



Evaluating ASTER data and field spectrometry for lithological discrimination in semi-arid region, Northeast Kohat Plateau, Pakistan

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Received: 13 September 2023 / Accepted: 11 March 2024 / Published online: 10 April 2024
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Abstract

This study employs data of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) sensor to delineate and map the distribution of sedimentary lithologies in the semi-arid region of Kohat Plateau, Pakistan. False color composites (FCC) and various image transformation and enhancement techniques including the principal component analysis (PCA), minimum noise fraction (MNF), and band rationing (BR) were used successfully to differentiate four lithological classes. These lithologies include chemically/biochemically formed beds of the marine environment and detrital sequences of marginal marine to the riverine environment. FCC from original reflectance data, PCA, and BR techniques displayed more prominent lithological variation. To map the lithology and show the potential of ASTER data, field spectrometry over the barren lithologies was carried out. The end-member spectra from field spectrometry shows strong agreement with the pixels spectra from ASTER scene. The Spectral Angle Mapper (SAM) mapping method was then used to produce a classified lithological map, where the image pixels spectra proved more suitable reference, in comparison to the end-member spectra. The accuracy of the classified lithological map was evaluated based on field-based point data, which resulted an overall accuracy of 70% and a Kappa coefficient value of 0.679. Carbonates and evaporites showed relatively higher user and producer accuracies which are attributed to their topographic behavior and weathered scree over the adjacent rock unit. The final lithological map provided a clearer picture of surface geology where the existing geological maps lacked lithological continuity.

Keywords ASTER data · Lithology · SAM · Pakistan

Introduction

Field-based identification, differentiation and mapping of lithological units are often time and cost-intensive. Inaccessibility in rugged terrains is a major obstacle for field-based geological surveys at a local scale. Space-borne remote sensing data is an efficient alternative and is effectively utilized for the seamless mapping of lithological units from local to regional scales (Gomez et al. 2005; Hewson et al. 2005; El Janati et al. 2014; Van der Meer et al. 2014). Retrieving lithological information using remote sensing images minimizes human input and provides information about the regions which are otherwise inaccessible (Nemmour-Zekiri and Oulebsir 2020). Within the domain of remote sensing, the multispectral sensors has been proved effective for identification and mapping of earth's surface features, through the response of selective wavelengths in visible, shortwave and thermal infrared region of electromagnetic spectrum (Feng et al. 2020). A

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multispectral dataset with a high spatial resolution gives more clear and more accurate spatial information related to the location and shape of different features on the ground, whereas, the spectral response reflects its spectroscopic information (Shao et al. 2019). Importantly, the shortwave infrared portion of the multispectral spectrum provides significant spectral variation for lithological discrimination (Beirami and Tangestani 2020), even the chemical composition at the hand specimen level can be estimated both qualitatively and quantitatively (Zaini et al. 2014).

The most commonly used multispectral satellite datasets for geological applications includes data of Land Remote Sensing Satellite System (Landsat), ASTER, and Sentinel-2. The potential of Landsat (mostly Landsat 7 and 8) and Sentinel (mostly 2) has been successfully explored for geological applications (including mineral exploration and lithological mapping) (Gad and Kusky 2006; Bentahar and Raji 2021; Seleim et al. 2022), but both have a limitation of less spectral resolution in the SWIR part of the electromagnetic spectrum. Whereas the ASTER has been proved more effective multispectral sensor for lithological discrimination and exploring the surface distribution of hydrothermal alteration zones in arid to semi-arid terrains (Fakhari et al. 2019; Beirami and Tangestani 2020; Khan et al. 2020). Different combinations of original reflectance data (i.e., untransformed data recorded by the sensors) and transformed image data have the capability to discriminate the surface exposed mineral mixtures and lithologies. The advanced image processing and transformation techniques utilized for geological applications include the principal component analysis (PCA), minimum noise fraction (MNF), Independent Component Analysis (ICA), and Band Ratio (Rajendran et al. 2011; Rajendran 2016; Rajendran and Nasir 2019a, b; Beirami and Tangestani 2020).

The Kohat plateau of Sub-Himalayas in Pakistan contains economical reserves various different earth crust's natural resources. For an instance the gypsum, rock salt, coal and hydrocarbons are extensively reported and produced from Paleogene succession of Kohat Plateau (Malkani et al. 2017; Qureshi et al. 2019, 2020). Although, it has been mapped thoroughly by Geological Survey of Pakistan (GSP) and other researchers but these maps lacks continuity between adjacent sheets or they are very local scale (Fig. 2). Therefore, this research attempts an integrated advanced remote sensing and field spectrometry to generate a detailed and seamless lithological map. Furthermore, the study area lies in the semi-arid to temperate climatic zonation (Sarfaraz et al. 2014), therefore this research will also explore the potential of remote sensing

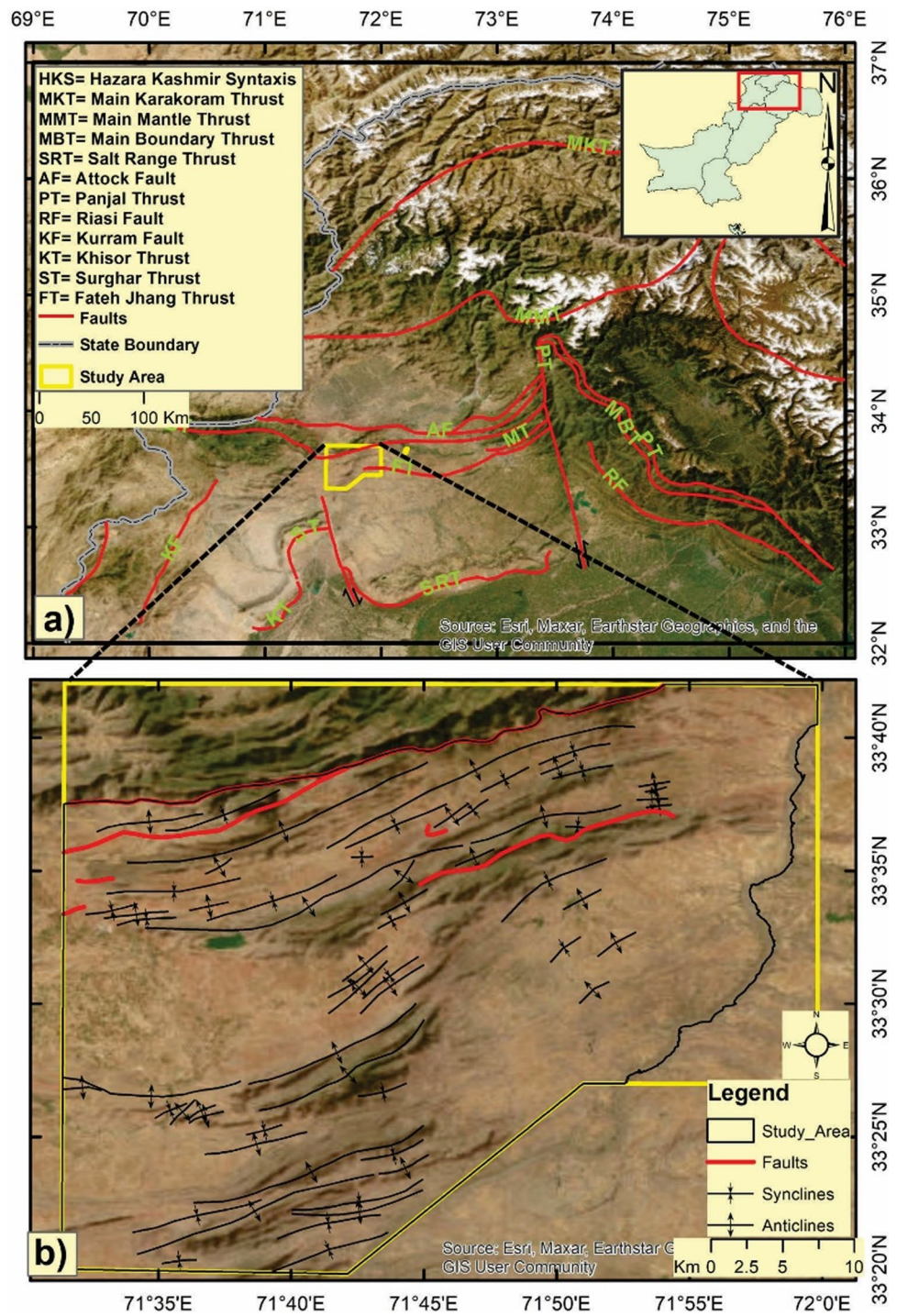
based approach for lithological discrimination in such climatic zones with considerable vegetation cover.

Study area and geology

The study area covers a north-eastern segment of Kohat Plateau, located in the northwestern apex of the sub-Himalayas tectonic division (Ahmad et al. 2001; DiPietro and Pogue 2004). Kohat Plateau is tectonically sutured by Main Boundary Thrust (MBT) in the north and Trans-Indus Ranges (TIR) in the south. Whereas the east–west extent is truncated by Indus River in the east and by the Kurram Fault in the west (Fig. 1a). The Kohat Plateau displays east–west folding of middle Eocene to Miocene sedimentary succession, associated with thrust splays emerging from shale bearing formations of late Paleocene to middle Eocene (Ikram et al. 2020). The presence of double decollement within the subsurface stratigraphic record, causes the intense crustal deformation of the rocks, leading to the high geomorphic relief at the surface level (Abbasi and McElroy 1991; Ghani et al. 2018).

The Miocene–Pliocene Rawalpindi and Siwalik groups mark the surface stratigraphy of the entire plateau, with limited exposures of Paleocene–Eocene shales and carbonates restricted to northern Kohat Plateau adjacent to MBT (Table 1 and Fig. 2). The MBT along the northern margin brings the Jurassic carbonates to the surface, which are thrust over the Miocene Rawalpindi Group (Meisner Jr. et al. 1974; Ahmad et al. 2001). The stratigraphic record shows that up to early Eocene, the plateau remained below the sea-level as evidenced by the outcrops of Paleocene–early Eocene marginal-marine to marine successions (i.e., Hangu, Lockhart, Patala and Panoba formations). The deposition of evaporites (i.e., Bahadur Khel Salt and Jatta Gypsum) are indicative of restricted marginal marine/coastal conditions in the early Eocene. The early Eocene marks the initiation of siliciclastic (marginal marine) influx which deposited in the form of red beds of Kuldana Formation in response to the uplift and subsequent establishment of the initial drainage system associated with Himalayan orogeny (Pivnik and Wells 1996; Raza 2001). The middle Eocene Kohat Formation which is predominantly foraminifera bearing limestone marks marine transgression and inundation of the plateau by sea after the deposition of the Kuldana Formation. The absence of Oligocene strata in the Plateau is an indication of the time of non-deposition until the establishment of the Indus River drainage which led to the deposition of the molasses of the Miocene–Pliocene Rawalpindi and Siwalik groups (Pivnik and Wells 1996).

Fig. 1 **a** Google Earth image showing research study area by highlighting the structural framework of north Pakistan, and **b** structural lineaments and satellite view of landform of the study area (Kazmi and Rana 1982; Ahmad et al. 2001)



The extensive outcrops of the sedimentary successions in the plateau, including lithologies such as shales, limestone, gypsum, rock salt, and sandstone, hold significant economic importance for industries such as construction

(specially cement), agriculture, and energy production. The intercalated clastic and carbonates succession of the continent—marginal marine setting contains the economic reserves of coal and lateritic beds of middle to late

Table 1 Stratigraphic column of the exposed lithologies in the study area (Meissner Jr. et al. 1974a)

Age	Formation	Lithology	Description
Miocene	Kamlial		Purple gray and dark red, medium to coarse grained sandstone with intercalations of mudstone and conglomerate.
	Murree		Dark red to purple and reddish gray sandstone and siltstone, purple to reddish brown mudstone.
Eocene	Kohat		Light gray to cream color, hard, fine to medium crystalline limestone, with occasional greenish gray shales.
	Kuldana		Brownish red, silty shales.
	Shekhan		Sheikhan: Yellowish gray, massive limestone.
	Jatta		Jatta: Light grey to whitish gypsum
	Panoba		Panoba: Grayish green, silty and soft shales.
Paleo-cene	Bahadur Khel		BahadurKhel: White to blackish salt.
	Patala		Dark gray to cream color, thin bedded, shales with occasional limestone
	Lockhart		Dark gray to yellowish, nodular, limestone.

LEGEND Limestone Salt Gypsum Sandstone Shale

Paleocene age in various localities of southern Kohat Plateau, the marginal marine shallow lagoonal to sabkha flats deposition bears significant potentials of various economic minerals like gypsum, rock-salt, limestone and hydrocarbon source rock potential (Pivnik and Wells 1996; Malkani et al. 2017; Qureshi et al. 2019, 2020).

Materials and methods

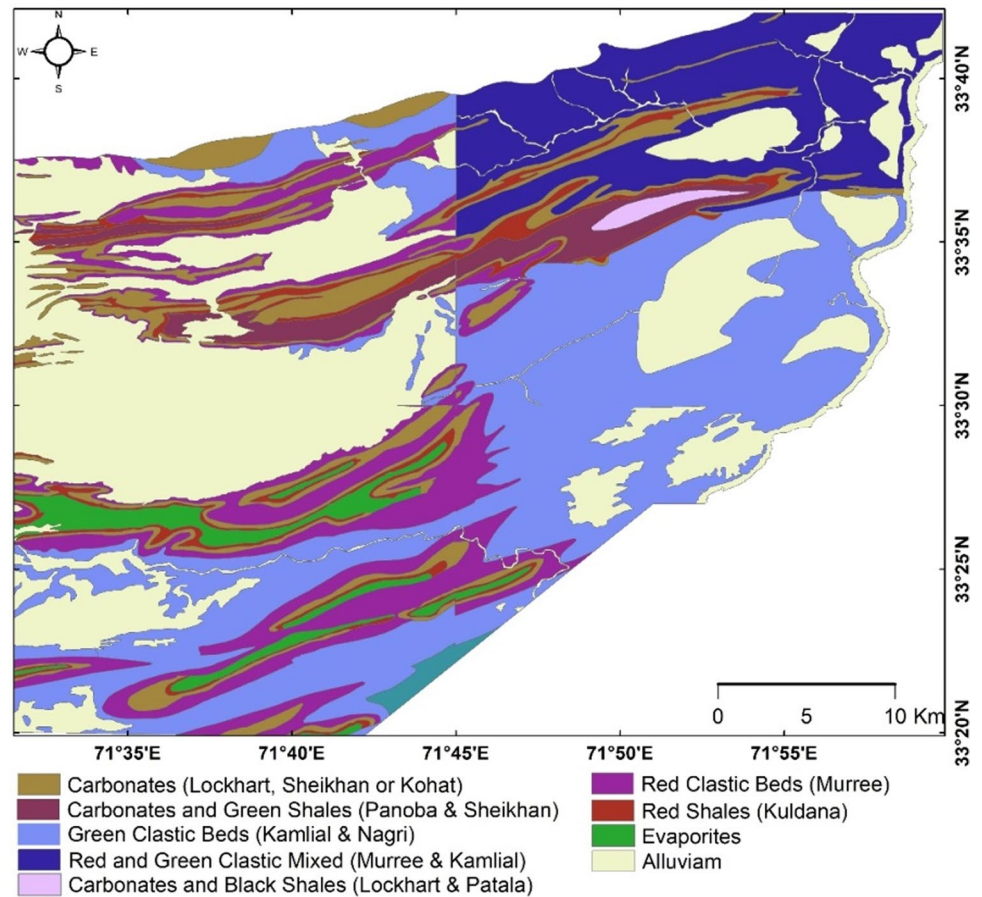
Dataset

Multiple datasets have been used in this study which include; (1) ASTER images, (2) field spectroradiometer measurements and (3) published geological maps (GSP sheets nos. 38O-10, 11, 14, and 15 by Arbab and Shah (1995), Hussain et al. (1995), Khan et al. (1995), Rehman and Ashraf (1998). ASTER is mounted on Terra Platform (i.e., a spacecraft of Earth Observing system), launched in December, 1990 as a joint venture of NASA (National Aeronautics and Space Administration), METI (Ministry of Economic, Trade and

Industry, Japan), and Japan Space System. The ASTER acquired data in 14 bands in the Visible-Near Infrared (VNIR), Shortwave Infrared (SWIR) and Thermal Infrared (TIR) portion of the electromagnetic spectrum, with the spatial resolution of 15 m, 30 m, and 90 m, respectively (Table 2). Whereas, a specialized band (3b) is also added for recording a stereoscopic image for DEM construction (Yamaguchi et al. 1999; Abrams 2000). The distinctive spectral bands in the Visible to Shortwave Infrared (VNIR-SWIR) regions have potential to map minerals as well as lithological formations (Abrams 2000; Rajendran and Nasir 2014; Rajendran 2016; Rajendran and Nasir 2019a, b; Benthahar and Raji 2021).

In this study, the existing geological maps of Meissner et al. (1974b) at 1:150,000 scale and Geological Survey of Pakistan maps at 1:50,000 were used for the initial understanding of geology of the study area and for planning traverses based field data collection. The Spectroradiometer (i.e., PSR + 3500) was used to acquire the endmember spectra of different lithological classes for understanding the spectral responses of different formations and

Fig. 2 Lithological map of the study area (GSP sheets nos. 38O-10, 11, 14 and 15 by Arbab and Shah (1995), Hussain et al. (1995), Khan et al. (1995), Rehman and Ashraf (1998))



ground truthing. The traverses for collecting the spectral data were also planned based on the surface repetition and outcrop thicknesses. The ASTER satellite dataset was selected for retrieving geological information due to its wide spectral range, high spatial resolution, and high radiometric quality. The ASTER level 7XT scene (AST_07XT_00310172002060656_20210608001611_20378) acquired on October 17th, 2002 were used in the study area. The scene selection is based on its minimum cloud coverage, and availability of all bands in visible to short wave infrared. The ASTER level 7XT is available in the USGS LPDAAC platform with readymade corrections, including the geometric, crosstalk and atmospheric corrections. The spectral bands in the VNIR, SWIR and Thermal Infrared (TIR) were pre-processed and processed using Envi 5.3, to categorize lithologies. The complete workflow for this research is summarize in the Fig. 3.

Field spectroradiometry and petrography

Spectral measurements of the targeted lithological classes have been carried out, using a portable spectroradiometer (i.e., PSR + 3500). The PSR + 3500 records the wavelengths response from 350 to 2500 nm, with the spectral resolution of 2.8 nm (for 350–700 nm), 8 nm (for 700–1500 nm) and 6 nm (for 1500–2500 nm). The sensor has different lenses providing the range of field of view (FOV) from 4, 8, and 25 degrees (<https://www.alphaomega-electronics.com/en/spectrometers-spectro-radiometers> accessed 2nd Feb, 2024). The spectral profiles of each lithological class are dependent on its physical and optical characters and chemical composition, hence can be used as a standard for correlating with the spectral response recorded by the ASTER sensor (<https://spectralevolution.com/remote-sensing>). The field-based

Table 2 Summary of major specifications of ASTER sensor (<https://terra.nasa.gov/about/terra-instruments/aster>)

Instrument	VNIR	SWIR	TIR
Bands	1–3	4–9	10–14
Wave-lengths (µm)	0.52–0.60 0.63–0.69 0.78–0.86	1.60–1.70 1.60–0.86	2.145–2.185 2.185–2.225 2.235–2.285 2.295–2.365 2.360–2.430
Spatial resolution	15 m	30 m	90 m
Swath width	60 km	60 km	60 km
Cross track pointing	± 318 km (± 24°)	± 116 km (± 8.55°)	± 116 km (± 8.55°)
Quantization (Bits)	8	8	12

spectral record has also been successfully tested for image classification using the Spectral Angle Mapper (SAM) technique (Hecker et al. 2008; Zhang and Li 2014).

The petrographic studies of targeted lithologies was also carried out in the lab, to correlate the spectral behavior and major mineralogy. For petrography, the thin sections were prepared from the field samples, and analyzed under the polarized microscope (Nikon LV 100 ND). Where the minerals are analyzed and identified based on their optical properties in plan and cross light.

Image processing

Pre-processing

Prior to image processing (i.e., band ratios or PCA, MNF, and different RGB composite) the acquired dataset has been preprocessed. The preprocessing includes the conversion of pixel's digital values to reflectance values through the internal average relative reflectance (IARR) module in ENVI software. Whereas the geometric and atmospheric corrections were already performed for the level ASTER 7XT. The VNIR and SWIR bands were resampled to 30 m spatial resolution. After resampling, the bands were stacked in ascending sequential order of their wavelengths, to maintain the bands hierarchy. The final preprocessed image is then masked out to the ariel extent of the study area.

False color composite (FCC)

Lithological interpretation and discrimination from satellite imagery (i.e., ASTER) is based on the absorption and/or reflectance of certain mineral mixtures in specific wavelengths (Assiri et al. 2008). False Color Composite (FCC) is the display of the three selected bands in a user-defined RGB (red, green, blue) sequence, where the response of desired or most relevant bands can be visualized in different color tones. The selection of three bands for the best visual discrimination of different classes (e.g., different lithological classes in this case) is based on the Optimum Index Factor (OIF). OIF is a technique first introduced by Chavez et al. (1982) which defines the three bands with maximum variance and minimum correlation among numerous bands in the multispectral datasets (Gad and Kusky 2006). The computation of OIF is based on the overall standard deviation of the bands selected and the mutual correlation between them, where the rank of OIF is directly proportional to the sum of standard deviation and inversely related to the correlation (Chavez et al. 1982) (Eq. 1).

$$\text{OIF} = \frac{\sum \text{SD (bands in RGB)}}{\sum rR - G, rG - B, rR - B,} \quad (1)$$

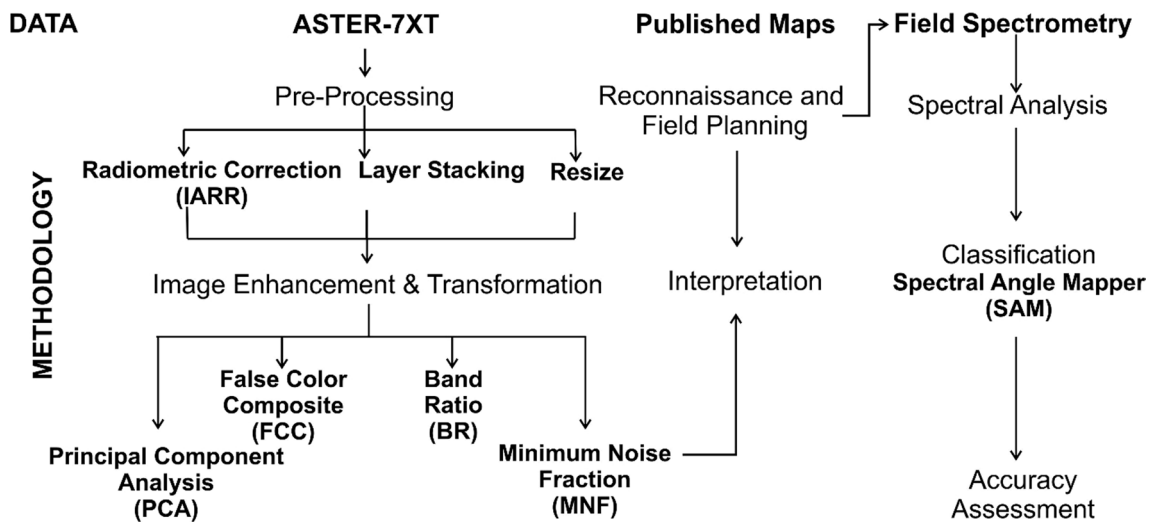


Fig. 3 Summarized workflow of the methodology

whereas, SD is the standard deviation and r represents the correlation value.

Principal component analysis (PCA)

Principal component analysis is a pixel-based statistical transformation technique of the multivariate, mutually correlatable reflectance data to retrieve the uncorrelated new dataset. PCA is a linear dimensionality reduction routine implementing mathematical orthogonal calculations where the highest degree of variability is attained by initial principal components (i.e., linear combinations) (Singh and Harrison 1985). PCA is an effective image processing technique enhances the spectral response from the exposed geological material by decreasing the irradiance effect over the reflectance and decreasing the redundancy in the original dataset (Crosta et al. 2003; Gasmi et al. 2016). In the past, PCA is widely used in geological applications, including lithological mapping, ore minerals, and lineaments detection, as it involves contraction of maximum information in a minimum number of bands and enhanced variance in visualization (Siegal et al. 1980; Qari et al. 2008; Serkan Öztan and Lütfi Süzen 2011; Nemmour-Zekiri and Oulebsir 2020).

The generalized formula covariance matrix calculation for PCA transformation is given in (Eq. 2)

$$\sum \text{COV} = \sum_{i=1}^n (xi - m)(xi - m)^r, \quad (2)$$

whereas, COV is the covariance matrix, xi is the spectral value of i th band, m is the mean of spectral values and r is the correlation value, for each pixel.

Minimum noise fraction (MNF)

Minimum noise fraction is an image processing technique that involves two successive PCA calculations for the reflectance data of all wavelengths, by doing so it decreases the dimensionality of original input data, reduces the noise component in it, and enhances the spectral and spatial variability surface material (Eq. 3). First PC calculation (also referred to as Noise Whitening) determines the covariance matrix for noise, which increases the signal–noise ratio by decorrelating and rescaling the noise, whereas, the second PC involves computation from the noise reduced data i.e., “Noise Whitened data” (Hashim et al. 2011). MNF has been proved much efficient for lithological discrimination of various different rock classes of igneous, sedimentary, and metamorphic origin (Green et al. 1988; Salehi et al. 2019).

The generalized equation for MNF transformation (assuming the uncorrelated signal and noise relation) is:

$$\sum_X^T = \sum_X^S + \sum_X^N, \quad (3)$$

whereas, $\sum_X^T$ is Covariance Matrix of (Xi) , $\sum_X^S$ and $\sum_X^N$ is covariance matrices of signal (noise whitened data) and noise, respectively and X represent the data matrix for n number of pixels and d dimensions i.e., $(X = n \times d)$.

Band ratio (BR)

Band ratio involves the division of each pixel's Digital Number (DN) of two bands with different spectral responses, by doing so this technique refines the variations in shapes of spectral profile between the bandwidth of the selected bands (Eq. 4). Band rationing technique is also capable of eliminating the shadow and topography effects on the spectral response (Rowan et al. 2006; Oztan and Suzen 2009). This technique has been successfully applied for the identification of a variety of different mineral groups and lithologies exposed at the surface (Ninomiya 2002; Hashim et al. 2011; Serkan Öztan and Lütfi Süzen 2011).

The generalized equation for band rotation is:

$$BR = Ref_i / Ref_j, \quad (4)$$

whereas Ref means the reflectance value and i and j is the band numbers used in the BR.

Results

Field survey and spectral measurements

Field observations and the available published maps (GSP sheet nos. 38O-10, 11, 14 and 15) showed the occurrence of repetitive surface exposures of various geological units (i.e., back from late Paleocene marine carbonates and shales to Miocene fluvial clastic sedimentary rock) and can broadly be classified into four major lithological classes i.e., carbonates, evaporites, red oxidized clastic and green clastic sedimentary rocks (Fig. 2). Carbonates includes limestones of different geological units deposited in different geological times and settings i.e., Sheikhan and Kohat formations of the Eocene age. Evaporites comprised of restricted exposure of sulfates i.e., Jatta Gypsum of Eocene age. The red clastic

succession contains sandstone and shales succession of Murree Formation (early Miocene age) followed by clastic beds of greenish sandstone and shales i.e., Kamliyal Formation (mid-late Miocene age). Apart from the major exposed sedimentary lithologies, shale bed of different formations also outcrops in the area, but these outcrops are mainly restricted to gorges or covered by massive carbonates ridges.

The spectral data (total of 464 spectra) of geological units were measured over the identified outcrops in study area (Table 3). The measurement of spectra per class is dependent on its structural repetition and spatial extent i.e., the more repetition and wide spatial coverage, the more spectra has been collected. These ground spectra assist in the selection of appropriate band windows (i.e., VNIR, SWIR or TIR from ASTER dataset) for the image processing and interpretation (Fig. 4). The spectral response of the satellite image is also categorized in different classes based on its correlation with these field based spectral record, where the ground spectra are resampled at the spectral resolution of ASTER sensor (Fig. 5).

Spectral analysis

The clastic sedimentary lithologies (i.e., red and green sandstones) of different age and origin both are showing more or less similar reflectance curves. The diagnostic absorptions in their spectra are observed at wavelengths 1.4, 1.9, 2.2 and 2.37 μm (Fig. 4d, e). These absorptions are related to the presence of hydrous clay minerals in the sandstone. Although the spectral shapes of both red and green detrital rocks are identical, however, the green sandstones are showing gradual increase in overall reflectance between 1.3 and 1.9 μm , which is characteristic of the chlorite and/or glauconite rich sandstones. The red sandstones are showing its typical relative flat reflectance shape between 1.3 and 1.9 μm (Fig. 4d, e) (e.g., Bowitz and Ehling 2008).

Table 3 List of lithological classes and number of ground spectra

Geological units (formation)	Lithology/class	Data points nos.
Kamliyal	Green clastic beds (sandstone and shales)	77
Murree	Red clastic beds (sandstone and shales)	120
Kohat	Limestone (carbonates)	102
Mamikhel/Kuldana	Shales	55
Sheikhan	Limestone (carbonates)	45
Panoba	Shales	39
Jatta	Evaporites (Gypsum)	12
Patala	Shales	14

The gypsum spectra show a total of seven absorption troughs in visible to short wave infrared wavelengths, with its diagnostic absorptions at 1.4–1.6 (triplet), 1.75, 1.94, 2.2, and 2.4 μm (Fig. 4a). These characteristic absorption features of gypsum are caused by the combination of bending and stretching in hydroxyl (OH) ion, SO_4 anion and molecular water in the gypsum crystals (e.g., Rajendran and Nasir 2021).

The calcareous lithologies (Shekhan and Kohat formations) reflect five major absorptions at 1.9, 2.00, 2.16, 2.35 and 2.55 μm wavelengths (Fig. 4b, c). These absorptions are caused by the vibrational processes of the carbonate anion (CO_3) (e.g., Hunt 1971; Gaffey 1987). The consecutive absorption troughs at 2.35 and 2.55 μm are distinctive features of carbonate rich rocks (e.g., Clark et al. 1990; Zaini et al. 2012).

Petrography

The red clastic lithologies include the sandstones and shales of different ages (i.e., Murree Formation of Miocene age and Kuldana Formation of Eocene age). Whereas, the green clastic lithologies represent the greenish sandstone of Miocene Kamlial Formation overlying the Murree Formation. The petrographic analysis reveals the presence of quartz, feldspar and micas as the major mineral composition in both the clastic lithologies (Fig. 5d, e). In addition to major minerals the red clastic lithologies contains hematite, leading to the brownish color tone. Whereas, the green clastic lithologies have glauconite/chlorite, leading to its greenish outcrop color (Fig. 5d, e). The calcareous lithologies include the limestones of Shekhan (Early Eocene) and Kohat (Middle Eocene) formations. The petrographic analysis of both the limestones shows that they are composed of skeletal allochems within the micritic/micropartic matrix. The Shekhan Formation gives yellowish outcrop coloration, caused by the iron-rich diagenetic phases dispersed within the matrix and along the stylolites. Whereas, in case of Kohat Formation the diagenetic iron-rich phases are restricted to the veins and not disseminated into the matrix (Fig. 5b, c). The evaporites present in the study area include Jatta Gypsum of Eocene age. The thin section photomicrograph shows gypsum as dominant mineral, with $\leq 10\%$ matrix (Fig. 5a).

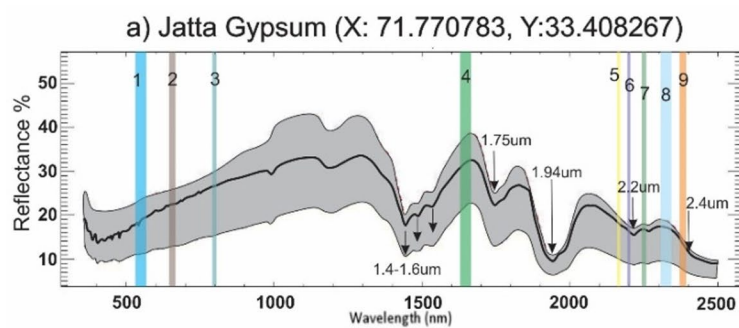
Image processing

Reflectance response of exposed lithologies shows distinctive variation in SWIR portion of electromagnetic spectrum (Fig. 4). Based on the presence of characteristic absorption features in the SWIR, the separability of various surface

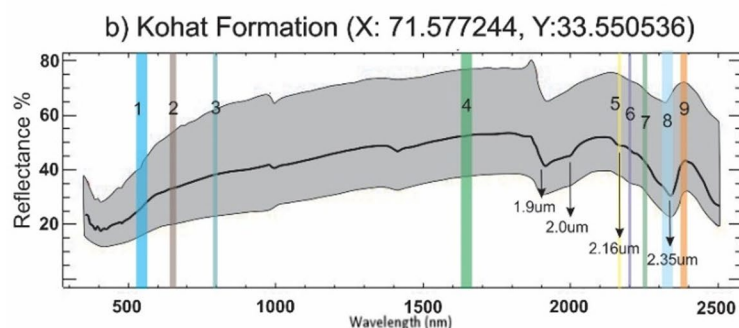
lithologies is high in bands combination of near and short-wave infrared. Among the available bands in VNIR-SWIR regions of ASTER sensor, the bands 4, 6 and 8 are covering the major spectral variation for all the four targeted lithological classes (Fig. 4). The OIF ranking also suggests the RGB 468 composite among one of the top six RGB combinations (Table 4). Therefore, the RGB 468 is selected to display the maximum lithological variation within the study area (Fig. 6). In Fig. 6, the yellowish hue represents calcareous lithologies, as the bands 4 and 6 records the reflections but band 8 covers the absorption around the 2.35 μm , in the RGB channels, respectively (Fig. 4b, c). The evaporite outcrops are distinguished in pink coloration, because the band 6 (around 2.2 μm) in Green channel of RGB composite is experiencing absorption relative to Red and Green channels (Fig. 4a). Although the RGB 468 composite captures the spectral variations of red and green clastic lithologies, but the reflectance values recorded at these channels are almost similar (Fig. 4d, e), therefore these lithologies are giving different shades of gray (Fig. 6).

PCA analysis

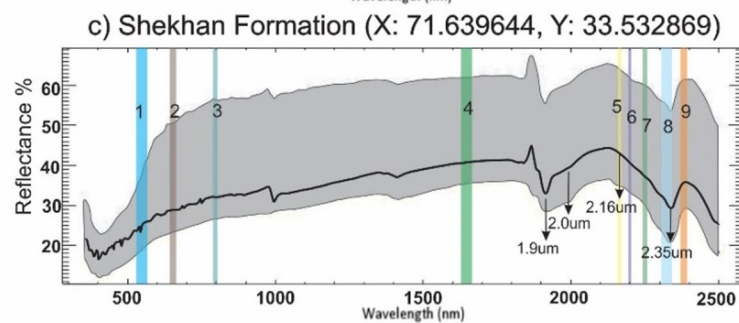
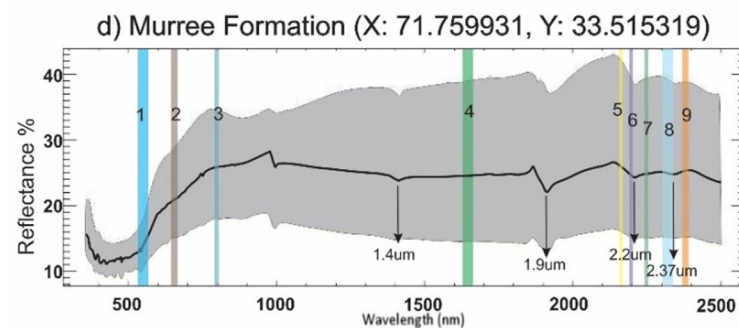
The first six principal component transformation represents the major lithological information (Fig. 7). The eigenvalues details of the principal component analysis shows that the first two PCs contains the maximum variance, with gradual decrease in the remaining PCs (Table 5). Table 5 also highlights contributions of each band for the individual PC. The PC1 highlights the surface topography and structural trends of rocks, whereas the PC2 represents the calcareous lithologies dark tone (Fig. 7a, b). The PC3 is marking the surface distribution of shale beds in bright pixels and the PC4 is representing the ferrous lithologies in black pixels (Fig. 7c, d). The alluvium is represented by PC5 in black tone, whereas the evaporites are represented black pixels in PC6 (Fig. 7e, f). Each PC is capable of highlighting one or two lithological class(es) in greyscale image. Therefore, a RGB composite is generated using PC6, PC2, and PC1 to visualize the maximum lithological variations in single image (Fig. 8). The OIF score table for all the nine principal components also enlist the combination of PC1, 2 and 6 as one of the best RGB combination for displaying maximum lithological variation (Table 6). The calcareous lithologies are highlighted in purple color (Car in Fig. 8b), whereas the evaporite outcrops are represented in aquamarine tone (Evp in Fig. 8b). The red clastic lithologies (i.e., sandstone and clays) are shown in blend of greenish–yellowish tone (RCB in Fig. 8b) and the greenish clastic lithologies are displayed in cyan (bluish to greenish) colors (GCB in Fig. 8).



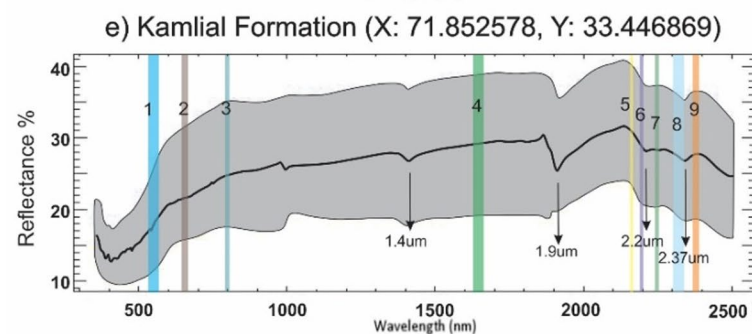
Evaporites



-----Carbonates-----



Red Clastics



Green Clastics

Fig. 4 Ground spectra of targeted lithological classes and the location of available bands in the ASTER datasets (curves are the spectral response, gray shaded zone represents maximum to minimum variation range, whereas the colored strips are the ASTER (VNIR-SWIR) bands locations)

MNF analysis

The eigenvalues of MNF transformation shows that the first three MNFs contains the maximum variance. Although the eigenvalues drops gradually onwards, but still some lithological information is contained upto the MNF5 (Fig. 9). The MNF1 is expressing the surface structural patterns, whereas the MNF2 results mark the ridges of calcareous lithologies in black, and the oxidized red beds in bright tones (Fig. 9a, b). The greyscale visualization of MNF5 picks the evaporites ridges in sharp black tone, whereas the loose recent alluvium is highlighted in bright pixel of MNF4 (Fig. 9d, e). The RGB composite is generated from MNF5, 2 and 1, representing the maximum lithological discriminations (Fig. 10). The parrot green shades in the output image represent the red clastic outcrops, the green clastic outcrops are shown in sky blue, the carbonates dominated ridges are shown in dark purplish tones and the dark navy-blue coloration represents the evaporites (“RCB, GCB, Car and Evp” respectively in Fig. 10).

Band rationing (BR)

The study assesses the effectiveness of band ratios derived from all possible combinations of ASTER layers, including thermal infrared (TIR), in delineating outcrops containing target mineral mixtures. Given the variability in composition and quantity of minerals within exposed lithologies, detecting them with the spatial resolution of ASTER data poses a challenge. Nevertheless, the research aims to evaluate the efficacy of band ratio analysis in identifying dominant mineralogy. Results indicate that certain band ratios, including $B13/B10$, $(B5/B3) + (B1/B2)$, and $(B7 + B9)/B8$, are successful in highlighting abundant minerals such as quartz, calcite, and oxidized iron-bearing minerals (e.g., Gozzard 2006) (Fig. 11).

The band ratios derived from the VNIR and SWIR bands of the ASTER dataset proved highly effective in distinguishing between various minerals, as their characteristic absorption features are predominantly found in the VNIR-SWIR range of the electromagnetic spectrum. Notably, the unique absorption and reflectance patterns of calcite in the SWIR zone, exhibiting high reflectance in bands B7 and B9 (~ 2.26 and $2.4 \mu\text{m}$, respectively) and an absorption trough in band B8 ($\sim 2.33 \mu\text{m}$) (Fig. 2), are significant. Consequently, the band ratio $(B7 + B9)/B8$ effectively identifies areas abundant

in calcite, represented by brighter shades (highlighted in red, as demonstrated in Fig. 11a). Whereas, the oxidized iron rich red lithologies show reflection peaks in B2 and B5 (i.e., 0.807 and $2.167 \mu\text{m}$) of ASTER sensor, whereas the absorption is recorded in B1 and B3, therefore, the BR $(B5/B3) + (B1/B2)$ marked the mineral mixture with iron oxides in brighter reflections (highlighted in red, Fig. 11c).

The TIR band window is effective for detecting quartz dominated lithologies, as quartz exhibits characteristic spectral response in TIR zone of electromagnetic spectrum. Quartz exhibits significant thermal emissivity absorption in the ASTER B13 band ($\sim 10.5 \mu\text{m}$) and relatively higher emissivity in B10 ($\sim 8.2 \mu\text{m}$) (Rolim et al. 2020). Consequently, the band ratio $(B13/B10)$ effectively highlights quartz-dominated mineral mixtures in darker shades (highlighted in red, Fig. 11b). An RGB composite is created from the quartz (Red), calcite (Green), and oxidized iron-rich (Blue) bands to represent lithological variations within a single frame (Fig. 11d). This composite reveals calcareous lithologies in a blend of green, red clastic lithologies in reddish tones, green clastic lithologies in bluish hues, and evaporites in black pixels (Fig. 11d). The varying mineral mixtures result in a spectrum of shades in the RGB composite; i.e., yellow indicates areas with a mixture of calcareous minerals c and quartz enrichment (Fig. 11d).

Classification and accuracy assessment

Image classification is performed to produce a lithological map of the area, representing the surface distribution of interpreted lithologies (Fig. 12). This study combines field spectrometry and satellite data, utilizing the spectral characteristics of outcropped lithologies. To perform classification, the Spectral Angle Mapper (SAM) technique is employed. The SAM classification is applied using the end member field spectra and image pixel's spectra separately. The visual comparison of both classification shows that the classification based on the image pixels represents the maximum lithological representation, relative to end-member spectra (Fig. 12). Accuracy assessment of the pixel's based classification is performed to validate its results. The point based field data is overlaid and compared with the lithologies marked in the final map. Total of 85 field data points were selected randomly, the numbers of samples from each class are listed in the table (Table 7). Overall accuracy calculated for the classified lithological map was about 76% and the Kappa coefficient is 0.67. The carbonates and evaporites class yielded the highest separability (i.e., User accuracies $> 80\%$), whereas the clastic sedimentary rock classes manifest relatively low separability (i.e., user accuracies 60–70%).

Fig. 5 Photomicrographs of all major lithological classes, showing the major mineral abundance. **a** Gypsum, **b** Kohat Formation’s bioclastic limestone, **c** Shekhan’s Formation bioclastic limestone, **d** Murree Formation’s sandstone, **e** Kam-lial Formation’s sandstone

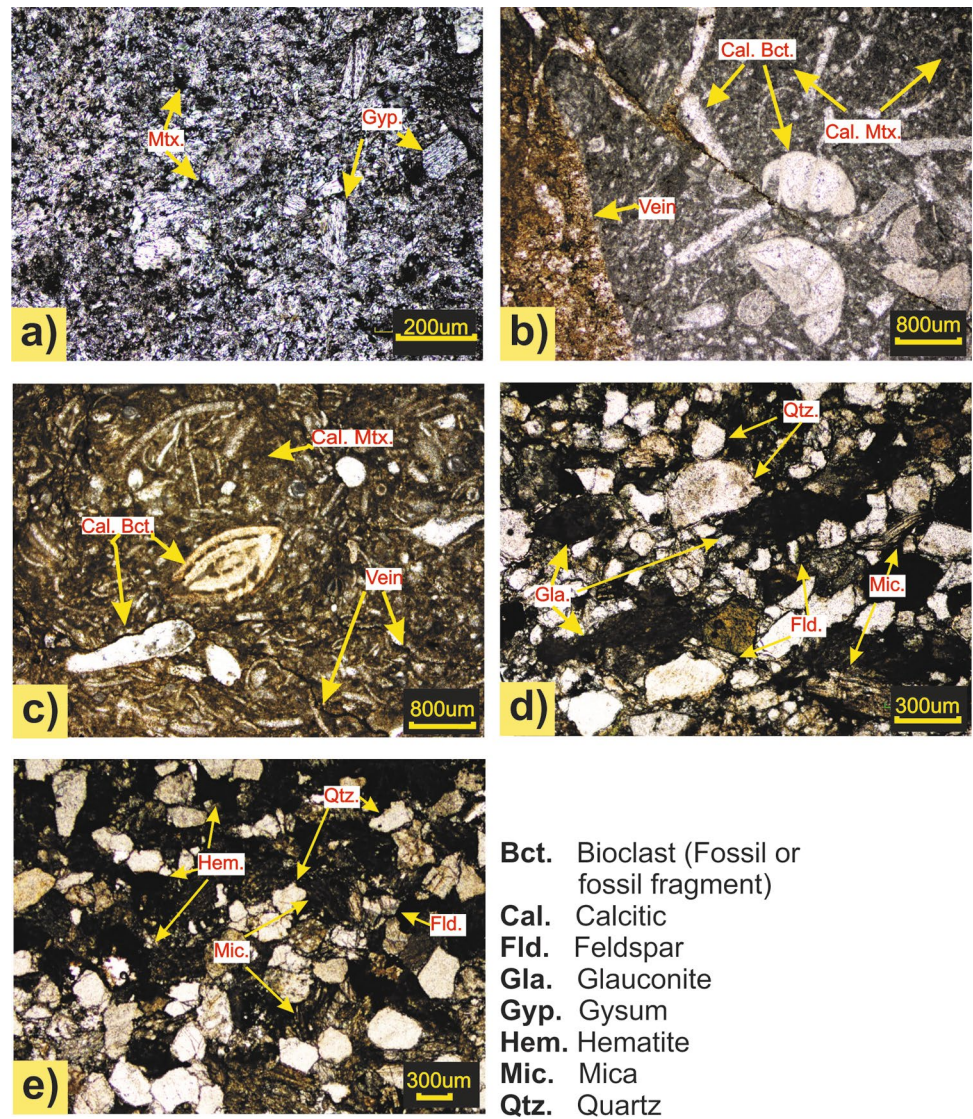


Table 4 List of different bands combinations from the reflectance data, with respect to their OIF highest ranking

S. no.	R	G	B	OIF score
1	B2	B3	B8	0.42
2	B2	B3	B9	0.41
3	B2	B8	B9	0.41
4	B3	B8	B9	0.40
5	B2	B3	B7	0.40
6	B4	B6	B8	0.39

Discussion

Reflectance data vs lithological variation

The SWIR part of spectral profile contains diagnostic absorption/reflection features for various mineral groups,

hence provides an effective tool for remotely detecting the surface exposure of different minerals and mineral mixtures (Zaini et al. 2014; Fakhari et al. 2019; Rajendran and Nasir 2019a, b; Beirami and Tangestani 2020). For visualizing the lithological variation in FCC, the SWIR dataset of ASTER sensor is targeted (i.e., bands 4, 6 and 8). The RGB 468 composite recorded absorption in one of the three bands in RGB composite for calcareous lithologies and evaporites, whereas in case of clastic lithological class these bands mainly experience deep absorption (Fig. 4). Therefore, the two chemical/ biochemical (carbonates and evaporites) lithological classes are highlighted in sharp brighter colors and clastic lithologies (red and green sandstones) reflect dull colors in the FCC (Fig. 6). The diagnostic absorption trough for carbonate rich lithologies, corresponding to CO₃ absorption feature at wavelength of 2.34 μm, which is recorded by the band 8 of ASTER SWIR dataset (Beirami and Tangestani 2020). The evaporite lithological class displayed its characteristic

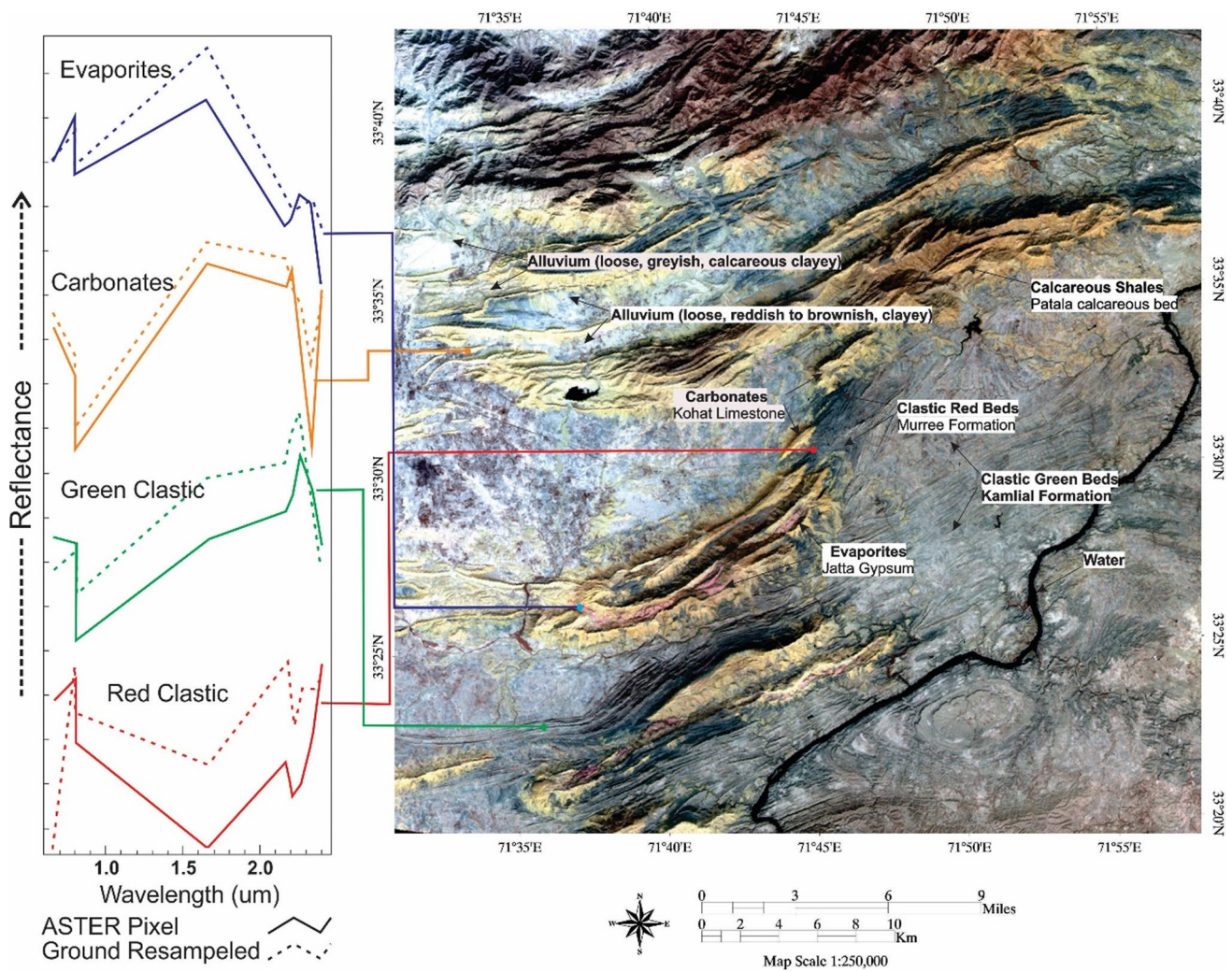


Fig. 6 FCC 468, showing the surface exposures of different sedimentary rock classes in different colors, with comparison of pixel-based and field-based spectral profiles from each class

absorption at 2.2 μm wavelength, which is corresponding to the absorption related to the presence of hydroxyl (OH^-) ion in Gypsum (Van Gorp et al. 2014). The spectral signature of iron rich lithologies are influenced by the electronic configuration of Fe^{+3} and Fe^{+2} cations and shows diagnostic spectral response in the VNIR to NIR [i.e., absorption in the 5.50 μm to 880 μm for Hematite (Fe_2O_3) and 4.80 μm to 9.20 μm for Goethite (FeOOH)] (Galvao and Vitorello 1998; Heller Pearlshien and Ben-Dor 2020). These iron rich clastic rocks reflect reddish to brownish color at surface, possibly due to effect of ferric minerals (e.g., hematite) (Fig. 5). Similar surface coloration is indicated by clastic sedimentary succession in this research, the spectral reflectance pattern

is also same as described for iron enriched earth material (Fig. 4). Whereas, the available bands of ASTER sensor do not cover this diagnostic spectral response of these clastic lithologies, but the bands 4, 6 and 8 of the ASTER-SWIR portion mainly experience flat curve with minor reflection at 2.35 μm (recorded by band 8) (Fig. 4). Field based spectral analysis represents similar spectral profile for the red and green clastic sedimentary lithologies, with relatively higher reflectance for red beds, accounts for the different coloration in the FCC (Fig. 4). Whereas the greenish surface coloration of these green detrital rocks may be due to the presence of glauconite (Fig. 5).

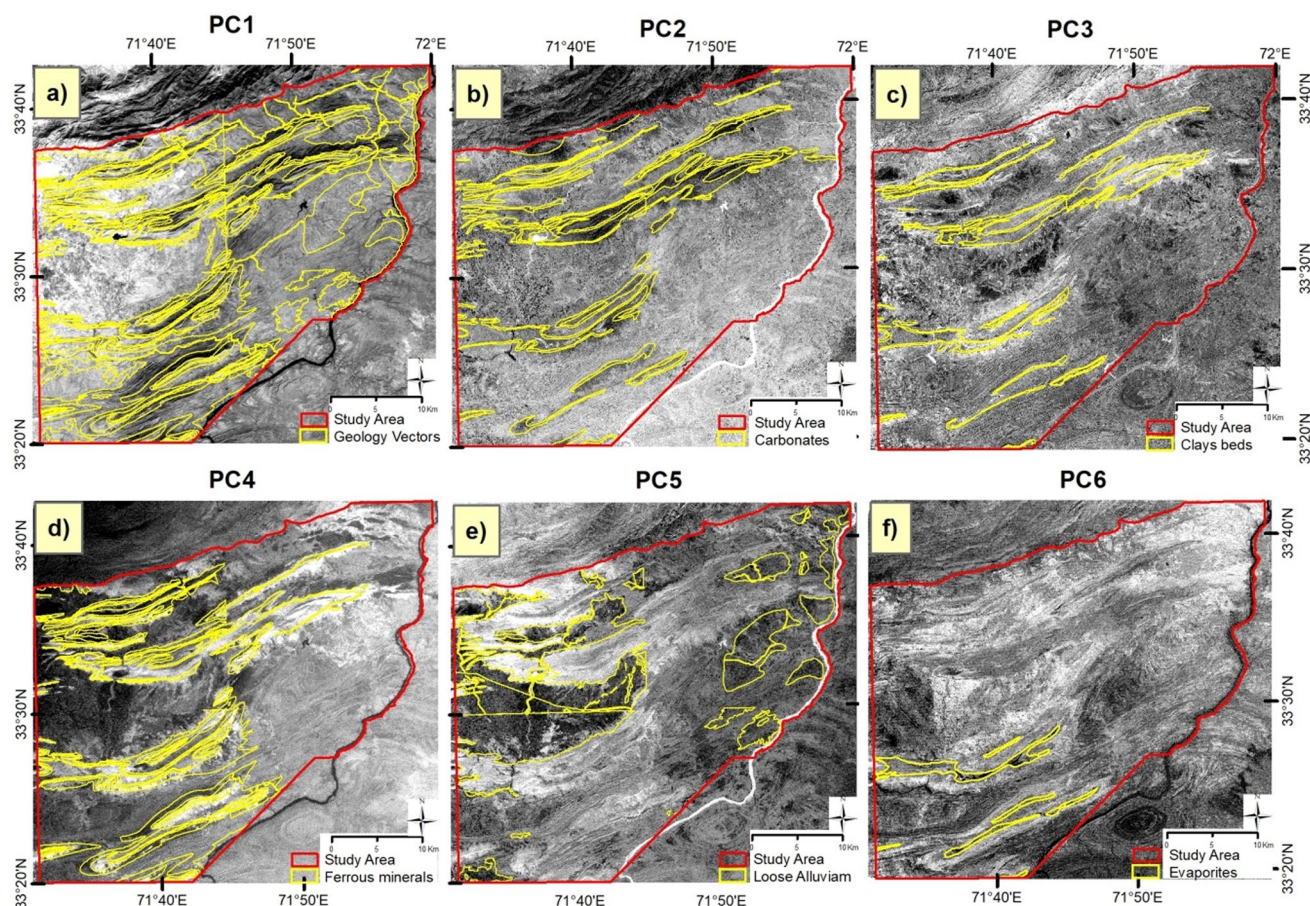


Fig. 7 First six principal components, highlighting lithological heterogeneity in greyscale

Table 5 Statistical details of contribution of each band against the individual principal components

Principal components	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7	Band 8	Band 9	Eigenvalues
PC1	0.244	0.337	0.248	0.313	0.352	0.367	0.362	0.387	0.359	0.906215
PC2	0.458	0.669	-0.398	-0.327	-0.06	-0.131	0.039	0.009	-0.235	0.031136
PC3	0.278	0.262	0.753	0.144	-0.158	-0.107	-0.280	-0.360	-0.148	0.028633
PC4	-0.077	0.041	-0.224	0.546	0.235	0.268	0.165	-0.339	-0.612	0.018968
PC5	0.302	-0.055	-0.351	0.188	0.108	0.173	-0.359	-0.514	0.559	0.008158
PC6	-0.712	0.531	0.055	-0.221	0.122	0.202	-0.07	-0.265	0.170	0.002809
PC7	0.200	-0.277	0.190	-0.590	0.574	0.189	0.186	-0.285	-0.130	0.001643
PC8	-0.058	0.043	0.004	0.145	0.102	-0.668	0.586	-0.344	0.234	0.001229
PC9	0.079	-0.076	0.028	-0.147	-0.653	0.460	0.501	-0.267	0.077	0.000978

Italicized values represent the positive correlation and major contributing bands

Fig. 8 **a** RGB composite of PC-6, PC-2 and PC-1 displaying the lithological variation in area. The red boundary marks the study area and the yellow box marks the inset. **b** Close-up view of the inset, showing the correlation of the lithological variation and the vector data from the GSP published map. **c** Zoomed view of the GSP published maps for the inset in **a**

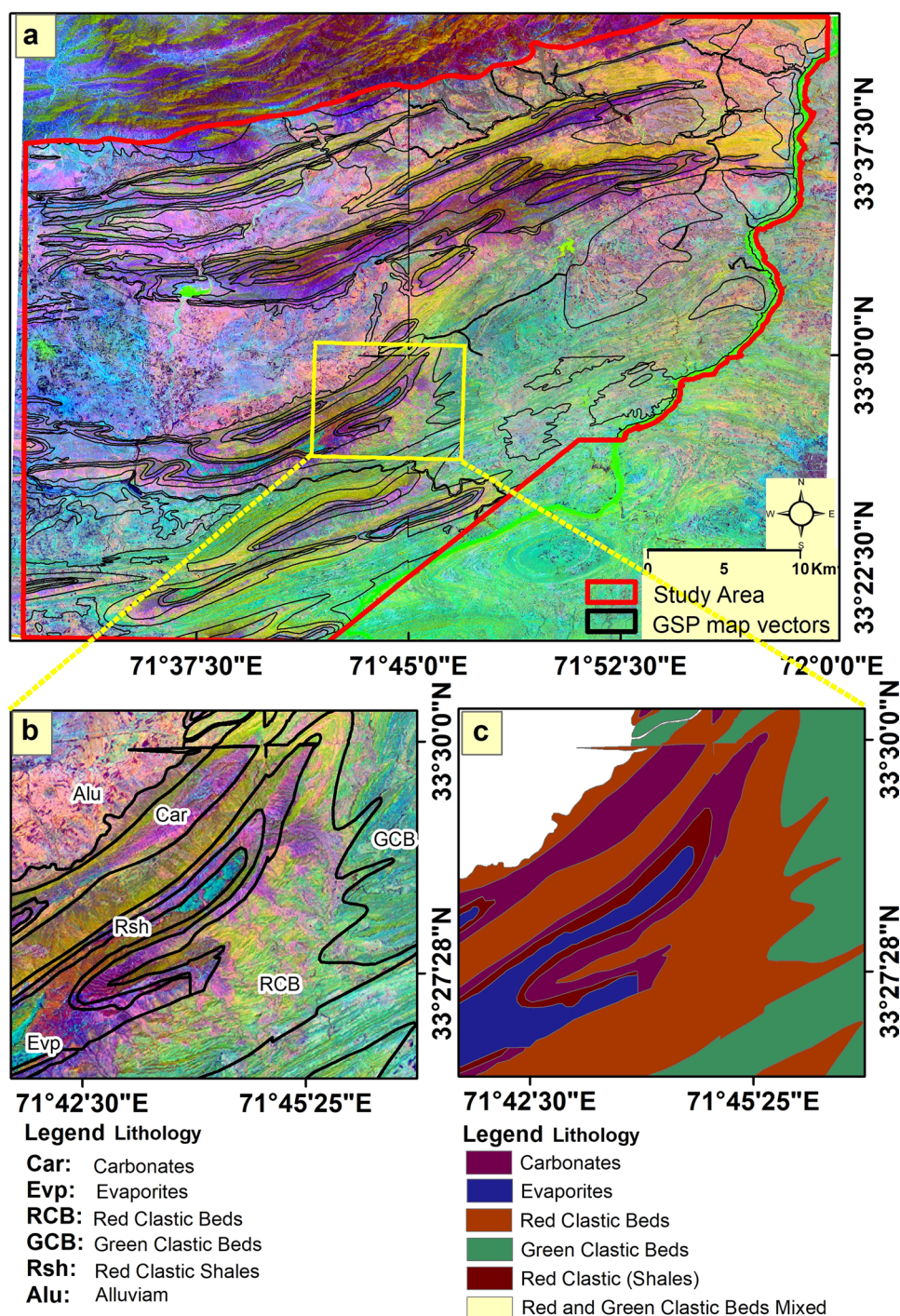


Image processing vs lithological variation

Nemmour-Zekiri and Oulebsir (2020) utilizes the combination of first three principal components (i.e., PC 1, 2 and 3) for characterizing the lithological variation of

igneous, meta-sedimentary and sedimentary complex. Rajendran et al. (2013) delineated the various mineralized zones (including the manganese, serpentinite and alteration zone) and also mapped the host lithologies of igneous and sedimentary origin, using composites of 1 to 5 principal

Table 6 List of different bands combinations from the PCA data, with respect to their OIF highest ranking

S. no.	Bands combinations in RGB			OIF score
1	B1	B6	B9	36.9×10^{11}
2	B2	B4	B5	35.9×10^{11}
3	B1	B4	B6	22.2×10^{11}
4	B1	B2	B4	17.2×10^{11}
5	B2	B5	B6	16.7×10^{11}
6	B1	B2	B6	14.1×10^{11}

components from ASTER dataset (Rajendran and Nasir 2013, 2019a, b). Similarly, various RGB combinations of MNF transformed VNIR and SWIR bands from ASTER, Landsat-8 and Sentinel-2 satellite sensors provided the

significant discrimination of sedimentary succession in the Buka Daban peak of northern Tibet, China (Xi et al. 2022). This study also utilizes the combination of PCA and MNF transformed bands for visualizing the lithological variation (Figs. 8, 10). These composites effectively displayed maximum lithological discrimination, as their eigenvalue and standard deviation statistics also shows contrastive wider range, and covers maximum variability (Table 8). Band ratios involving mainly the VNIR and SWIR bands of ASTER sensor has been applied for detecting various different minerals and mineral mixtures (Gozzard 2006; Rajendran and Nasir 2013, 2019a, b; Beirami and Tangestani 2020; Khan et al. 2020). However, the potential of TIR bands from ASTER sensor also has been experimented for mapping the quartz rich outcrops (Gozzard 2006; Rajendran and Nasir 2019a, b). Band rationing technique in this

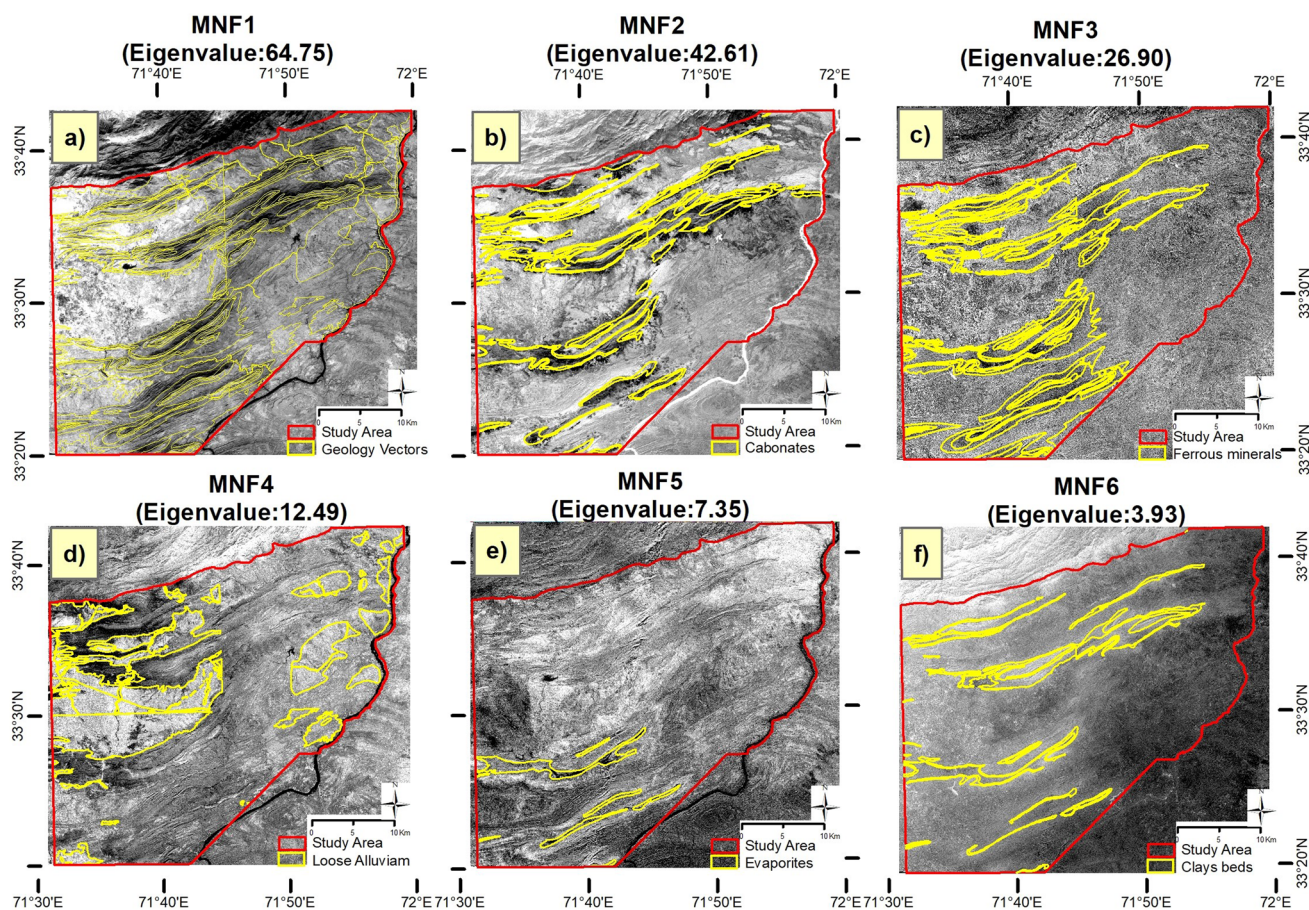
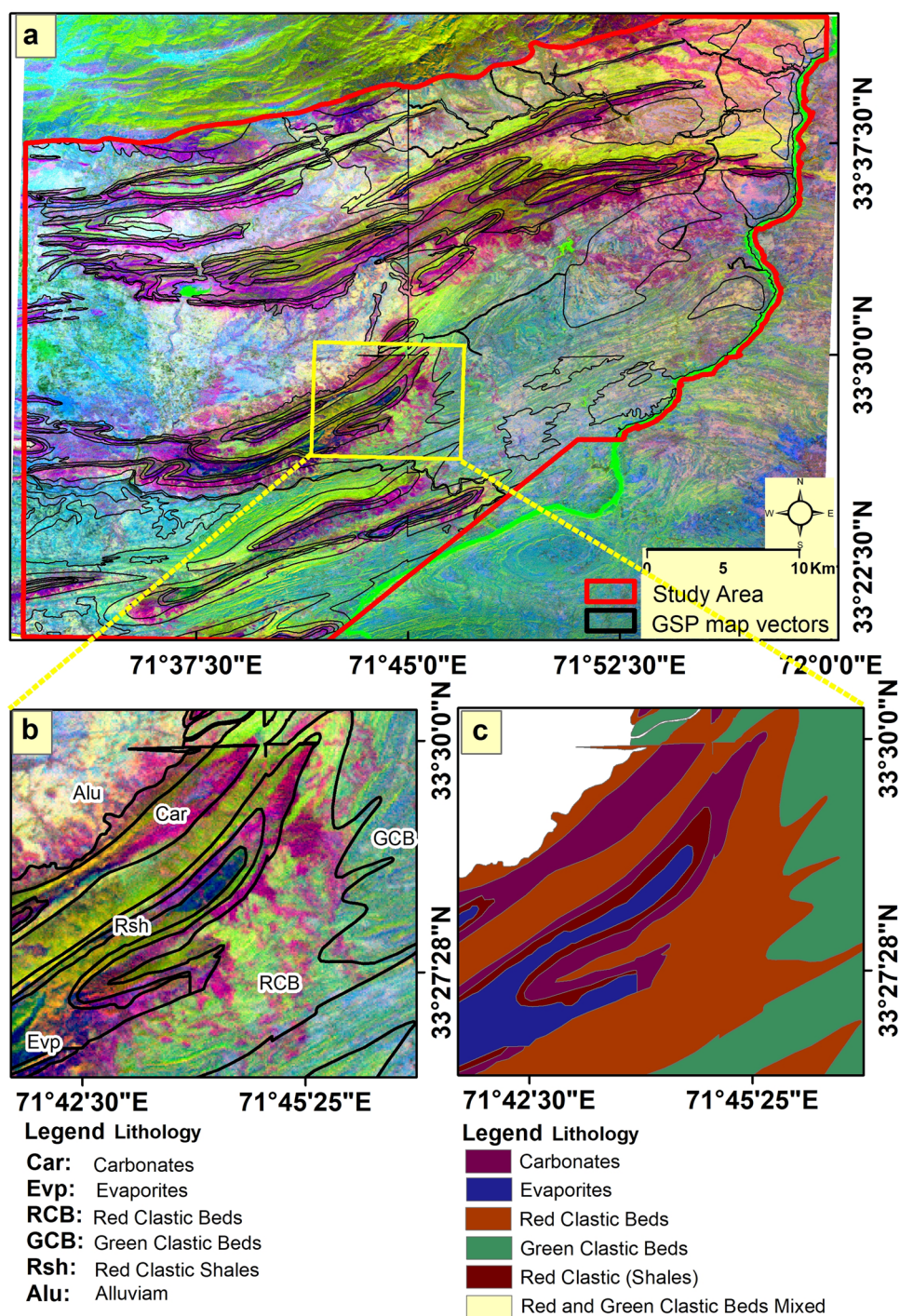
**Fig. 9** Greyscale images of the first six MNF, with the eigenvalues of each MNF layer

Fig. 10 **a** RGB composite of MNF-6, MNF-2 and MNF-1 displaying the lithological variation in area. The red boundary marks the study area and the yellow box marks the inset. **b** Close-up view of the inset, showing the correlation of the lithological variation and the vector data from the GSP published map. **c** Zoomed view of the GSP published maps for the inset in **a**



study also mainly targeted the VNIR and SWIR bands for carbonates, evaporites and clastic sedimentary succession. The carbonates and oxidized clastic sedimentary lithologies are highlighted in brighter tones, in their respective

band ratios (Fig. 11), as these involve the ratio of higher reflectance values to relatively lower reflectance. Whereas the TIR bands (B13 and B14) are used for mapping quartz abundance zones, which involves the ratio of relatively low

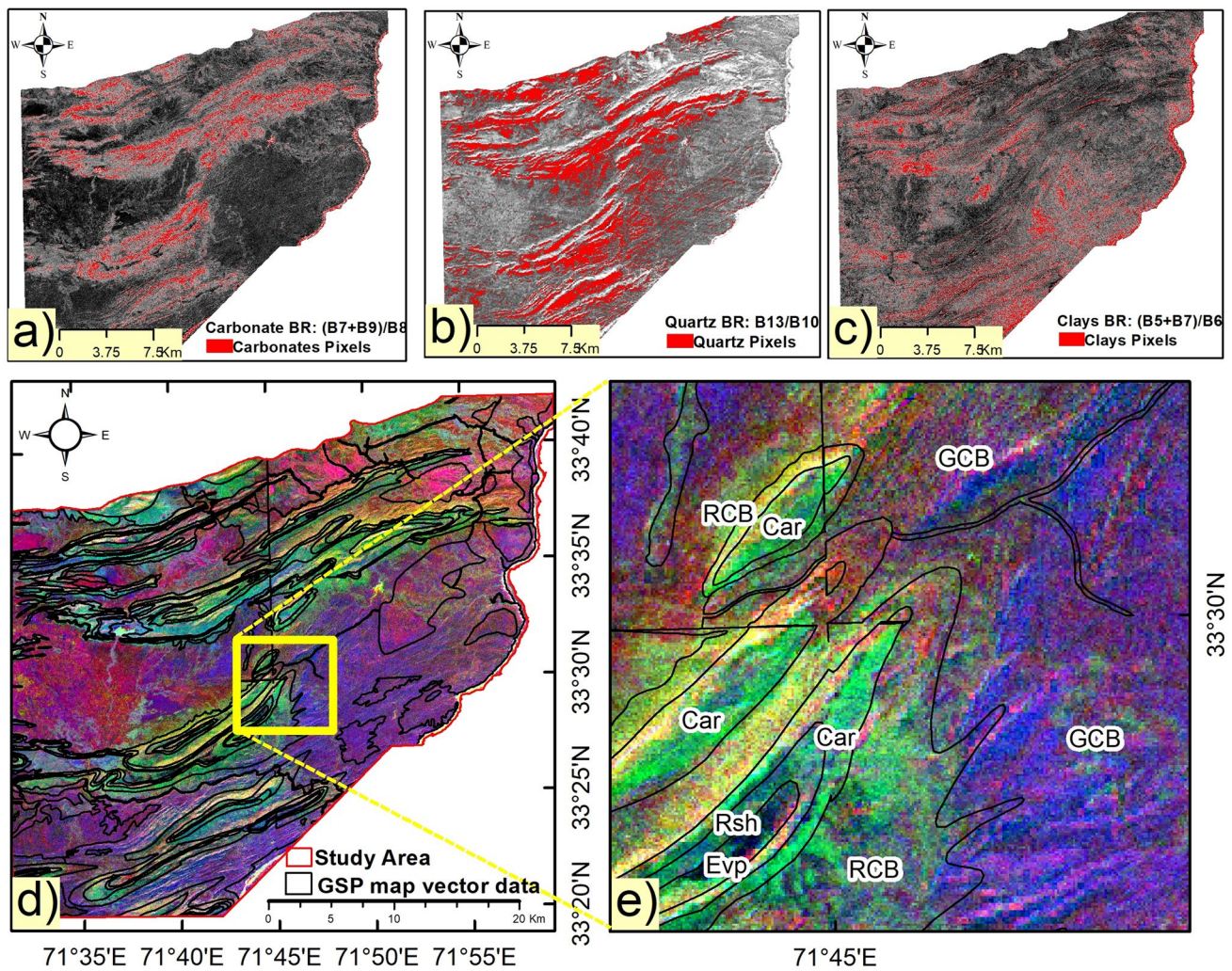


Fig. 11 Displaying the greyscale band rationing results for calcite, quartz rich, and clays rich (a–c). **d, e** RGB composite from band ratios to highlight the lithological variation and correlation with GSP published maps

emissivity to higher emissivity values low reflective bands to relatively high reflective bands, so the quartz rich lithologies are characterized by their darker shades (Fig. 11).

Comparison with existing maps

The detailed geological maps for the study area are available at scale of 1:50,000, published by Geological Survey of Pakistan (Maps No. 38O-10, 11, 14 and 15). The human error combined with the limitations of inaccessibility to

difficult terrains leads to the some irrational geological interpretations. For an instance, the Miocene clastic units abruptly changed to undivided succession in the northeastern patch of study area. Similarly, the lithological boundaries at places are not continuous and also represent the abrupt lithological variation at places (Fig. 13). Whereas, the integrated remote sensing based approach of the present study successfully overcome these shortcomings associated with the conventional geological mapping (Fig. 14). The same approach has been adopted previously for high

Fig. 12 Classified lithological map, following the SAM classification. **a** ASTER pixel's based. **b** Field end members based

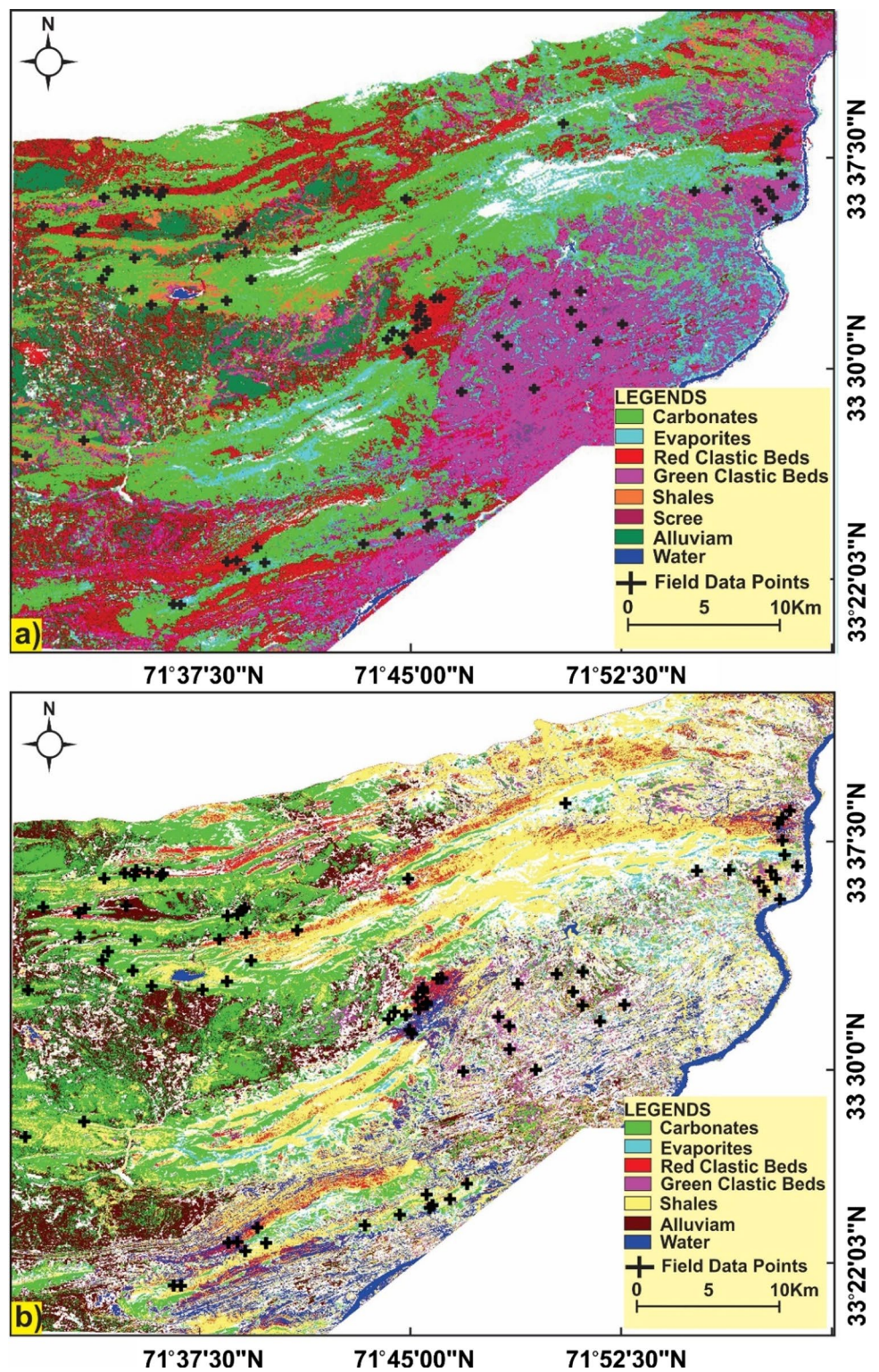


Table 7 Accuracy assessment chart of the four major sedimentary rocks classes

	Green clastic	Red clastic	Carbonates	Evaporites	Total (user)	User accuracy (%)	Producer accuracy (%)
Green clastic	16	4	3	2	25	64	94
Red clastic	0	17	8	0	25	68	80.9
Carbonates	1	0	22	2	25	88	66
Evaporites	0	0	0	10	10	100	71.4
Total (producer)	17	21	33	14	85	—	—

Blue shaded values, highlights the numbers of correctly classified points

Table 8 Standard deviation and eigenvalue of selected bands for image enhancement, from PCA, MNF and ICA dataset, used for the lithological discrimination

Basic Stats	Minimum	Maximum	Mean	Standard deviation	Eigenvalue
PC 1	−4.68	9.27	0.0	0.94	0.89
PC 2	−1.91	1.56	−0.0	0.18	0.03
PC 6	−0.44	1.58	−0.0	0.05	0.00
MNF 1	−32.89	120.71	−0.00	8.05	64.75
MNF 2	−39.53	143.73	0.00	6.53	42.62
MNF 6	−61.34	30.33	−0.00	1.98	3.94

resolution geological mapping. The Özkan et al. (2018) used the ASTER data in combination with field data to map the lithological variation in the accretionary complex (Özkan et al. 2018). Similarly, the same integrated remote sensing and field data methodology has been followed for the geological mapping at 1:20,000 scale (Rezaei et al. 2020).

Limitations

Weathering and varying mineral mixture also effects the remote sensing based lithological identification (Grebby et al. 2014; Beirami and Tangestani 2020). Similar geological processes and also the narrow ariel extent at some places affected the efficiency of lithological discrimination in the studied area. The producer's accuracy from assessment chart also showed that the carbonates and evaporites class are over classified due to, their topographic land forms (i.e., mainly ridge forming) and also

due to their scree cover over the adjacent lithologies. Some geological units specially the late Paleocene to early Eocene shales (i.e., Patala and Panoba) reflected same shades similar to the carbonates class, because their spectral response on field-based measurement display reflection/absorption peak at same bands of ASTER (Fig. 14). The spatial resolution of 30 m is also a major barrier in remotely detecting the lithological entities having thickness less 30 m, as the satellite records the cumulative spectral response of the surface material over ariel extent of 30 m (i.e., the size of one pixel). For targeting the surface lithological at finer scale or aerially small mineral deposits, the latest satellite products (e.g., World View 3) and also the customized unmanned aerial vehicles (UAVs) can provide better results (Mars 2018; Booysen et al. 2020).

Conclusion

Multispectral dataset of ASTER sensor proves to be significantly effective for characterizing and delineating the aerial extent of four major lithological classes of sedimentary origin (i.e., carbonates, evaporites, oxidized iron rich red clastic and green clastic beds), in the semi-arid climatic regions with steppe type vegetation. Spectroradiometry conducted in the field yielded spectral signatures of exposed lithologies, enabling the identification of optimal bands from satellite datasets for the application of different image enhancement techniques. Comparing the results of various image transformation techniques with published maps (i.e., GSP maps no. 38O-10, 11, 14

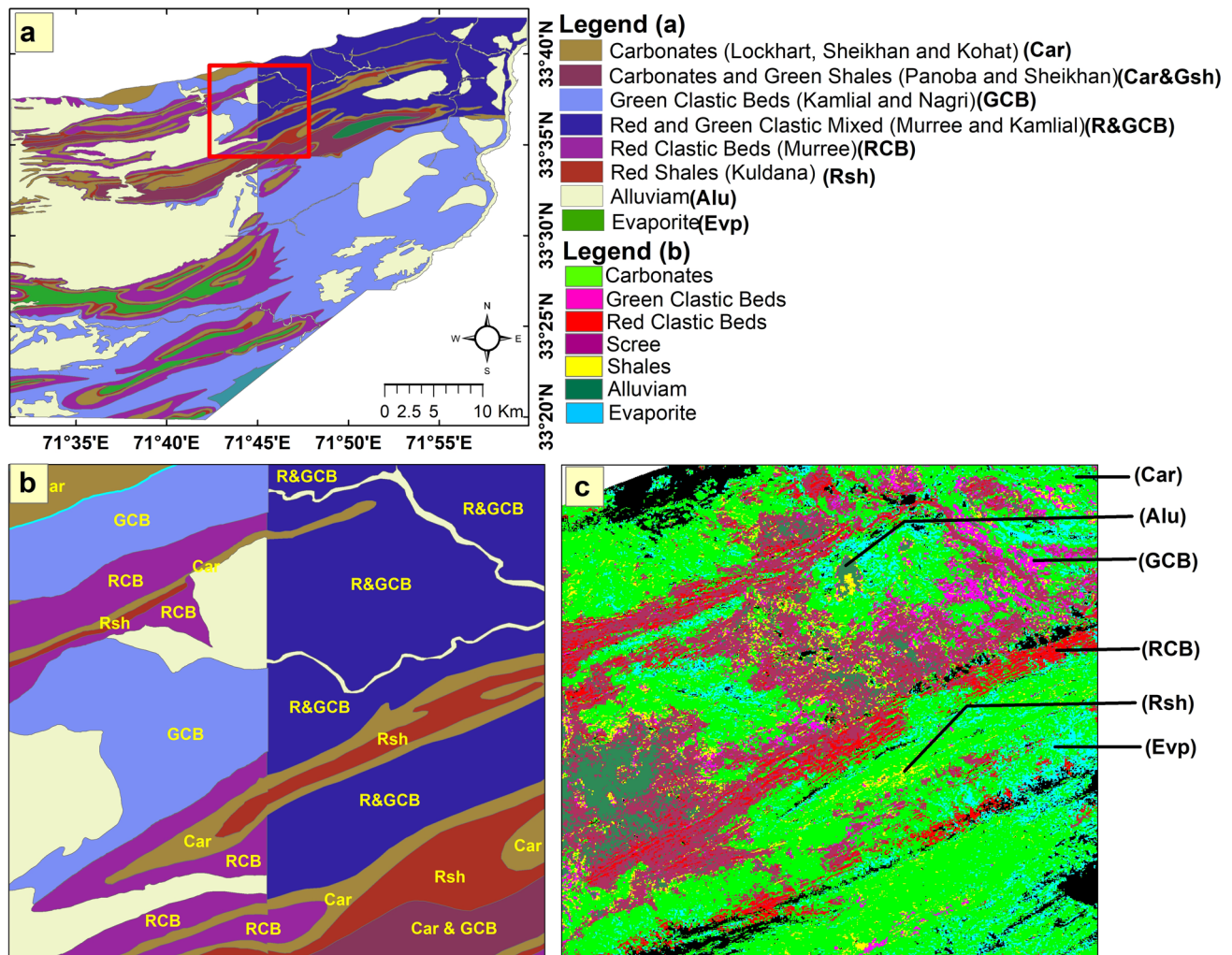


Fig. 13 Comparison of classified lithological map with existing map. **a** Geological map of study area with an inset (red box) covering a part for comparison. **b** Existing geological map of inset. **c** ASTER based classified lithological map of inset

and 15 mapped by Arbab and Shah (1995), Hussain et al. (1995), Khan et al. (1995), Rehman and Ashraf (1998) reveals the potential of ASTER data to characterize various lithologies which are otherwise mapped as single undivided features e.g., the Red and Green clastic beds in the north east of the study area, furthermore the results of satellite image transformation are spatially continuous, which are otherwise marked with abrupt truncations in published maps (Figs. 2 and 13). The Spectral Angle Mapper (SAM) technique for generating a classified

lithological map, displayed significantly better results and the spectral signatures from the image pixels are observed as the best choice as reference in SAM classification. The spectral coverage of ASTER in SWIR range covers the major variation, exhibits by the spectral response of various lithological materials, but its spatial resolution (i.e., 30 m) creates ambiguity at places where the aerial exposure is thin (i.e., outcrop thickness is less than 30 m).

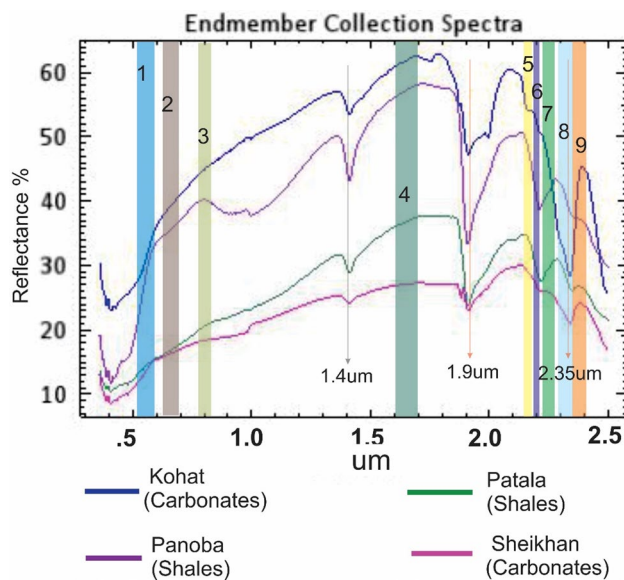


Fig. 14 Spectral profile of undifferentiated lithologies, showing their overlapping response with respect to VNIR and SWIR range of ASTER dataset

Acknowledgements The authors strongly acknowledge the GIS and Space Applications in Geosciences Laboratory-GSAG Lab (National Centre of Excellence in Geology-NCEG, University of Peshawar, Pakistan) affiliated with National Center of GIS and Space Applications-NCGSA (Institute of Space Technology, Islamabad, Pakistan), for providing the well-equipped platform for completing this research work.

Author contributions The conceptualization and exhibition of all steps are done by the principal/corresponding author, the coauthors provided the technical support and guidance in the methodology.

Funding The GIS and Space Applications in Geosciences Laboratory-GSAG Lab, NCE in Geology, Peshawar, Pakistan (affiliated with National Center of GIS and Space Applications-NCGSA, IST, Islamabad, Pakistan) provided the financial support from its component on Geological Applications, for collecting the field data and laboratory analysis.

Availability of data and materials The data and materials used in this research is from all open sources, and mentioned in the references.

Declarations

Conflict of interest This research work has no conflicts of interest/competing interest.

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