years represents a potential source of uncertainty because changes in vegetation cover, mining activity, surface weathering, and land cover conditions may have modified local spectral responses. However, the primary objective of this study is lithological mapping, and the major lithological units within the Mount Isa Inlier represent Proterozoic geological formations that remain stable over decadal timescales [61–65]. Their spectral characteristics are predominantly controlled by mineralogical composition rather than short-term environmental changes [16,18,23]. While surface processes such as weathering, vegetation growth, soil moisture variability, and anthropogenic disturbance may influence the spectral response of exposed surfaces [11], they do not substantially alter the intrinsic mineralogical properties of the underlying rock units. Furthermore, the study area is located in a remote region, far from major settlements and intensive land use activities, making significant anthropogenic disturbance during the study period unlikely. Consequently, although temporal differences may contribute to local variability and classification uncertainty, they are unlikely to be the primary driver of any performance differences observed between ASTER and PRISMA. Therefore, the comparison remains valid for evaluating the relative capability of multispectral and hyperspectral datasets for lithological discrimination in a geologically complex terrain.

2.3. Spectral Characteristics

To characterize the spectral behaviour of lithological units in the study area, spectral signatures were extracted from homogeneous regions of the satellite imagery and used as endmembers (Figures 3 and 4). The homogeneous regions of interest (ROIs) were selected based on the integration of geological map information and visual interpretation of satellite imagery to ensure representative lithological consistency. Representative spectra were extracted from ROIs corresponding to the same lithological classes used in the final classification map (22 lithological classes). These image-derived endmembers represent the characteristic reflectance patterns of dominant surface materials and were employed as reference inputs in the classification process, improving the representation of real surface conditions and enhancing classification accuracy [13,18,78,79].

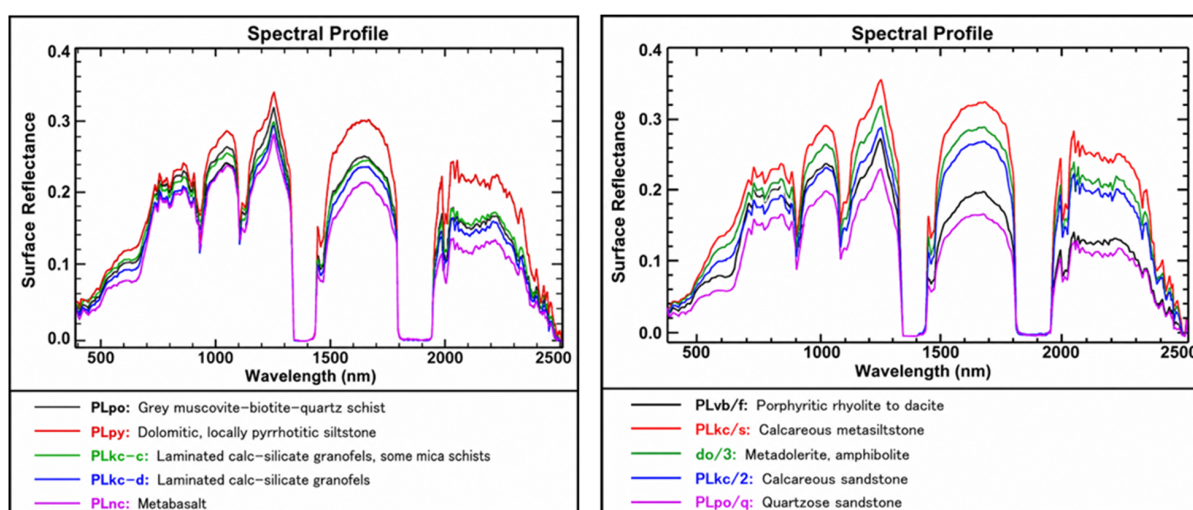


Figure 3. Cont.

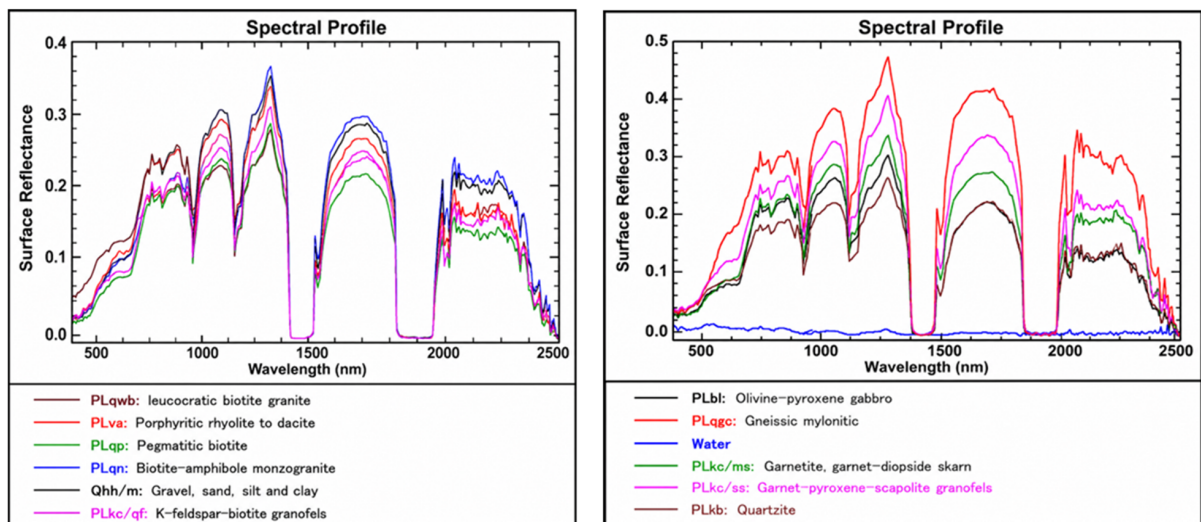


Figure 3. Representative PRISMA surface reflectance spectra extracted from homogeneous regions of interest (ROIs) corresponding to the lithological classes used in the final classification map. Spectra were derived from the PRISMA image used in this study.

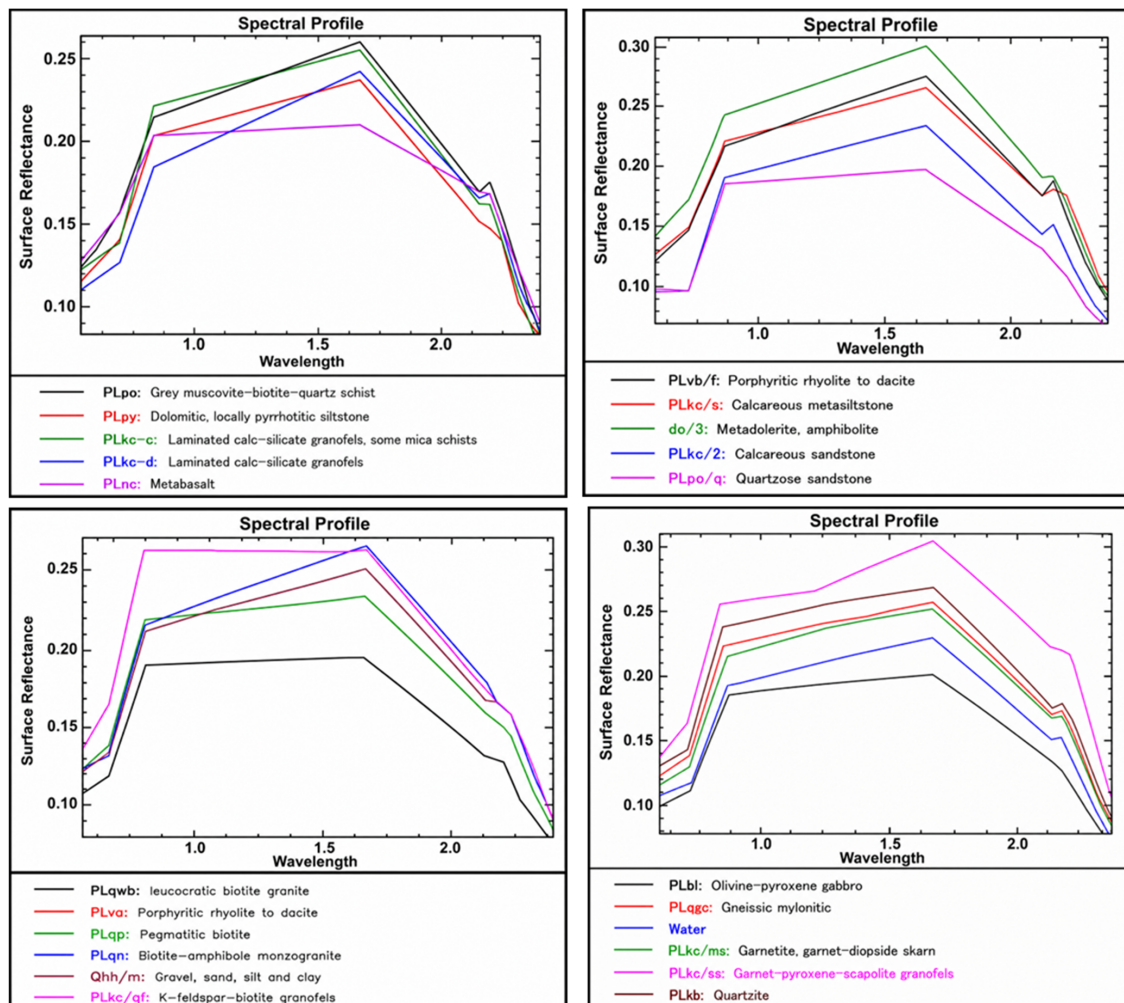


Figure 4. Representative ASTER surface reflectance spectra extracted from homogeneous regions of interest (ROIs) corresponding to the lithological classes used in the final classification map. Spectra were derived from the ASTER image used in this study.

Representative spectral signatures derived from the PRISMA hyperspectral, and ASTER multispectral datasets are shown in Figure 3 and Figure 4, respectively. While both datasets capture variations among the lithological units, the PRISMA spectra provide a more detailed representation of spectral characteristics owing to their higher spectral resolution. The ASTER spectra show broader spectral responses with fewer distinguishable features. These differences demonstrate the potential advantages of hyperspectral data for lithological discrimination and mineralogical characterization.

2.4. Methods

The methodological framework of this study consists of several sequential steps, including image preprocessing, processing, and postprocessing (Figure 5).

2.4.1. Preprocessing

Preprocessing is an essential step in remote sensing analysis because raw satellite imagery often contains geometric distortions, atmospheric effects, and sensor noise that may affect the accuracy of subsequent analysis [51,54]. In this study, the preprocessing workflow included atmospheric correction (evaluated), layer stacking, image subsetting, resampling, and Minimum Noise Fraction (MNF) transformation.

For the ASTER dataset (Level 1T), geometric correction is already applied; however, atmospheric correction is not included in this product. Therefore, the ASTER imagery was radiometrically calibrated and converted from digital numbers (DNs) to top-of-atmosphere (TOA) reflectance prior to analysis. Atmospheric correction was subsequently evaluated using the FLAASH module; however, the corrected data resulted in lower classification accuracy compared to the original reflectance dataset. An additional atmospheric correction test was conducted using the Dark Object Subtraction (DOS) method. The DOS-corrected imagery produced classification accuracies comparable to, or slightly lower than, those obtained from the original TOA reflectance dataset. Similar results were observed for the FLAASH-corrected imagery. These findings suggest that the tested atmospheric correction methods did not provide measurable improvements in classification performance for this study. Therefore, the original TOA reflectance dataset was retained for subsequent analyses. Although atmospheric correction is generally recommended for quantitative spectral analysis, the classification approach adopted in this study relies primarily on relative spectral differences rather than absolute reflectance values. Previous studies have shown that atmospheric correction is not always necessary for classification-based applications, particularly when training and classification data are on the same relative scale [80,81].

For the PRISMA dataset, Level-2C (surface reflectance) products were used, for which both geometric and atmospheric corrections had already been applied. Therefore, no additional atmospheric processing was required. Consequently, both ASTER and PRISMA datasets were analysed within a reflectance-based framework, ensuring consistency in spectral interpretation and enabling a meaningful comparison of classification performance between the multispectral ASTER and hyperspectral PRISMA datasets.

Layer stacking was performed by combining the available VNIR and SWIR bands into a single multiband dataset, facilitating efficient data handling and analysis. Image subsetting was then used to extract the study area from the full scene, reducing data volume and focusing the analysis on the region of interest.

To ensure spatial consistency between the datasets, all images used in the classification were resampled to a common spatial resolution of 30 m. For ASTER, the VNIR bands (15 m) were resampled to 30 m using the nearest-neighbour resampling method to match the native spatial resolution of the SWIR bands (30 m), while preserving the original spectral

values. The PRISMA hyperspectral dataset has an approximate spatial resolution of 30 m and therefore did not require additional spatial resampling. Following preprocessing, all datasets were co-registered to the same coordinate system and spatial grid to ensure pixel-to-pixel alignment during classification and accuracy assessment.

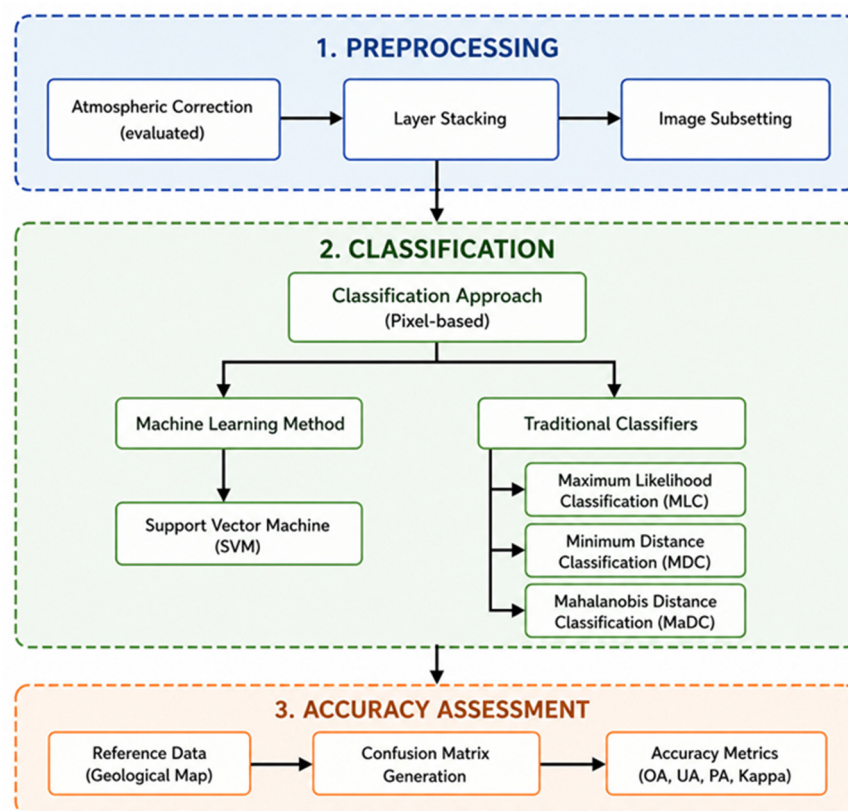


Figure 5. Flowchart of the methodological framework, including preprocessing, classification, and accuracy assessment.

Furthermore, the Minimum Noise Fraction (MNF) transformation was employed to enhance the signal-to-noise ratio of the datasets. The MNF transform reduces data dimensionality by separating noise-dominated components from those containing useful spectral information and ordering the components according to decreasing signal-to-noise ratio. The MNF eigenvalue distribution showed a rapid decrease after the first few components, indicating that most useful image information was concentrated within the leading MNF bands, whereas later components were increasingly dominated by noise. Preliminary experiments indicated that inclusion of additional MNF components did not improve classification performance. Therefore, only the first three MNF components were used for the Maximum Likelihood Classification (MLC) of the PRISMA dataset to reduce dimensionality, avoid singular covariance matrix problems, and ensure stable classification performance [82,83]. In contrast, all MNF components were retained for ASTER data because of its substantially lower spectral dimensionality and were used in all classification processes.

2.4.2. Image Processing

Supervised Classification

Supervised classification requires selecting representative training samples that correspond to known lithological classes [51,84,85]. Training samples were selected based on geological maps and image interpretation. A total of 22 lithological classes were defined in the study area (Table 3). For each class, multiple training pixels (regions of interest)

were collected from homogeneous areas to ensure adequate spectral representation and spatial coverage.

Training endmembers were selected from these homogeneous ROIs to characterize the spectral properties of each lithological unit. In the absence of field spectral measurements, geological maps and image-derived spectra were used as reference data. The implications of this reference data choice for accuracy assessment are discussed in Section 2.4.3.

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm widely used in remote sensing classification due to its strong generalization capability and effectiveness with high-dimensional data [57,86]. The algorithm identifies an optimal separating hyperplane in the feature space that maximizes the margin between different classes. By employing kernel functions, SVM can transform non-linearly separable data into a higher-dimensional space where linear separation becomes possible. This characteristic makes SVM particularly suitable for complex spectral datasets such as multispectral and hyperspectral imagery, where spectral signatures of lithological units may overlap [87].

The Support Vector Machine (SVM) classifier with a Radial Basis Function (RBF) kernel was implemented in ENVI software. SVM is a supervised machine learning algorithm widely used in remote sensing classification because of its ability to handle high-dimensional datasets and complex class boundaries [57]. The SVM classifier was implemented using a Radial Basis Function (RBF) kernel. The penalty parameter (C) was set to 100, and the kernel parameter (gamma) was set to 0.111. These parameter values were retained for all SVM classification experiments to ensure methodological consistency and facilitate direct comparison between the ASTER and PRISMA datasets.

Mahalanobis Distance Classification (MaDC)

Mahalanobis Distance Classification is a statistical classifier that assigns each pixel to the class with the minimum Mahalanobis Distance from the class mean [51,88]. Unlike simple distance-based methods, this approach considers the variance and covariance structure of the spectral bands within each class. By accounting for the statistical distribution of the training data, Mahalanobis Distance classification (MaDC) can improve class discrimination when spectral variability differs between classes [89].

Minimum Distance Classification (MDC)

Minimum Distance Classification is one of the simplest and most computationally efficient supervised classification techniques used in remote sensing [54]. The algorithm computes the Euclidean distance between each pixel's spectral values and the mean spectral signature of each training class. Each pixel is then assigned to the class whose mean spectral value is closest to it. Although this method is straightforward and fast, it does not consider class variance or covariance, which can lead to misclassification when spectral signatures of different lithological units are similar [53,90].

Maximum Likelihood Classification (MLC)

Maximum Likelihood Classification (MLC) is a widely used statistical classification approach that assumes the spectral values of each class follow a normal (Gaussian) distribution [51,54]. The algorithm computes the probability that each pixel belongs to each class using the mean vector and covariance matrix derived from the training samples. The pixel is then assigned to the class with the highest probability. Because it accounts for class variability and statistical distributions, Maximum Likelihood is often considered one of the most reliable traditional classifiers for multispectral remote sensing data [91,92].

ROIs were manually delineated from homogeneous areas based on the Geological Survey of Queensland (GSQ) geological map and visual interpretation of the PRISMA imagery (Figure 6). Multiple ROIs were selected for each lithological class to ensure adequate spectral representation and spatial coverage across the study area.

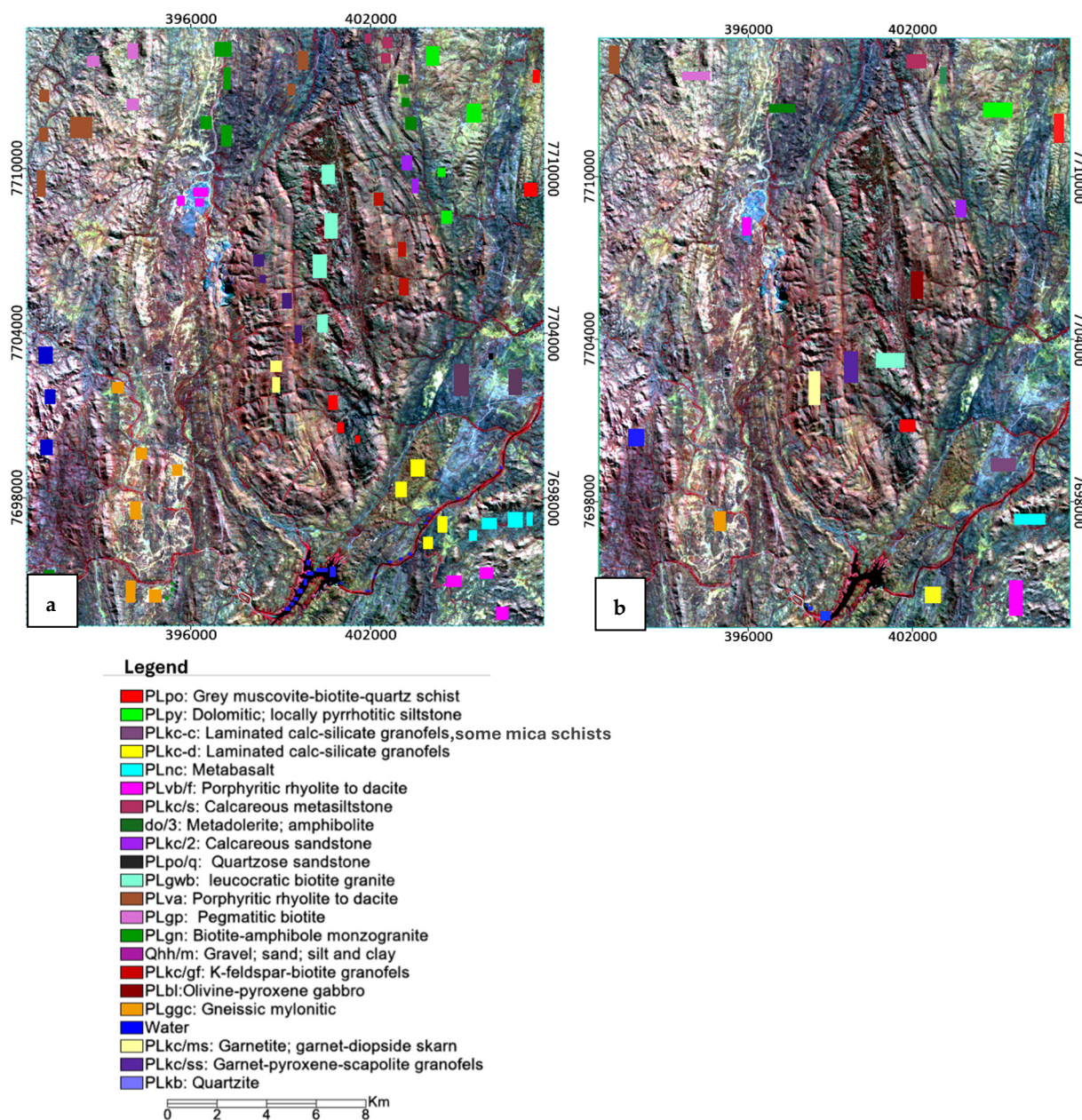


Figure 6. Spatial distribution of training (a) and independent (b) validation ROIs used for supervised lithological classification and accuracy assessment. Training and validation ROIs were spatially separated to ensure independent accuracy evaluation.

The number of training pixels extracted from the regions of interest (ROIs) for each lithological class is summarized in Table 5. Multiple ROIs were delineated for each class from spectrally homogeneous areas identified using the GSQ geological map and visual interpretation of the PRISMA imagery. The selected ROIs were distributed throughout the study area to ensure adequate spectral representation and spatial coverage.

Table 5. Number of training pixels extracted from regions of interest (ROIs) for each lithological class used in the supervised classification.

Lithological Unit	Rock Unit Name	Training Pixels
PLpo	Mount Roseby Schist	383
PLpy	Lady Clayre Formation	1042
PLkc-c	Corella Formation-c	1143
PLkc-d	Corella Formation-d	968
PLnc	Metabasalt	797
PLvb/f	Bulunga Volcanics	681
PLkc/s	Corella Formation-s	635
do/3	Mafic unit (do/3-MI)	868
PLkc/2	Corella Formation-2	360
PLpo/q	Mount Roseby Schist (quartz-rich)	102
PLgwb	Burstall Granite	1553
PLva	Argylla Formation	1707
PLgp	Playboy Granite	606
PLgn	Natalie Granite	1131
Qhh/m	Qa-QLD	395
PLkc/gf	Corella Formation-gf	356
PLbl	Ballara Quartzite	569
PLggc	Greens Creek Quartz Monzonite	1303
Water	Water	496
PLkc/ms	Corella Formation-ms	353
PLkc/ss	Corella Formation-ss	635
PLkb	Quartzite	818

For accuracy assessment, an independent set of validation ROIs was manually delineated for each of the 22 lithological classes (Table 6). Validation ROIs were manually delineated using the Geological Survey of Queensland (GSQ) geological map as the primary reference, together with visual interpretation of the PRISMA and ASTER imagery. Validation polygons were selected only within homogeneous lithological areas where the geological map and the spectral characteristics of the satellite imagery were in clear agreement, thereby minimizing mixed pixels and class ambiguity. These validation ROIs were spatially separated from the training ROIs and were used exclusively for accuracy assessment. No validation pixels were included in the training process. Training and validation ROIs were delineated as separate polygons, and no polygon was used for both training and validation.

Table 6. Number of independent validation pixels extracted from regions of interest (ROIs) for each lithological unit used in the accuracy assessment.

Lithological Unit	Rock Unit Name	Validation Pixels
PLpo	Mount Roseby Schist	385
PLpy	Lady Clayre Formation	646
PLkc-c	Corella Formation-c	510
PLkc-d	Corella Formation-d	357
PLnc	Metabasalt	432

Table 6. *Cont.*

Lithological Unit	Rock Unit Name	Validation Pixels
PLvb/f	Bulunga Volcanics	645
PLkc/s	Corella Formation-s	384
do/3	Mafic unit (do/3-MI)	154
PLkc/2	Corella Formation-2	220
PLpo/q	Mount Roseby Schist (quartz-rich)	40
PLgwb	Burstall Granite	561
PLva	Argylla Formation	455
PLgp	Playboy Granite	330
PLgn	Natalie Granite	290
Qhh/m	Qa-QLD	189
PLkc/gf	Corella Formation-gf	252
PLbl	Ballara Quartzite	510
PLggc	Greens Creek Quartz Monzonite	299
Water	Water	142
PLkc/ms	Corella Formation-ms	559
PLkc/ss	Corella Formation-ss	663
PLkb	Quartzite	418

2.4.3. Postprocessing and Accuracy Assessment

After the classification process, no additional postprocessing was applied in order to preserve the original classification outputs. The accuracy of the classification results was evaluated using a confusion matrix, which is one of the most widely used methods for assessing classification performance in remote sensing studies [93,94].

Accuracy assessment was performed using a pixel-based confusion matrix. Classification accuracy was assessed using an independent set of validation ROIs that were not used during classifier training. These validation ROIs were manually delineated from spatially separated homogeneous areas of the same lithological units. Overall Accuracy (OA), the Kappa coefficient, Producer's Accuracy, and User's Accuracy were calculated from the resulting confusion matrices. The reference class of each validation ROI was assigned using the GSQ geological map supported by visual interpretation of the satellite imagery.

Based on the confusion matrix, several accuracy metrics were calculated, including Overall Accuracy (OA) and the Kappa coefficient, which indicate the level of agreement between the classification results and the reference data [93–95]. Overall Accuracy represents the percentage of correctly classified pixels, while the Kappa coefficient measures the agreement between the classification and reference data, accounting for agreement that may occur by chance. These accuracy assessment metrics were used to compare the performance of the classification algorithms employed in this study and to identify the most reliable approach for lithological mapping.

All image preprocessing and analysis were carried out using ENVI (version 5.6.3, L3Harris Geospatial), QGIS (version 3.40.12), and ArcGIS Pro (version 3.6, Esri). Regions of interest (ROIs) were manually delineated based on geological maps and expert interpretation. The workflow did not involve custom scripting, and all processing steps were conducted using standard tools within the aforementioned software.

3. Results

Lithological classification maps derived from the ASTER and PRISMA datasets are presented in Figures 7 and 8, respectively, while the corresponding accuracy assessment results are summarized in Table 7.

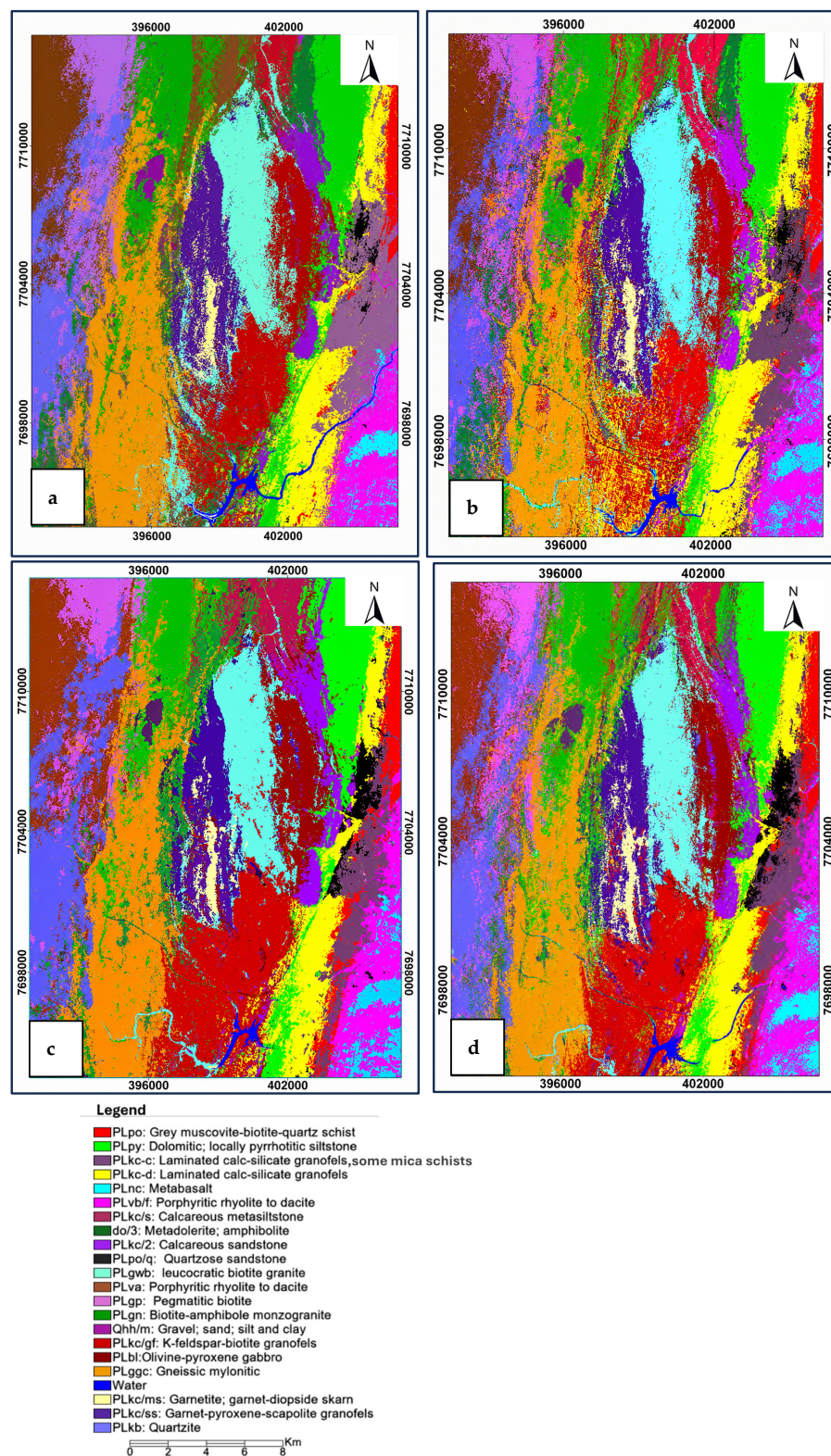


Figure 7. Lithological classification map produced using the (a) SVM, (b) MaDC, (c) MDC, and (d) MLC algorithms for PRISMA datasets.

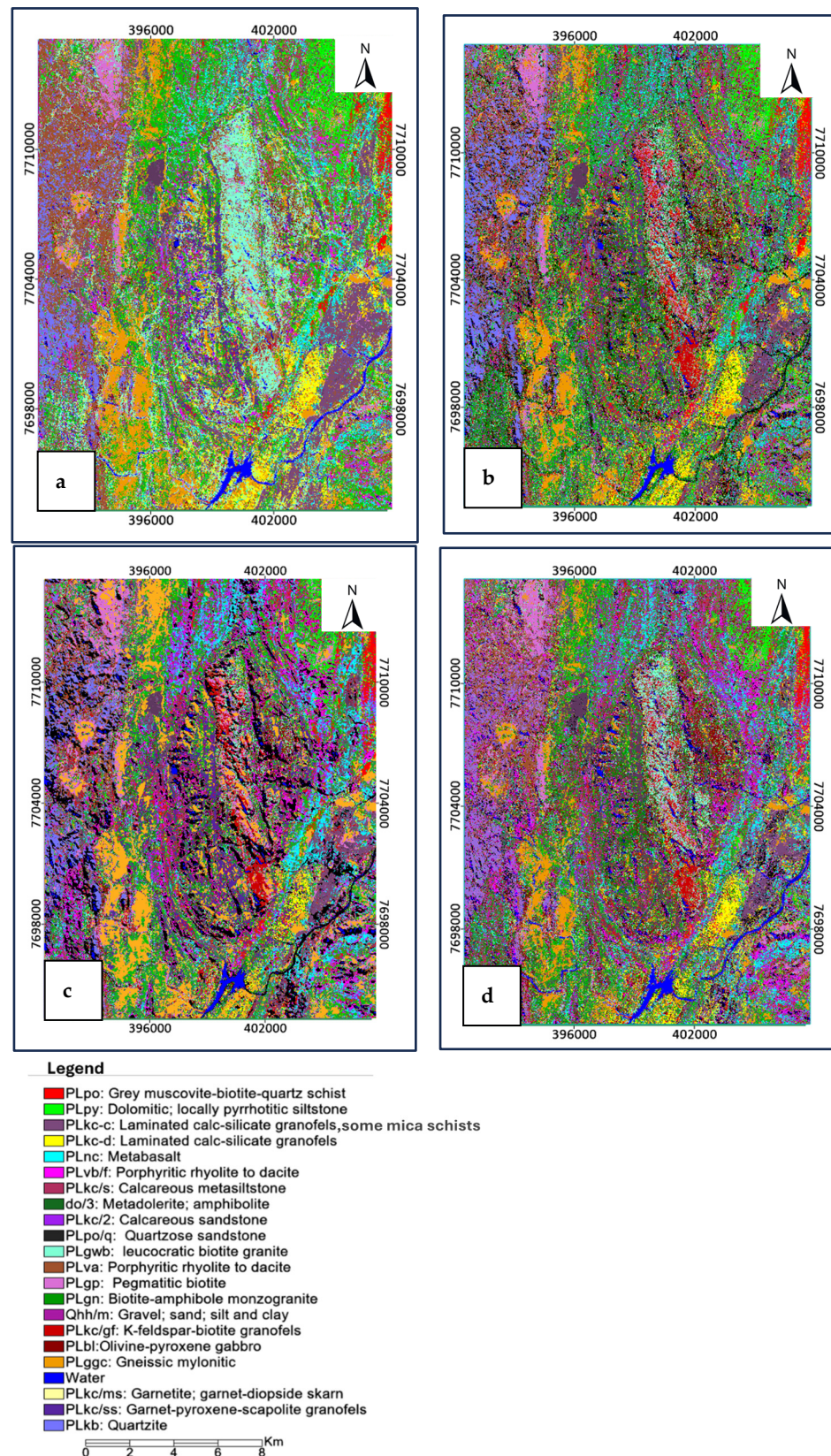


Figure 8. Lithological classification map produced using the (a) SVM, (b) MaDC, (c) MDC, and (d) MLC algorithms for ASTER datasets.

Table 7. Accuracy comparison of supervised classification algorithms applied to PRISMA hyperspectral and ASTER multispectral imagery based on Overall Accuracy and Kappa coefficient.

Method	PRISMA Overall Accuracy (%)	PRISMA Kappa Coefficient	ASTER Overall Accuracy (%)	ASTER Kappa Coefficient
Support Vector Machine Classification (SVM)	82.03	0.81	27.63	0.24
Mahalanobis Distance Classification (MaDC)	73.59	0.72	25.22	0.22
Minimum Distance Classification (MDC)	80.37	0.79	22.02	0.18
Maximum Likelihood Classification (MLC)	59.05	0.57	33.29	0.30

Among the evaluated classifiers, the Support Vector Machine (SVM) achieved the highest classification performance for the PRISMA dataset, with an Overall Accuracy (OA) of 82.03% and a Kappa coefficient of 0.81. The Minimum Distance Classification (MDC) also produced high classification performance, achieving an Overall Accuracy of 80.37% and a Kappa coefficient of 0.79. The Mahalanobis Distance Classification (MaDC) yielded an Overall Accuracy of 73.59% and a Kappa coefficient of 0.72, whereas the Maximum Likelihood Classification (MLC) produced the lowest performance for the PRISMA dataset, with an Overall Accuracy of 59.05% and a Kappa coefficient of 0.57 (Table 7).

The class-wise accuracy assessment for the SVM classification (Table 8) indicates considerable variation among lithological units. Several classes, including PLpo, PLpy, PLkc-d, PLgn, Qhh/m, and PLkc/gf, achieved high Producer's and User's Accuracy values, demonstrating strong spectral separability. In contrast, lower accuracies were observed for PLnc, PLvb/f, PLkc/ms, PLkc/ss, Water, and PLkb, indicating greater confusion among lithological units with similar spectral characteristics.

Table 8. Class-wise accuracy assessment for selected lithological units (SVM classification applied to the PRISMA dataset).

Class	Producer's Accuracy (%)	User's Accuracy (%)
PLpo	95.58	99.73
PLpy	100	97.73
PLkc-c	92.35	95.73
PLkc-d	98.88	90.05
PLnc	77.31	76.43
PLvb/f	84.03	83.64
PLkc/s	81.51	94.85
do/3	90.91	60.61
PLkc/2	96.82	90.25
PLpo/q	77.50	100
PLgwb	96.08	67.63
PLva	96.04	78.18
PLgp	94.85	71.95
PLgn	98.62	86.67
Qhh/m	95.24	98.90

Table 8. *Cont.*

Class	Producer's Accuracy (%)	User's Accuracy (%)
PLkc/gf	96.03	94.53
PLbl	78.04	93.21
PLggc	86.62	98.85
Water	31.69	100
PLkc/ms	30.05	56.57
PLkc/ss	66.82	54.56
PLkb	48.56	95.75

The confusion matrix (Table 9) indicates that most classification errors occurred between lithological units with similar spectral characteristics. The strongest confusion was observed between PLnc (Metabasalt) and PLvb/f (Bulonga Volcanics), where 99 validation pixels of PLvb/f were classified as PLnc and 93 validation pixels of PLnc were classified as PLvb/f. Additional confusion was observed between PLgwb and PLkc/ss, with 118 PLkc/ss pixels classified as PLgwb, between PLva and PLkb, with 81 PLkb pixels classified as PLva, and between PLkc/ms and PLkc/ss, where 95 PLkc/ss pixels were classified as PLkc/ms and 367 PLkc/ms pixels were classified as PLkc/ss. These misclassifications reflect the spectral similarity among these lithological units and highlight the challenges associated with discriminating lithologies that exhibit overlapping VNIR–SWIR spectral responses.

For the ASTER dataset, classification accuracies were substantially lower than those obtained from the PRISMA imagery. Among the evaluated algorithms, Maximum Likelihood Classification (MLC) achieved the highest Overall Accuracy (33.29%) with a Kappa coefficient of 0.30, followed by Support Vector Machine (SVM) (27.63%, Kappa = 0.24), Mahalanobis Distance Classification (MaDC) (25.22%, Kappa = 0.22), and Minimum Distance Classification (MDC) (22.02%, Kappa = 0.18) (Table 7). These results indicate that the limited spectral resolution of the multispectral ASTER sensor restricts its ability to discriminate spectrally similar lithological units in this geologically complex area.

Across all four supervised classification algorithms, the PRISMA hyperspectral dataset consistently outperformed the ASTER multispectral dataset in terms of both Overall Accuracy and Kappa coefficient (Table 7). The revised accuracy assessment was based on a completely independent validation dataset composed of validation ROIs that were spatially separated from the training ROIs. Consequently, the reported Overall Accuracy, Producer's Accuracy, User's Accuracy, and Kappa coefficients represent an unbiased estimate of classification performance and are not affected by overlap between training and validation samples. This improvement is primarily attributed to the substantially higher spectral resolution of PRISMA, which captures narrow diagnostic absorption features and provides greater spectral discrimination among lithological units. It should be noted that the ASTER and PRISMA datasets were not processed to the same reflectance level, as ASTER was analysed using TOA reflectance while PRISMA was provided as a Level-2C surface reflectance product. Additional atmospheric correction experiments using both FLAASH and Dark Object Subtraction (DOS) did not improve the classification performance of the ASTER imagery relative to the original TOA reflectance dataset. These findings suggest that the observed performance differences are primarily related to differences in spectral resolution rather than to the atmospheric correction strategy.

Table 9. Confusion matrix for the SVM classifier applied to the PRISMA dataset.

	PLpo	PLpy	PLkc-c	PLkc-d	PLnc	PLvb/f	PLkc/s	do/3	PLkc/2	PLpo/q	PLgwb	PLva	PLgp	PLgn	Qhh/m	PLkc/gf	PLbl	PLggc	Water	PLkc/ms	PLkc/ss	PLkb	Total
PLpo	368	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	369
PLpy	0	646	0	1	0	0	1	0	0	0	3	0	0	0	0	6	3	0	1	0	0	0	661
PLkc-c	0	0	471	3	5	4	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	492
PLkc-d	17	0	21	353	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	392
PLnc	0	0	4	0	334	99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	437
PLvb/f	0	0	13	0	93	542	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	648
PLkc/s	0	0	0	0	0	0	313	14	0	0	0	0	0	0	0	0	1	0	1	0	1	0	330
do/3	0	0	0	0	0	0	32	140	0	0	0	0	0	0	0	0	28	1	1	1	0	28	231
PLkc/2	0	0	0	0	0	0	1	0	213	0	6	0	0	0	0	3	13	0	0	0	0	0	236
PLpo/q	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0	0	0	0	31
PLgwb	0	0	0	0	0	0	11	0	0	0	539	0	0	0	0	0	59	1	50	19	118	0	797
PLva	0	0	0	0	0	0	25	0	0	0	0	437	9	1	0	0	0	6	0	0	0	81	559
PLgp	0	0	0	0	0	0	0	0	0	0	0	17	313	0	0	0	0	0	0	0	0	105	435
PLgn	0	0	0	0	0	0	0	0	0	0	0	0	0	286	9	0	0	32	3	0	0	0	330
Qhh/m	0	0	0	0	0	0	0	0	0	0	0	0	0	2	180	0	0	0	0	0	0	0	182
PLkc/gf	0	0	0	0	0	0	0	1	0	0	3	0	0	0	0	242	7	0	3	0	0	0	256
PLbl	0	0	0	0	0	0	0	0	7	0	9	0	0	0	0	0	398	0	3	4	6	0	427
PLggc	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	259	1	0	0	1	262
Water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	45
PLkc/ms	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	168	95	0	297
PLkc/ss	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	367	443	0	812
PLkb	0	0	0	0	0	0	0	0	0	0	0	1	8	0	0	0	0	0	0	0	0	203	212
Total	385	646	510	357	432	645	384	154	220	40	561	455	330	290	189	252	510	299	142	559	663	418	8441

4. Discussion

The classification results highlight the critical role of spectral resolution in lithological discrimination and support the integration of hyperspectral satellite data with machine learning for geological mapping [18,25,39].

The accuracy assessment indicates that nearly all classification algorithms performed considerably better on the PRISMA dataset, which can be attributed to the fundamental differences in spectral resolution between multispectral and hyperspectral sensors. Multispectral sensors record reflectance in a limited number of relatively broad spectral bands, whereas hyperspectral sensors capture hundreds of narrow, contiguous spectral bands, providing a more detailed representation of surface materials.

These findings are consistent with those reported by Shirkhani et al. (2025) [39], who compared ASTER and PRISMA imagery for mineral mapping in the Bafq mining district, Iran. Their study demonstrated that PRISMA provided superior discrimination of spectrally similar geological materials owing to its higher spectral resolution. A similar pattern was observed in the present study, where PRISMA consistently achieved substantially higher classification accuracies than ASTER across all evaluated classifiers. However, whereas Shirkhani et al. (2025) [39] focused primarily on mineral mapping, the present study evaluated lithological classification across 22 lithological units in the geologically complex Mount Isa Inlier using four supervised classification algorithms. Despite these differences in study objectives and geological setting, both studies demonstrate the clear advantage of hyperspectral imagery for discriminating spectrally similar geological materials. This agreement suggests that the improved spectral resolution of PRISMA provides robust benefits for geological remote sensing across a range of geological environments.

In geological remote sensing, many rock-forming minerals exhibit diagnostic absorption features within the Shortwave Infrared (SWIR) region, associated with hydroxyl, carbonate, and metal–oxygen bonds. Because these features are often narrow and subtle, they may not be fully captured by multispectral sensors. Hyperspectral sensors such as PRISMA can resolve these characteristics, improving mineralogical identification and lithological discrimination [13,16,18,40,42]. For example, carbonate-bearing units exhibit strong absorption near $\sim 2.33\ \mu\text{m}$, clay-rich lithologies show Al–OH absorption near $\sim 2.20\ \mu\text{m}$, and mafic units display broad absorption features around $\sim 1.0\ \mu\text{m}$ [1,23,40,42].

The depth and clarity of these absorption features vary between lithological units and directly influence classification performance. Units with strong and well-defined spectral signatures, such as carbonate- and mica-rich lithologies, achieve higher classification accuracy, whereas spectrally featureless or overlapping units, such as quartzite, exhibit lower separability. These observations indicate that classification performance is closely linked to the spectral properties of lithological units rather than being solely algorithm-driven.

As reported in Section 3, the Support Vector Machine (SVM) achieved the highest classification accuracy for the PRISMA dataset, with an Overall Accuracy of 82.03% and a Kappa coefficient of 0.81 (Table 7). This performance reflects the ability of SVM to model complex nonlinear relationships within high-dimensional hyperspectral data [36,57]. Hyperspectral datasets contain numerous correlated spectral variables, and SVM is particularly effective in extracting meaningful patterns from such data. Previous studies have similarly demonstrated that SVM often outperforms conventional classifiers such as Maximum Likelihood in high-dimensional remote sensing applications [20,96].

The class-wise accuracy assessment (Table 8) provides important insights into the spectral separability of individual lithological units. Lithological units such as PLpo, PLpy, PLkc-d, PLgn, Qhh/m, and PLkc/gf achieved high Producer's and User's Accuracy values, indicating distinct spectral characteristics and reliable discrimination by the SVM classifier. In contrast, lower classification accuracies were observed for PLnc, PLvb/f, PLkc/ms,

PLkc/ss, and PLkb, reflecting the spectral similarity and overlap among these lithological units. Although the Water class also exhibited relatively low Producer's Accuracy, it was represented by only 142 validation pixels. Therefore, its class accuracy should be interpreted with caution because the relatively small validation sample size may have amplified the effect of individual misclassified pixels.

The confusion matrix (Table 9) indicates that most classification errors occurred between lithological units with overlapping spectral characteristics. The most pronounced confusion was observed between PLnc (Metabasalt) and PLvb/f (Bulonga Volcanics), as well as between PLkc/ms and PLkc/ss, suggesting that these units exhibit similar spectral responses within the VNIR–SWIR wavelength range despite differences in geological origin.

The classification patterns also reflect the influence of metamorphism and alteration processes. In the Mount Isa Inlier, deformation and metamorphism modify mineral assemblages and spectral responses, leading to mixed spectral signatures and partial overlap between classes. This explains the moderate reduction in classification accuracy for certain units despite the high spectral resolution of PRISMA.

From a geological perspective, hyperspectral remote sensing combined with machine learning effectively discriminates major lithological units in complex terrain. Accurate mapping of carbonate-bearing formations, schists, and granitic intrusions is particularly relevant for mineral exploration, as these units are commonly associated with hydrothermal alteration and ore-forming processes.

In contrast, classification performance for the ASTER dataset was considerably lower than that obtained from the PRISMA imagery. Maximum Likelihood Classification (MLC) achieved the highest Overall Accuracy (33.29%) and Kappa coefficient (0.30), followed by SVM (27.63%, Kappa = 0.24), Mahalanobis Distance Classification (25.22%, Kappa = 0.22), and Minimum Distance Classification (22.02%, Kappa = 0.18). These results demonstrate that the limited spectral resolution of ASTER restricts its ability to discriminate spectrally similar lithological units in complex geological environments [1,40,42].

The classification accuracies obtained for ASTER imagery in this study are lower than those reported in some previous lithological mapping investigations. For example, previous ASTER-based studies have often reported substantially higher classification accuracies in areas containing fewer lithological classes and lower geological complexity [6,31]. Several factors may explain this difference. First, the study area is characterized by high geological complexity and includes 22 lithological classes with partially overlapping spectral characteristics. Second, the classification was conducted at a regional scale, whereas many previous studies focused on fewer lithological units or smaller areas with greater spectral separability [1,5,6]. Third, ASTER provides only nine VNIR–SWIR bands for lithological discrimination, which limits its ability to distinguish spectrally similar rock types and subtle mineralogical variations [1,16,18,67,68]. Finally, differences in preprocessing procedures, training sample selection, validation strategies, machine learning implementation, and geological conditions may also contribute to variations in reported classification accuracies among studies [6,31]. Therefore, the lower ASTER accuracy observed here should be interpreted within the context of the challenging geological setting and the large number of lithological classes considered.

Several additional factors influence classification accuracy. Training data quality plays a critical role, as inadequate or poorly distributed samples can reduce classification reliability [51]. Environmental factors such as vegetation cover, soil, and weathering can also modify spectral responses and reduce class separability [15,18,25].

These factors likely contributed to some of the observed misclassification, particularly in spectrally heterogeneous and weathered zones. Future studies could improve

classification reliability by incorporating independent validation datasets, field spectral measurements, and spatially distributed training samples.

As described in Section 2.4.3, classification accuracy was evaluated using an independent set of validation ROIs that were spatially separated from the training samples. This independent validation strategy provides a more reliable assessment of classification performance and reduces the potential for optimistic accuracy estimates associated with non-independent sampling. Classification errors are also influenced by spatial and geological factors. Misclassification is most likely concentrated along lithological boundaries and in spectrally heterogeneous zones, where abrupt transitions between rock units, structural deformation, and mixed pixels reduce class separability. This interpretation is consistent with the confusion matrix and class-wise accuracy results, which indicate that classification uncertainty is highest for spectrally overlapping lithological units. A full spatial error map was not produced due to the limited availability of independent validation data.

Overall, these findings confirm that classification performance is controlled not only by algorithm choice but also by geological complexity and surface conditions. Careful interpretation within geological context is therefore essential. Future research could further evaluate the integration of hyperspectral imagery with advanced machine learning and deep learning approaches using spatially independent validation datasets. Such developments may improve the robustness and transferability of lithological classification in structurally complex and spectrally heterogeneous geological terrains.

Beyond confirming the general advantage of hyperspectral data, this study highlights specific contributions. Whereas Bahrami et al. (2024) [31] focused on ASTER data and Ali-Bik et al. (2025) [38] applied PRISMA in a different geological setting (Sinai), this study presents a direct, side-by-side comparison of ASTER and PRISMA datasets within the Proterozoic Mount Isa Inlier. The results demonstrate that improvements in classification accuracy are lithology-dependent, with the greatest gains observed for units with strong diagnostic absorption features. Hyperspectral data provides the greatest advantage in complex terrains where subtle mineralogical differences must be resolved. From an applied perspective, these findings support the use of hyperspectral remote sensing for improved lithological discrimination and mineral exploration targeting in similar geological settings.

Limitations and Future Challenges

Several limitations should be considered when interpreting the results of this study. First, although independent validation ROIs were used, both the training and validation data were derived from geological map interpretation and manually delineated image-based ROIs rather than field observations. Consequently, some uncertainty may remain in areas with complex lithological boundaries or mixed pixels.

Second, field-based geological observations and in situ spectral measurements were not available for validation. The reference data were derived from existing geological maps and image interpretation, which may introduce uncertainty in areas with complex lithological boundaries or mixed pixels.

Third, the ASTER and PRISMA datasets were acquired in different years (2005 and 2022, respectively). Although lithological units are generally stable over geological timescales, temporal differences in surface conditions such as weathering, vegetation cover, and soil moisture may have influenced the spectral responses observed in the imagery.

Fourth, the study evaluated only four supervised classification algorithms (SVM, MLC, MDC, and MaDC). The objective of this study was not to provide an exhaustive comparison of all available machine learning classifiers, but rather to evaluate the relative lithological mapping performance of multispectral (ASTER) and hyperspectral (PRISMA) datasets under a consistent classification framework. Therefore, the selected classifiers

were chosen to represent both conventional statistical and machine learning approaches while maintaining methodological consistency between datasets. Additional classifiers such as Random Forest (RF), Artificial Neural Networks (ANNs), Gradient Boosting, and deep learning methods may provide further insights and should be investigated in future research.

Future work should focus on the integration of field spectroscopy, the acquisition of field-based geological observations for independent verification, the fusion of hyperspectral and multispectral datasets, and the evaluation of advanced machine learning and deep learning frameworks. Such developments would further improve the robustness, transferability, and operational applicability of lithological mapping in complex geological environments.

5. Conclusions

This study investigated the effectiveness of multispectral and hyperspectral satellite imagery for lithological mapping by comparing classification results derived from ASTER and PRISMA datasets using several supervised classification algorithms. The results demonstrate that hyperspectral imagery significantly improves lithological discrimination compared with multispectral data. The accuracy assessment showed that the PRISMA hyperspectral dataset achieved substantially higher classification accuracy across most classification algorithms. In particular, the Support Vector Machine (SVM) classifier achieved the highest classification performance for the PRISMA dataset, with an Overall Accuracy of 82.03% and a Kappa coefficient of 0.81. Classification accuracy was evaluated using an independent set of validation ROIs that were spatially separated from the training samples, providing a more robust and reliable assessment of classifier performance. Nevertheless, future studies would benefit from additional field-based validation and in situ spectral measurements to further strengthen the reliability of lithological mapping. In contrast, the classification results obtained from the multispectral ASTER dataset were considerably lower. Among the evaluated classifiers, the Maximum Likelihood Classification achieved the highest accuracy for ASTER imagery, although the overall classification performance remained moderate. The gap reflects the difficulty of resolving subtle diagnostic mineral absorption features using a limited number of broad spectral bands, particularly in a geologically complex study area containing 22 lithological classes. These findings demonstrate the practical value of hyperspectral satellite data for regional lithological mapping in complex geological terrains.

Overall, the results confirm that hyperspectral remote sensing provides a powerful tool for improving lithological mapping and geological interpretation. However, multispectral datasets such as ASTER remain valuable due to their wide spatial coverage and long-term data availability. Future work should (i) adopt spatially independent validation (block-based cross-validation or held-out field sites), (ii) incorporate field-based spectral and geological measurements, (iii) test sensor fusion of ASTER and PRISMA, and (iv) evaluate deep learning classifiers alongside conventional methods to build on the framework presented here. The use of spatially independent validation ROIs further increases confidence in the reported classification accuracies and demonstrates the robustness of the proposed methodology.

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Abbreviations

The following abbreviations are used in this manuscript:

PRISMA	PRecursore IperSpettrale della Missione Applicativa
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
SVM	Support Vector Machine
MaDC	Mahalanobis Distance Classification
MDC	Minimum Distance Classification
MLC	Maximum Likelihood Classification
OA	Overall Accuracy

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