Detecting Lithium Brine in Afghanistan Using Spaceborne Hyperspectral Data

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Abstract

The purpose of this thesis is to utilize hyperspectral remote sensing technology for the identification and evaluation of lithium mineral deposits in Afghanistan. Afghanistan boasts unique geological formations with substantial potential for lithium resources beneath its land crust. The focal point of this project revolves around exploring and developing lithium brine-rich deposits in the Dashti-e-Nawar field, an exceptional brine accumulation that also harbors essential boron (B) deposits, crucial for decarbonization efforts. These efforts aim to expand the understanding of lithium mineralization beyond a specific location and explore the possibility of transferring spectral signatures to identify lithium deposits in areas beyond Dashti-e-Nawar. To identify the potential of lithium deposits in Dashti-e-Nawar, Afghanistan, advanced feature extraction algorithms such as Principal Component Analysis (PCA), supervised and unsupervised classification techniques, spectral matching, and spectral profile analysis were applied to PRISMA hyperspectral spaceborne data. Through this analysis, various types of lithium minerals including Gypsum, Hectorite, Kaolinite, and Lepidolite were identified across the dry lake of Dashti-e-Nawar. Furthermore, the analysis revealed the presence of Boron and Borax deposits in the study area (Dashti-e-Nawar) as well as in the mountainous regions on both the eastern and western sides, indicating significant potential for Boron and Borax deposits in Dashti-e-Nawar, Ghazni, Afghanistan. The spectral profiles of lithium minerals in Dashti-e-Nawar were analyzed and compared to reference spectra of lithium minerals from the United States Geological Survey (USGS) spectral library and the JPL spectral library using ERDAS Imagine software. The results demonstrate that Dashti-e-Nawar spans an approximate area of 361.6 km^2 of lithium mineral resources over the dry lake. To identify the lithium (Li) mineral spectral signature, PRISMA data was used to compare with the reference spectra from Bolivia, a known lithium area. The analysis of lithium (Li) spectral signatures revealed a distinctive absorption pattern, with a narrow absorption feature in the near-infrared (NIR) region and a broad absorption feature in the short-wave infrared (SWIR). The most useful bands for identifying the lithium spectral signature using PRISMA hyperspectral data were found at 1372.72 nm (NIR) and 1904.06 nm (SWIR). The natural environmental conditions in Afghanistan facilitate relatively easy in-field exploration in certain areas, and hyperspectral imaging (HSI) proves helpful for regional geological mapping and mineral identification. With this advantageous combination of lithium sources, Afghanistan is well-positioned to emerge as a major global producer of lithium in the future.

Keywords: PRISMA Hyperspectral data, lithium mineral deposits, lithium brine-rich deposits, Dashti-e-Nawar, boron deposits, Principal Component Analysis (PCA), supervised and unsupervised classification, spectral matching, spectral profile analysis, visible-near-infrared (VNIR), short-wave infrared (SWIR) Gypsum, Hectorite, Kaolinite, Lepidolite, lithium carbonate, and lithium chloride.

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SECTION 1

1. Introduction

Remote sensing is used in various Earth observation applications to its ability to capture unique spectral signatures of surface material. In the field of earth science, remote sensing techniques have been widely employed for various geological applications, including the mineral industry, water quality assessment, and the oil and gas industries. Hyperspectral remote sensing technology has been utilized in mineral exploration for more than three decades (Bedini, 2017). This study presents a review of Prisma hyperspectral data in detecting lithium minerals and demonstrated significant value in the investigation of various minerals, including lithium deposits in brine types, also the review of the study encompasses a wide range of topics, including hyperspectral remote sensing, space-borne imagery, mineral exploration, and ore deposits lithium (Li).

It highlights the importance of spatial resolution in achieving favourable results in hyperspectral exploration projects. This study primary objective is to identify and quantitatively measure the surface materials or minerals in the study area by capturing calibrated reflectance spectra in hundreds of narrow and contiguous spectral bands. These spectral bands cover the range of the Visible Near InfraRed (VNIR; 400 to 1300 nm) to Short Wave InfraRed (SWIR; 1300 to 2500 nm) regions in the electromagnetic spectrum. Within these wavelength ranges, different types of rocks and altered minerals display unique spectral absorption features, which makes them well-suited for the spectral sensing of various minerals (Booysen et al., 2021a). The spectral features, resulting from electronic transitions and vibrational processes in minerals, provide valuable mineralogical and geochemical information.

These features can be leveraged to identify mineral species, assess their relative abundance, and characterize physicochemical variations. Geological remote sensing has been extensively employed in mineral deposit exploration, although its potential for investigating economically significant ore minerals remains underexplored (Sabins, 1999). Recent advancements in satellite technology have led to more advanced hyperspectral systems with increased spatial and spectral resolutions. The present study focuses on evaluating the effectiveness of the launched Italian Space Agency's (ASI) PRISMA hyperspectral satellite for exploring lithium brine deposits. This study introduces a systematic methodology that combines hyperspectral data and proximal spectral sensing technology to estimate the amounts and spatial patterns of certain minerals related to surface-exposed alteration products typically associated with lithium mineralization in brine and carbonate-hosted thermal spring systems. Several approaches are suggested to identify the distinctive absorption features from hyperspectral reflectance spectra (Bedini, 2017). The study provides a review of hyperspectral remote sensing Prisma data applications and product in the field of minerals detection. As PRISMA hyperspectral data is rather a product of spectroscopic measurements. Spectroscopy refers to the interaction between matter and electromagnetic radiation, typically involving the measurement of light intensity as a function of wavelength or frequency.

It provides information about the composition, structure, and properties of materials and minerals. Hyperspectral data, on the other hand, is obtained using hyperspectral sensors or imaging spectrometers, which capture many spectral bands across a wide range of wavelengths. These sensors collect data from multiple points on the electromagnetic spectrum, enabling the characterization of materials based on their unique spectral signatures. In the case of PRISMA, it is a hyperspectral satellite sensor that collects data across various spectral bands. Therefore, PRISMA hyperspectral data is a result of spectroscopic measurements made by the sensor, allowing the analysis and interpretation of the composition and properties of minerals and other materials based on their spectral signature.

The term spectroscopy refers to physical methods that separate radiation based on specific properties, such as wavelength. The resulting distribution of intensities is known as a spectrum. Spectroscopy is employed to investigate the interaction between electromagnetic energy and matter, particularly by examining the wavelengths of light that are either reflected or absorbed by objects like minerals. This resolution aids in characterizing minerals and materials. Imaging spectroscopy, also known as hyperspectral remote sensing, involves imaging sensors that measure the spectrum of solar radiation reflected by Earth's surface materials across multiple adjacent wavebands. The resulting image, or data cube, can be visualized similarly to a regular image, except instead of the typical three RGB channels, there can be hundreds of bands. This allows for the identification and often quantification of minerals based on the shape of the spectral curve (Clark et al., 2003).

1.1. Research questions and purpose

This project utilizes Prisma hyperspectral remote sensing data to study lithium deposits. The aim is to enhance our understanding of the functionality of hyperspectral imaging to identify lithium-brine minerals or mineralization in the Dashti-e-Nawar playa located within Ghazni Afghanistan. This study seeks out to address three main questions, in the field of identifying and analysing lithium minerals by using Prisma hyperspectral remote sensing data.

- Can PRISMA hyperspectral data be used to detect lithium?
- Which wavelength bands are most effective in detecting lithium?
- Can the spectral signature for lithium observed in Dashti-e-Nawar be applied to detect lesser-known lithium deposits?

These questions are essential for understanding the capabilities of PRISMA hyperspectral data and for comprehending the variations in lithium (Li) and various mineral types found in brine deposits. The knowledge is crucial for the production and utilization of lithium-ion batteries. With these objectives in mind, the brine deposits project in the dry lake of Dashti-e-Nawar, Afghanistan, required the examination of evaporative sediment. This step is vital for investigating the mineral characteristics and plays a pivotal role in the project's execution, heavily relying on Prisma hyperspectral data techniques to uncover the mineralization features within these regions. The investigation will analyse different lithium minerals and other valuable deposits present in the evaporite sediment in the Dashti-e-Nawar region.

SECTION 2

2.1. Hyperspectral Remote Sensing

Remote sensing is a field that involves gathering data from a distance, typically using satellites or airborne sensors, and analysing that data to gain insights into the features being observed (Sahoo et al., 2013). In other words, remote sensing provides a powerful and versatile toolset for acquiring information about the Earth's surface.

It supports a wide range of applications in environmental science, natural resource management, urban planning, agriculture, climate studies, and disaster management, making it an essential tool for researchers, policymakers, and decision-makers about the Earth (Abad-Segura et al., 2020). Hyperspectral remote sensing is a specialized technique within the broader field of remote sensing. It involves acquiring and analysing data in numerous narrow and contiguous spectral bands, typically ranging from the visible to the infrared regions of the electromagnetic spectrum in accordance with Lillesand et al., Remote Sensing and image interpretation, (Sahoo et al., 2013). Recent advances in remote sensing and geographic information have opened new directions for the development of hyperspectral sensors.

This new technology combines imaging and spectroscopy in a single system, often requiring new processing methods. Hyperspectral data sets consist of 100-200 spectral bands with narrow bandwidths, while multispectral data sets have 5-10 bands with large bandwidths or multispectral data sets typically comprise 5-10 bands with larger bandwidths, unlike hyperspectral data. (Brezini & Deville, 2023). In other words, PRISMA hyperspectral satellite sensor captures data with narrow bandwidths. Specifically, the spectral bandwidths of PRISMA's imaging spectrometer range from approximately 0.01 to 0.03 nanometres.

These narrow bandwidths allow for precise and detailed spectral measurements across a wide range of wavelengths, enabling accurate analysis and identification of various materials and their properties. PRISMA consists of two sensor modules: Hyperspectral Camera and PAN (Panchromatic Camera). The Hyperspectral Camera module is a prism spectrometer with two bands: VIS/NIR (Visible/Near Infrared) and NIR/SWIR (Near Infrared/Shortwave Infrared), providing a total of 237 channels. Its main objective is high-resolution hyperspectral imaging of land, vegetation, inner waters, and coastal zones.

The PAN module is a high-resolution optical imager co-registered with Hyperspectral Camera data for image fusion testing. Its specifications are a spatial resolution of 30 m, operating in VIS/NIR band (400-1010 nm) with 66 channels and NIR/SWIR band (920-2505 nm) with 171 channels. It uses push-broom scanning with a swath width of 30 km and a field of regard of 1000 km on each side. PAN module: Spatial resolution of 5 m, using push-broom scanning with the same swath width and field of regard as PRISMA is in a sun-synchronous orbit at an altitude of 614 km (THE CEOS DATABASE: MISSION SUMMARY - PRISMA, n.d.)) and (PRISMA (Hyperspectral), n.d.).

Hyperspectral sensors provide a more detailed and comprehensive observation of the Earth's surface by capturing a larger number of finely spaced spectral bands, allowing for enhanced spectral analysis and interpretation. In the early 1980s, scientists at the Jet Propulsion Laboratory (JPL) developed the first hyperspectral instrument called the Airborne Imaging (*Imaging Spectroscopy | Capabilities*, n.d.) As the first satellites with hyperspectral imaging capabilities were NASA's Earth Observer-1

(NMP/EO-1) and the European Space Agency's Project for On Board Autonomy (PROBA). NMP/EO-1 was launched in November 2000 and had a spectrometer called Hyperion, which could capture data in 242 spectral bands. PROBA, launched in October 2001, carried a hyperspectral instrument called the Compact High-Resolution Imaging Spectrometer (CHRIS) and could download a maximum of 19 spectral bands of data (Middleton et al., 2013).

Hyperspectral sensors are not designed for specific applications, and today, we are witnessing the rapid development of hyperspectral image processing technology (Sahoo et al., 2013). Hyperspectral data is often represented as a data cube. Each pixel in hyperspectral imagery (HSI) corresponds to a spectral vector that reflects the characteristics of the land cover, making it possible to derive the reflectance behaviours of the pixels in the image (Bodkin et al., 2009).

The rich spectral information helps to discriminate surface features and objects or minerals' better than traditional multispectral imaging systems. A hyperspectral data cube is a three-dimensional array where each pixel contains a spectrum of reflectance values across multiple narrow and contiguous spectral bands. The dimensions of the data cube typically include the spatial dimensions (rows and columns) representing the image pixels and the spectral dimension representing the different bands or wavelengths.

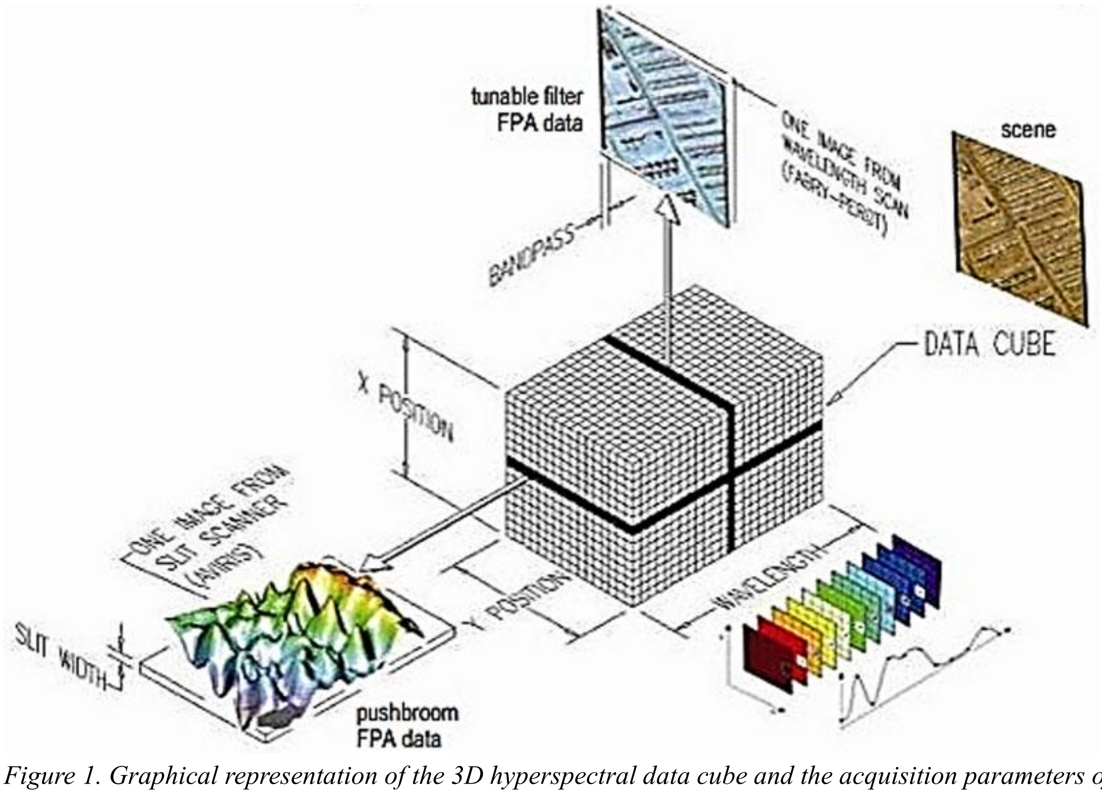

Figure 1. Graphical representation of the 3D hyperspectral data cube and the acquisition parameters of scanning systems (Bodkin et al., 2009).

Each pixel in the data cube provides a spectrum that characterizes the unique reflectance properties of the corresponding location on the Earth's surface ("Hyperspectral Imaging Information," n.d.), as well as can see in the figure 1. scanning systems measure only one slice through the data cube at any given instant. Wavelength-scanning (tuneable filter-type) systems measure a slice at a fixed wavelength and slit-scanning (push broom) systems measure at a fixed position in one spatial dimension. The structure allows for the storage and analysis of vast amounts of spectral information. By organizing hyperspectral data in a data cube format, it becomes possible to explore and extract valuable information through various data processing and analysis techniques. This includes tasks such as spectral unmixing, classification, feature extraction, and change detection. Especially hyperspectral remote sensing data has significant potential for identifying mineral deposits. A case study utilizing AVIRIS data from 1995 over the Cuprite mining area in Nevada, US (van der Meer, 2004).

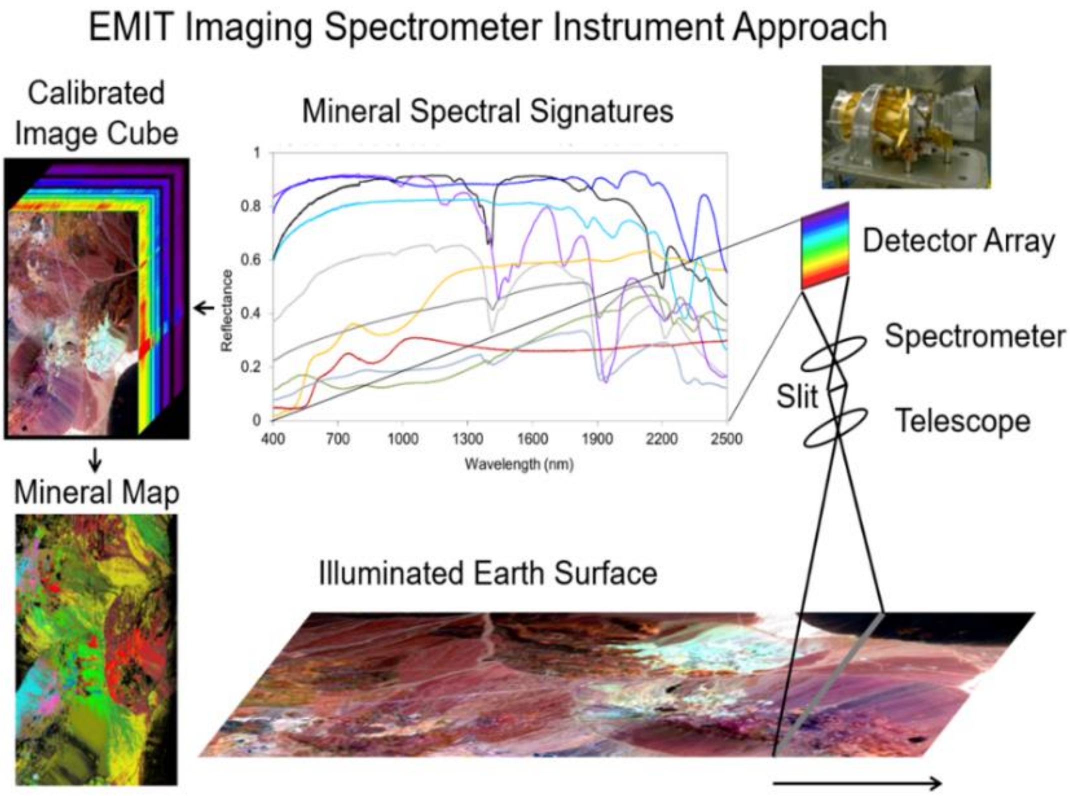

Figure 2. The Cuprite mine in Nevada, in 1995, showcased the efficacy of the hyperspectral data technique in interpreting the data based on the well-known alteration phases present in the region of minerals study (Team, n.d.).

In comparison, other imaging missions like Sentinel-2 or Landsat use only a small number of colour bands. Hyperspectral imaging is useful for many things like figuring out what types of crops are growing in an area, studying the rocks and minerals in the ground, checking the health of forests, monitoring the environment, and even for security purposes (Kruse, 2002). In other hand hyperspectral imaging provides high spatial resolution, detailed spectral information, limited spatial resolution, and specialized applications, but may cover smaller areas due to complexity and cost (Sahoo et al., 2013).

As we can see in the figure 2. EMIT (Emissions Monitoring and Interface Testbed). It is a system used for monitoring and testing various emissions, including greenhouse gases, from different sources such as industrial facilities and power plants. EMIT incorporates advanced sensing technologies and data analysis techniques to provide accurate and real-time information about emissions, helping in the assessment and management of environmental impacts. It is designed to support research and development efforts related to emission monitoring and control strategies. EMIT uses an advanced imaging spectrometer that captures the spectrum for every point in an image.

It measures sunlight reflected from minerals on Earth's surface in the visible to short wavelength infrared range. The instrument records the spectra for 1240 points across its swath. As the ISS moves, the image is gradually formed. The captured image cubes are calibrated, atmospherically corrected, and analysed to determine mineral composition for EMIT's scientific goals. Hyperspectral data, on the other hand, refers to the specific type of data captured by hyperspectral imaging systems (Team, n.d.). Hyperspectral imaging involves acquiring data across numerous narrow spectral bands, often spanning a wide range of the electromagnetic spectrum.

This allows for detailed spectral analysis of the observed scene or object, enabling the identification and characterization of minerals and materials based on their unique spectral signatures. EMIT is a system used for emissions monitoring and testing, while hyperspectral data refers to the type of data captured by hyperspectral imaging systems, which enables detailed spectral analysis for material and minerals identification and characterization (Bedini, 2017).

2.2. Study Area

The study area is shown in the figure. 4 was Dashti-e-Nawar dry salt County, Ghazni, Afghanistan with the coordinated (33°36'04.3"N 67°46'26.0" E). Dashti-e-Nawar is situated in southeast Afghanistan, far from the Ghazni province, the region is an extensive high-altitude plain located within the Koh-e Baba range and Koh-e-Safied, which are part of the Hindu Kush foothills Mountain range. It is a high desert plateau positioned in east-central Afghanistan, approximately 55 km northwest of Ghazni. The Dashti-e-Nawar basin is approximately 40 km long and 20 km wide, covering an area of 425 km2. It contains lithium deposits found in thick sediment layers formed through evaporation deposits (Mack, 2015a).

Figure 3. Study area, Dashti-e-Nawar, high quality lithium brine deposits including lithium and Boron, in southeast Afghanistan, (VMS) web map service, Eris standard En Map-Box software 2023.05.22.

Figure 4. Reference study area Salar de Uyuni, Bolivia known lithium brine deposits in south America, (VMS) web map service, Eris standard En Map-Box software 2023.05.22.

Bolivia has one of the world's largest lithium reserves in the world. It is in the Salar de Uyuni salt flats (Hancock et al., 2018). The Salar de Uyuni is situated in the southwestern part of Bolivia's Altiplano region, covering an area of over 10,000 square kilometres with 21 million metric tons of deposits. It is a valuable resource for the country's economy historically. Bolivia has sought to maintain control over its lithium resources. Lithium is a crucial element in the transition to renewable energy and is found abundantly in Bolivia, Argentina, and Chile. Bolivia specifically focuses on lithium industrialization through integrated mineral development, resource nationalism, and public-private partnerships (Hancock et al., 2018).

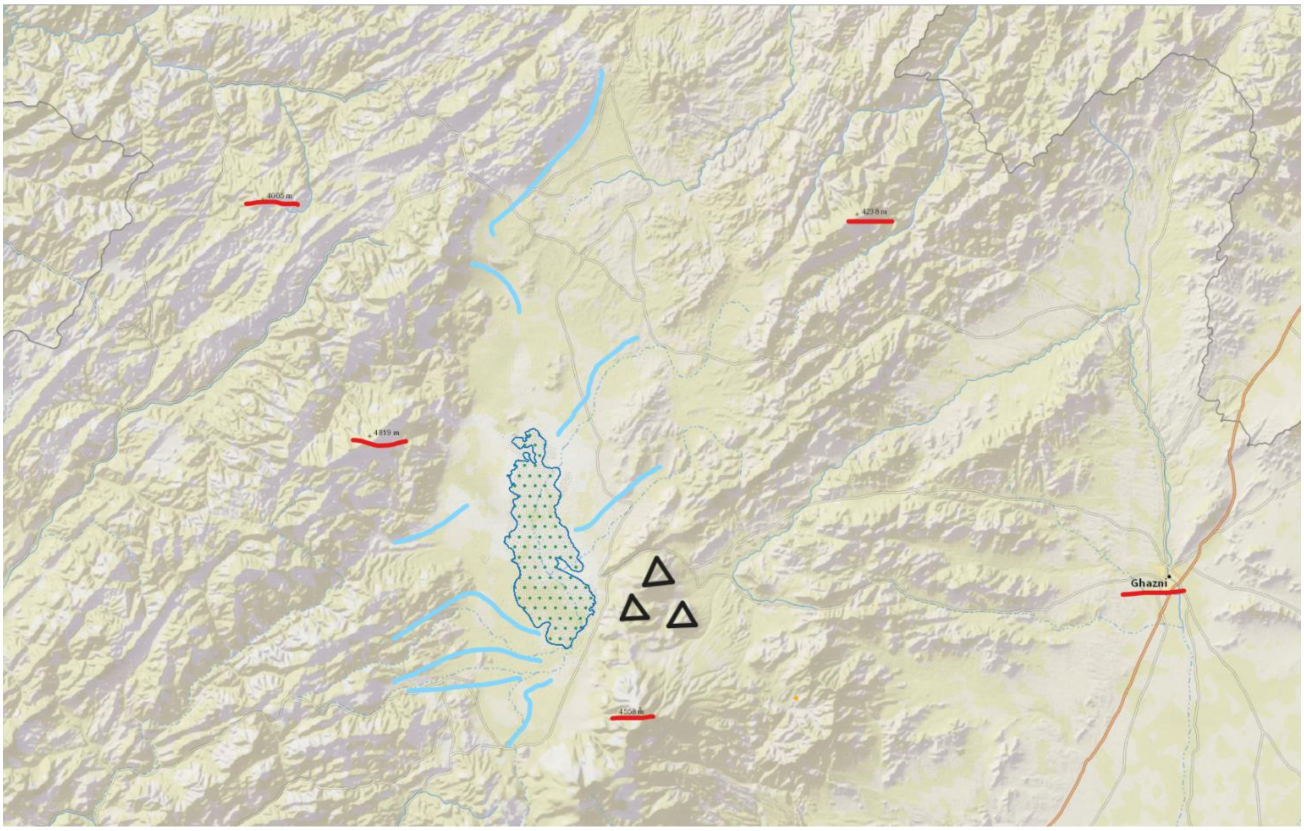

Figure 5. Dashti-e-Nawar dry lake, satellite map, (Esri National Geographic, En Map-Box 2023.05.22.), software shows the elevation of the study area and the water path from the surrounding area.

Dashti-e-Nawar itself is a large volcanic crater formed by a significant eruption that resulted in the collapse of the volcano's opening. The surface of the crater is solid and influenced by the Chinook wind. The climate in the region is hot and dry during summer and very cold in winter, with only three months of the year having temperatures above freezing. Dashti-e-Nawar is surrounded by a volcanic cone to the east and a high mountain to the west. The area is characterized by a plateau with various mountains, including Kohei Safed, which reaches a height of 4,819 m, and in the east, the highest peak reaches 4,558 m. Thermal spring deposits with high concentrations of lithium minerals can be found extending north eastward, north-westward, and south-eastward of the Dashti-e-Nawar dry lake. The study area of Dashti-e-Nawar (Ab-e-Nawar) has accumulated clay minerals and weathering chemical sediments from volcanic ash during past volcanic activity. In fig. 5 the water path is presented with turquoise lines and the Ab-e-Nawar itself is presented with green dots. The red line shows the elevation of the map and lastly the black triangles represent the mountains and importantly the volcanic cone.

Dashti-e-Nawar itself is a large volcanic crater formed by a significant eruption that resulted in the collapse of the volcano's opening. The basin contains evaporative mineral deposits, such as boron

(B), Lithium (Li), calcium, sodium (Na), Neodymium (Nb), Strontium (Sr), magnesium (Mg), and carbonate minerals. The surface sediment is covered by light grey to white, finely cracked mud clay, and there are no silt or sand fractions felt in the clay, (Stillings et al., 2015). The salt in the area contains minerals such as sodium (Na) and chloride (Cl), as well as commonly containing calcium (Ca), potassium (K), magnesium (Mg), and carbonate minerals (Mack, 2015a). The observation obtained those two headwaters from the west side of the lake and some others from the East, North, and south sides of the lake were connected, as can see in the figure 5. Dashti-e-Nawar basins, in east-central Afghanistan, have been of interest since the 1970s. In 2014, an investigation was conducted by the USGS to compare the results of a passive seismic survey of basin sediment thickness to an independently conducted gravity survey. This study used passive seismic equipment to assess sediment thicknesses in the 10's to 1000-meter range (Stillings et al., 2015). The result estimated a maximum thickness of 247 m. This method is less effective than other geophysical surveys (Mack, 2015a).

2.3. Geological Setting

Afghanistan is situated at the convergence zone of the Indo-Pakistan and Asian tectonic plates, which resulted in the formation of the Himalayas Mountain range. The country has a complex geological history characterized by the presence of various small blocks or "terranes" that separated from the Gondwana supercontinent around 50 million years ago. This intricate geological setting has contributed to the diverse range of geological features and mineral resources found in Afghanistan (Mack, 2015b). These terranes were subsequently added to the southern edge of the Asian continent in a series of accretion events.

In structural terms, the volcano of Afghanistan is situated at the heart of the Sistan, where Dashti-Nawar Group is a volcanic field in Afghanistan. It consists of a group of lava domes and stratovolcanoes at the southern end of the Dashti-e-Nawar depression and partly extends north of the same depression. They have been active during the Pliocene and Pleistocene. Dashti-e--Nawar lies southwest of Kabul, about one third the way to Kandahar. The city of Ghazni is about 55 kilometres east of Dashti-e-Nawar. Neogene basin and is restricted (according to aero geophysical data) to the intersection of two diagonally positioned, relatively broad zones of increased permeability.

The long history of igneous activity in the region seems to have finally concluded with only two recent volcanoes in the Pleistocene (Object, n.d.): The eruptive centre of the Dashti-e-Nawar caldera near Ghazni, which last erupted about 2.2 million years ago, sending a massive volcanic lahar mudflow all the way to the Indus River (Khan et al. 1985; Shroder 2014); and the Kohi-e-Khanneshin carbonatite eruptive center in the lower Helmand, which was emplaced in the Pleistocene around 0.61 million years ago.

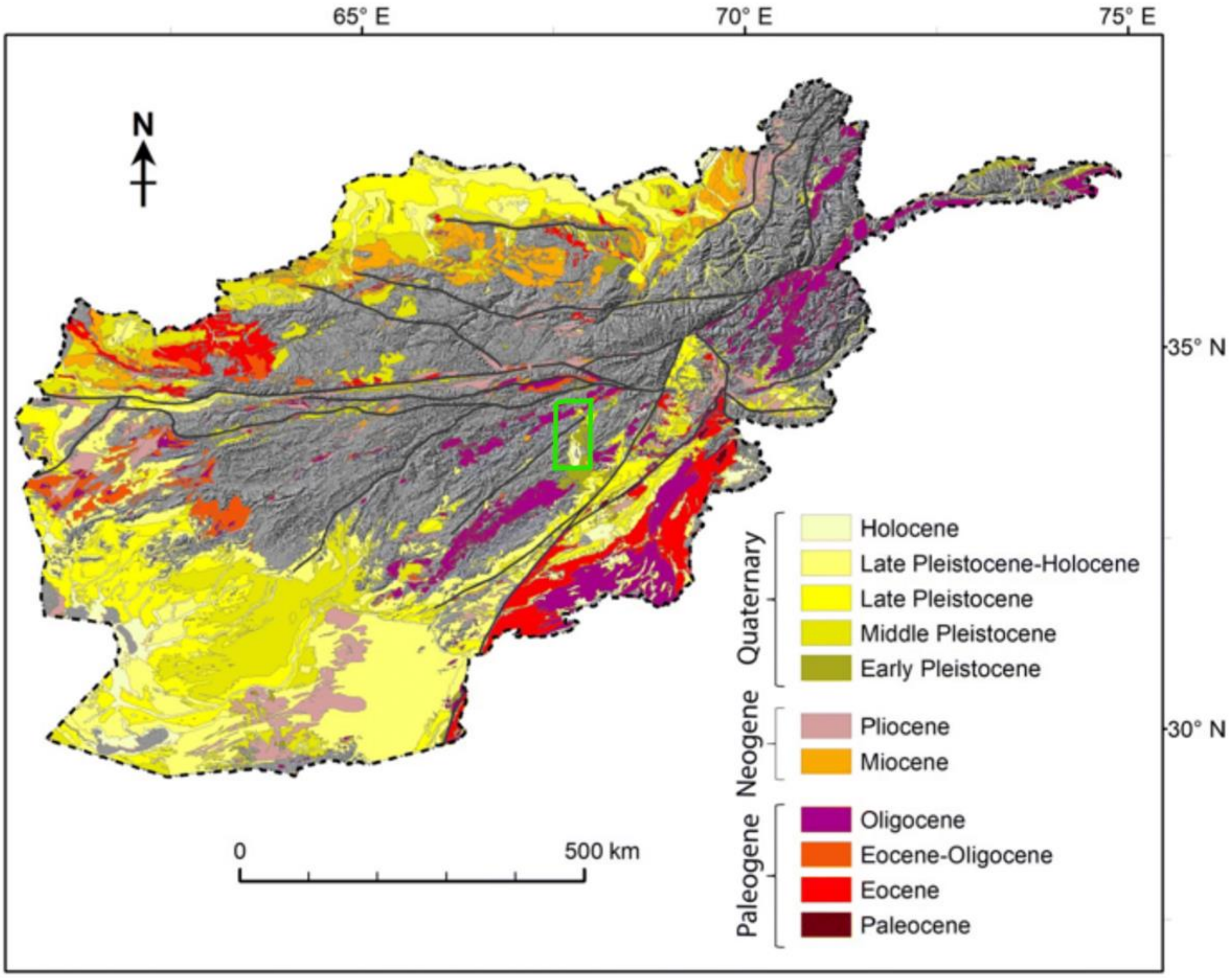

Figure 6. Cenozoic geologic maps of Afghanistan. The map is modified from Doebrich et al. (2006). Cenozoic rocks cover approximately half of the country (Shnizai, 2020). Dashti-e-Nawar is located in the lime-green rectangle area.

These volcanoes represent the final stages of the magmatic eruption from the subduction that once occurred beneath Afghanistan as the Indian plate moved northward beneath the Eurasian. The carbonate mixed with clay is widely distributed throughout the area but is most concentrated in the northern and eastern portions. In fig. 6 the study area consists mostly of Holocene and early Pleistocene from the Quaternary period. Furthermore, the sediment in Dashti-e-Nawar playa includes erosion, weathering chemical materials or sediment, and evaporation minerals. Over time, these processes can cause the playa to change shape and minerals composition, for example, salt sedimentation can increase the playa's size. Meanwhile, evaporation can concentrate salts and minerals in the area, creating unique mineral formations like lithium in brine (Miller et al., 2011).

Common cementing minerals in Dashti-e-Nawar include calcite, silica, spodumene, quarts, halite, kaolinite, and carbonites, in the southwest part of the lake some iron oxide and lithium boron accords in the study area. Over time, the layers of sediment become compressed and cemented, forming a solid rock. This process is known as lithification. In the study area Dashti-e-Nawar there are chemical rocks formed from the precipitation of minerals from three types of water, thermal spring water, surface water (snow melting and rainfall), and water from the mantel during the volcanic activity in Dashti-e-Nawar for 2.2 million years ago.

2.4. Formation of evaporite deposits in Dashti-e-Nawar basin

Evaporite deposits in Dashti-e-Nawar, located in a region characterized by arid or semi-arid environments and closed basins, are the result of a geological process involving evaporation, precipitation, and deposition. In this region, the high rates of evaporation and limited water circulation contribute to the formation of these deposits. The process begins with the presence of water in Dashti-e-Nawar, which contains various minerals and salts in dissolved form. Due to the arid climate and high temperatures, the water rapidly evaporates, leaving behind concentrated solutions of dissolved lithium (Li) minerals, salts, and some other elements. The evaporation process is driven by the energy from the sun, causing the water to transform into vapor and escape into the atmosphere.

As the water evaporates, the concentration of lithium minerals and salts in the remaining solution increases. Eventually, the solution can reach a point of saturation, where it can no longer dissolve any additional minerals or salts. At this stage, the excess minerals and salts begin to precipitate out of the solution and form solid crystals. The precipitated minerals and salts accumulate over time, gradually building up into evaporite deposits. These deposits can consist of various minerals, including lithium-bearing minerals such as lithium carbonate (Li2CO3) or lithium chloride (LiCl) and other deposits such as Boron (B) and Borax (Na2B4O7 · 10H2O). The specific composition of the evaporite deposits in Dashti-e-Nawar depends on the types and concentrations of minerals present in the original water source ("Evaporite | geology | Britannica," 2023).

The mineral crystals formed in the evaporite deposits can exhibit a range of shapes and sizes, depending on factors such as temperature, pressure, and the specific chemical properties of the minerals involved. Common crystal forms found in evaporite deposits dashi-e-Nawar include halite (rock salt), gypsum, and (potassium chloride). Evaporite deposits in Dashti-e-Nawar serve as important sources of lithium, a valuable mineral widely used in various industries, including battery production for electric vehicles and renewable energy storage. The presence of these deposits in the region has attracted attention from mining companies and researchers interested in lithium extraction. (Acharya, 2018).

As the concentrated solution in Dashti-e-Nawar continues to evaporate, more minerals and salts are added to the mixture, leading to the continued growth of crystals (Warren, 2021). The specific minerals that precipitate out of the solution depend on the composition of the original water source, which can vary in terms of the types and concentrations of dissolved minerals and salts. Over time, the crystals settle and accumulate on the bottom of the basin or lakebed in a process known as deposition. As new layers of crystals form, they may bury and compress the previously deposited layers. This compression, along with geological processes such as tectonic activity, can contribute to the solidification and consolidation of the evaporite deposits (Miller et al., 2011).

Various minerals can be found in evaporite deposits in Dashti-e-Nawar. Halite, commonly known as rock salt, is a prevalent mineral in such deposits. Gypsum, a hydrated calcium mineral, is another common component. Additionally, minerals like lepidolite and Hectorite, which contains lithium, and tuff, a type of volcanic ash, can also be present in these deposits. Evaporite deposits are not unique to Dashti-e-Nawar and can be found in different environments worldwide. Salt flats, salt pans, and playas are some examples of locations where evaporite deposits form. These deposits have significant economic importance as sources of industrial elements. Lithium, an essential component in the production of batteries for electric vehicles and renewable energy storage, is extracted from lithium-bearing minerals found in evaporite deposits (Mack, 2015b). Additionally, evaporite deposits are sources of salt used in food production, gypsum utilized in construction materials, and potash, a vital ingredient in fertilizer production (Warren, 2021). In conclusion, the evaporite deposits in Dashti-e-Nawar are the result of the evaporation of water, which leaves behind concentrated solutions of dissolved lithium minerals, Boron, and salts. As these solutions become saturated, the minerals and salts precipitate out, forming mineral crystals that accumulate over time to create the evaporite deposits found in the region (Warren, 2021).

2.5. Lithium Mineralogy

Pegmatites are the usual source of minerals associated with lithium, such as spodumene, lepidolite, and petalite are common minerals in pegmatite rocks. Economically lithium can be extracted from brines in evaporite sedimentary deposits, such as study area Dashti-e-Nawar. And lithium can also be found in commercially viable amounts in sedimentary rocks “clay” that contain the lithium mineral. Lithium is a chemical element with the symbol Li and atomic number 3, it is a soft, silvery-white metal that belongs to the alkali metal group of elements, along with sodium (Na), potassium (K), rubidium (Rb), Caesium (Cs), and francium (Fr). Lithium is highly reactive and flammable, and it is commonly found in small amounts in the Earth's crust, as well as in the oceans and thermal (*Lithium | Definition, Properties, Use, & Facts | Britannica*, 2023).

It was first discovered by the Swedish chemist August Arfwedsson when he analysed the mineral Petalite and identified a new alkali metal element, "Lithium". He discovered lithium in 1817 and built his laboratory at Stockholm city. Lithium has become an essential element in numerous industrial and technological applications, such as batteries, ceramics, and pharmaceuticals. Its significance has grown with the advancement of green technologies, as it plays a vital role in producing environmentally friendly electricity.

Lithium is a highly reactive element that is not commonly found in its pure form in nature. It can be economically extracted from various minerals found in valuable deposits. The extraction of lithium primarily occurs from three types of deposits: brine, pegmatite, and sedimentary rocks. Brine and pegmatite serve as the main sources of commercial lithium production. The global reserves of lithium are estimated to be approximately 26 million metric tons by 2022. In the Dashti-e-Nawar landlocked dry lake, several common lithium minerals contain, which is listed in Table 1 shows lithium minerals that are found in Pegmatite rocks in Nuristan Afghanistan. The pegmatites, those of Nilaw and Mawi especially, occur as veins of highly variable size, from 10 cm to 40 meters in thickness and from a few meters to a few kilometres in length (*Pegmatites of Laghman, Nuristan, Afghanistan*, n.d.)

Table 1. Four most common Lithium-bearing pegmatite minerals located in Nuristan Afghanistan (Ahmadi et al., 2017).

Mineral name	**Chemical formula**	**Lithium content**	**Appearance (colour and Ilustre)**
Spodumene	LiAlSi2O6	3.7	White, colourless, grey, pink, yellow, green; vitreous
Petalite	LiAlSi4O10	1.6 - 2.27	Colourless, grey, yellow, or white; vitreous to pearly
Cookeite	$(LiAl_4\square)\ [AlSi_3O_{10}]\ (OH)_8$	1.33	White, yellowish green, pink, brown
Lepidolite	K2 (Li Al)5 - 6{Si6 7Al2-1O20} (OH, F)4	1.39 - 3.6	Colourless, grey/white, Lilac, yellow, or white; vitreous to pearly
Amblygonite	$LiAl\ (PO_4)\ F$	3.44	Milk-white, yellow, beige, salmon-pink, pale green, light blue, grey; colourless in transmitted light.

Pegmatite minerals and evaporite minerals are two distinct types of minerals that form under different geological conditions. Pegmatite minerals are formed in intrusive igneous rocks, typically in large, coarse-grained veins or dikes. These rocks result from the slow cooling and crystallization of magma deep within the Earth's crust such as Nilaw and Mawi in Nuristan Afghanistan. While eevaporate Minerals, on the other hand, form from the precipitation and deposition of minerals and salts due to the evaporation of water in arid or semi-arid environments such as Dashti-e-Nawar.

They typically occur in sedimentary environments such as salt flats, playas, or closed basin settings. The evaporite minerals tend to have smaller crystal sizes, typically ranging from microscopic to a few millimetres, some evaporite minerals can form visible crystals, they are generally smaller compared to pegmatite minerals. Pegmatite minerals often exhibit exceptional crystal sizes, ranging from centimetres to meters in diameter. They can contain crystals that are significantly larger than those found in other types of rocks. The Pegmatite minerals can consist of a wide range of minerals, including feldspars (such as orthoclase and plagioclase), quartz, micas (such as muscovite and biotite), tourmaline, beryl, garnet, and many more. They often contain rare elements and minerals that are not commonly found in other rock types.

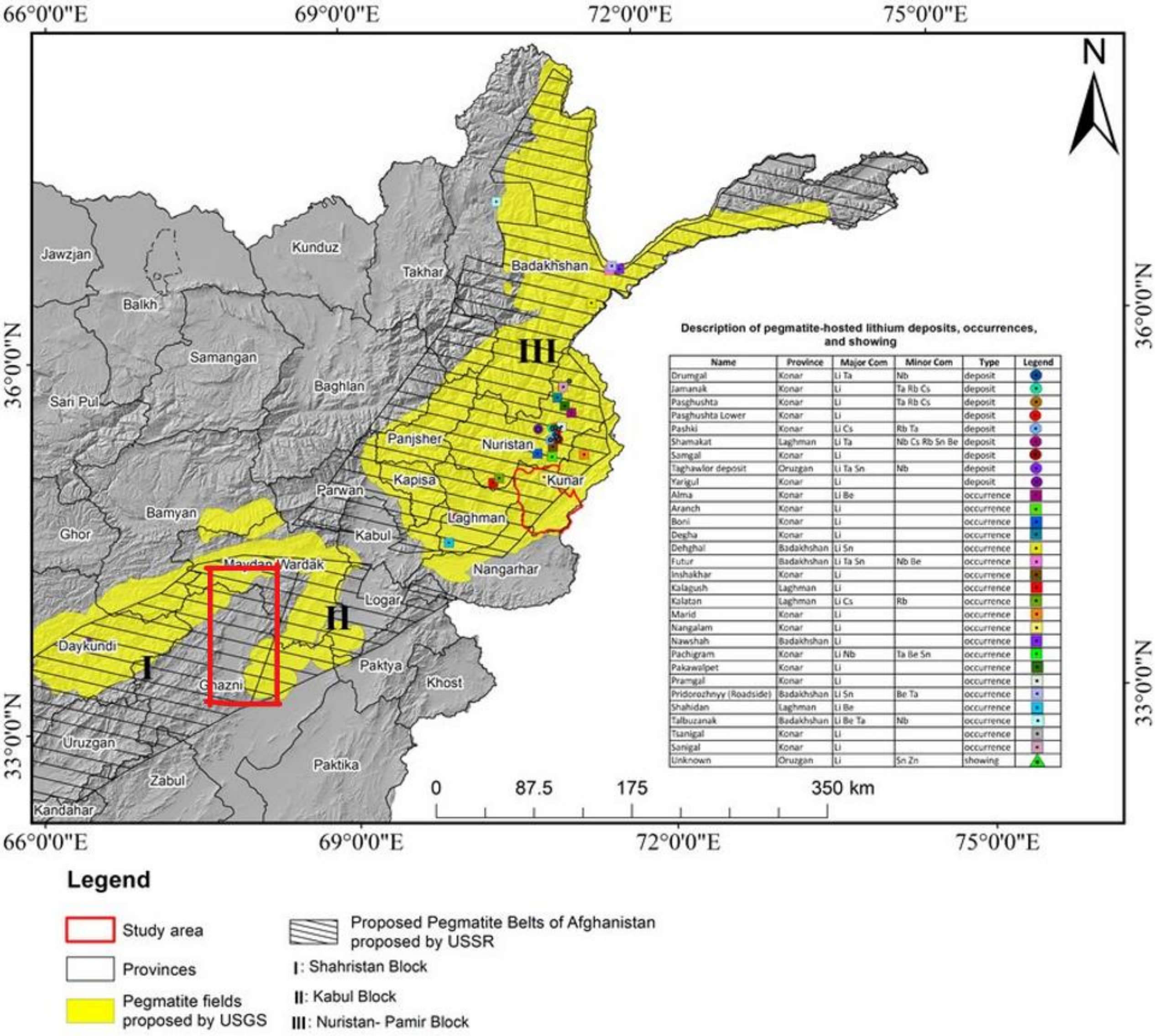

Figure 7. The distribution of Li deposits within the pegmatite belts of Afghanistan adapted from (Fenogenov and Musazai 1989, Abdullah et al. 2008, Cocker 2011, Mosazai et al. 2017). The red rectangle is where the study area is located.

Afghanistan indeed has four large pegmatite belts totalling 18,320 square kilometres, with corresponding information provided in Table 2, which suggests a significant presence of lithium-bearing Pegmatite minerals in those areas. Pegmatites are known to contain various minerals, including spodumene, petalite, lepidolite, and amblygonite, zinnwaldite, triphylite, and eucryptite among others (Ahmadi et al., 2017). In the study area Dashti-e-Nawar has been also found lithium minerals in Pegmatite e.g., Petalite, because there are large Pegmatite belts occur on the north, east and south of the study area Dashti-e-Nawa (Ahmadi et al., 2017)

Table 2. Pegmatite fields of rare metals Pgmatite, and Pegmatite belts of Afghanistan with their area.

Large geological structure (blacks)	**Large Pegmatite region**	**Pegmatite field a**	**Area km^2**
Sharistan	Helmand & Maidan	Tagawler, Kawang, Behsud, Maidan	1146 km^2
Kabul	Kabul	Shakardara-Guldara	60 km^2
Nuristan	Nuristan	Panjshir, Nejrab, Tagab, Jegdalek, Shamakat, laghman, Jalalabad, Marid, Dara-e-Pech, Paech-garm	8038 km^2
Pamir	Badakhshan	Talbuzang, Kukcha, Eshkashem, Shiwa	9076 km^2
Total	Lithium pegmatite in Afghanistan		18320 km^2

A comprehensive review of lithium in Salar deposits and the geological condition in Afghanistan reveals some interesting findings (Mack, 2015c). The Salar formation is influenced by geologic conditions that typically extend over a regional scale. Consequently, it is not uncommon to find smaller Salars near larger systems throughout Afghanistan. These smaller salars may also contain valuable minerals and a few could potentially be economically viable for artisanal production.

The studied Salars can be categorized into two main groups. The first group is located north of the Hari Rud Fault, which belongs to the Tajik Block and is part of the Eurasian Plate. The remaining systems are situated on or very close to the edges of the Afghan Block. Further subdivision of the sites on the Afghan Block is based on regional climate patterns and active surface geological and hydrological processes.

The largest and most well-understood subgroup is the Sistan-Godzareh system, which includes lakes like Chakhansar and Farah, as well as the lakes formed in the Godzareh Depression, namely Godzareh East, Central, and West. The second subgroup, known as the Eastern Group, consists of Dasht-e-Nawar and Abe-e-Istada. The third subgroup is the solitary Namaksar-e-Herat site. It's worth noting that all these subgroups share a common origin resulting from the same genetic processes, as discussed in detail below. The differentiation of these subgroups becomes relevant when considering the economics of resource production. Understanding the geological conditions and subgroups of Salar deposits in Afghanistan provides valuable insights into the potential for lithium extraction and its associated economic prospects in the region.

Table 3. The four most common lithium-bearing minerals found in the economic deposits in Dashti-e-Nawar are found in brine.

Mineral name	Chemical formula	Lithium content	Appearance (colour and Ilustre)
Gypsum	$CaSO_4 \cdot 2(H_2O)$	Don't know	Colourless to white, often tinged other hues due to impurities; colourless in transmitted light.
Lepidolite	$K_2 (Li\ Al)_{5-6}\{Si_{6-7}Al_{2-1}O_{20}\}(OH, F)_4$	1.39 - 3.6	Colourless, grey/white, Lilac, yellow, or white; vitreous to pearly
Kaolinite	$Al_2Si_2O_5(OH)_4$	Low lithium content	Colourless, grey, yellow, or white; vitreous to pearly
Hectorite	$Na_{0-3}(Mg, Li)_3Si_4O_{10}(OH)_2$	0.54	White, opaque: earthy

These eevaporate minerals primarily consist of compounds that are formed by the evaporation of water. Common evaporite minerals include halite (rock salt), gypsum, anhydrite (potassium chloride), and various carbonates such as calcite, calc and dolomite minerals. They are typically composed of abundant elements like sodium, potassium, calcium, and chlorine. While Pegmatite minerals are valued for their gemstone varieties (e.g., beryl, tourmaline) and their industrial applications (e.g., feldspars in ceramics, quartz in electronics).

They are often mined for their economic importance in various industries, and eevaporate minerals are economically significant as they are sources of important industrial materials. For example, halite is used as table salt, gypsum is used in construction materials, and potassium chloride (sylvite) is a primary source of potassium for fertilizer production. Table 3 shows which minerals are found over the study area Dashti-e-Nawar. Furthermore, pegmatite minerals form in igneous rocks and have large crystals, while evaporite minerals form through the evaporation of water in sedimentary environments and have smaller crystals. Pegmatite minerals are diverse in composition, often containing rare elements, while evaporite minerals primarily consist of compounds formed by the evaporation of water. Both types of minerals have economic significance but serve different industrial purposes.

2.5.1. Spodumene

Figure 8. Mineral spodumene Kunzite Laghman Afghanistan (Spodumene | Mineral | Britannica, n.d.)

Spodumene is the most abundant lithium-bearing mineral found in economic deposits. Its accusers as prismatic, lath-shaped, crystals in granites and pegmatite. Spodumene has a hardness of 6.5 to 7 on the Mohs scale and a density of 3.1-3.2 kg m3. It has a pronounced longitudinal cleavage and decomposes to kaolinite and montmorillonite on weathering.

Spodumene is a common mineral, but its two distinctly coloured transparent varieties, Kunzite (pink) and Hiddenite (green) are highly valued as gemstones. Hiddenite is much rarer than Kunzite and can be highly valued. Kunzite is known for its lovely pink colour but can fade upon prolonged exposure to sunlight. Spodumene is strongly pleochroism and can grow into enormous crystals. It is rarely seen on a matrix and can easily alter to other minerals and clay (*Spodumene | Mineral | Britannica*, n.d.).

2.5.2. Lepidolite

Figure 9. Lepidolite, cleavelandite, quartz Paprok, Nuristan Afghanistan (Lepidolite | Mineral | Britannica, n.d.)

Lepidolite is an uncommon form of Material Identification and Characterization Algorithm (MICA) that is found in pegmatite and has a hardness of 2.5-3 on the Mohs scale and a density of 2.8-3 kg m3. It has a lamellar cleavage, giving it crystal a book-type structure. Lepidolite can also contain potassium, rubidium, and cesium. It has a lamellar cleavage, giving the crystal a book-type structure. Lepidolite can also contain potassium, rubidium, and cesium, which may provide valuable by-products (Lepidolite | Mineral | Britannica, n.d.). Lepidolite, a common lithium mineral, is economically important as a source of lithium and rubidium. It is found in granite pegmatites and is useful for geological age determination.

2.5.3. Petalite

Figure 10. Petalite NB: Swedish "Ö"= Island, The Nyköpingsgruvan mine was opened in the 12th century and closed in 1878, with pegmatites found on the dumps (*Petalite*, n.d.).

Petalite is a monoclinic mineral with two cleavage directions. It often accuses with lepidolite in pegmatites and in some cases, there is evidence that it alters to spodumene. Petalite has a hardness of 6 on the Mohs scale and a density of approximately 2.4 kg m3 (Kunasz, 2006; Garrett, 2004). pegmatites are the type locality for 4 species: spodumene, petalite, tantalite-(Mn) and holmquistite. The element lithium was also discovered in petalite from (Utö Mines, Utö, Haninge, Stockholm County, Sweden, n.d.)

2.5.4. Hectorite

Figure 11. Hectorite formula: Na0.3(Mg, Li)3(Si4O1) (F, OH)2 Bentonite Mine No. 1, Hector, Cady Mountains, San Bernardino Co., California, USA (*Hector Bentonite Mine No. 1, Hector, Cady Mountains, San Bernardino County, California, USA*, n.d.)

Hectorite is a trioctahedral smectite clay mineral formed from the alteration of volcanic rocks by hydrothermal or hot spring activity, which is accurate in Dashti-e-Nawar Lake. The lithium substitutes for magnesium within the lattice structure of the mineral. It has a hardness of 1-2 on the Mohs scale and a density of 2-3 kgm^3.

2.6. The usage of lithium

Lithium has excellent physical and chemical properties, it plays an important role in the military, battery, special alloy, controlled thermonuclear reactions, and other fields. It is a useful element with many different uses. One important way it is used is in rechargeable batteries that power things like cars, phones, laptops, cameras, smoke detectors, solar panels, and motorcycles. It's also used in non-rechargeable batteries for things like pacemakers, clocks, and toys (Acharya, 2018).

When lithium is mixed with magnesium and aluminium, it makes those metals stronger but also lighter. This is important for making parts for planes, bikes, fast trains, and even Armor. There are also different kinds of lithium salts that have lots of uses. They're used in medicines for mental health conditions like bipolar disorder and depression. They're also used in making special types of glass and ceramics, storing fuels, and even keeping air conditioners cool (Bhattacharya et al., 2018).

SECTION 3

3. Materials and Methods

3.1. PRISMA Hyperspectral data

This study utilized the Prisma satellite, which is a high-resolution hyperspectral imaging satellite developed by the Italian Space Agency (ASI). The Prisma satellite is equipped with two sensor instruments, including the Hyperspectral Camera and Panchromatic Camera modules. The Hyperspectral Camera sensor is a prism spectrometer for two spectrums, VIS/NIR and SWIR/NIR. And the ppanchromatic camera module of the Prisma satellite is a sensitive instrument that is co-registered with the Hyperspectral Camera data.

It is designed to capture high-resolution black-and-white with a higher spatial resolution of 5 m. The Prisma Hyperspectral Camera records data with 234 spectral bands, with 66 bands over the VIS/NIR spectrum (interval 400-1010 nm), and 171 bands over the NIR/SWIR spectrum (920-1010 nm) and (1010-2500 nm). The bandwidth varies but is on average ca 12 nm. Spatial resolution is about 30 m. The PRISMA Earth Observation system combines a hyperspectral sensor with a medium-resolution panchromatic camera. The imaging spectrometer takes images with a pixel size of 30 m in a continuum of spectral bands ranging from 400 to 2500 nm. The system has a 30 km swath and can acquire images distant 1000 km in a single pass.

With a repeat orbital cycle of approximately 29 days, the PRISMA system provides the capability to acquire, downlink, and archive images over the primary area of interest defined in the following ranges: 180°W - 180°E and 70°S - 70°N. The relook time can be significantly reduced to less than one week. The PRISMA system was launched on orbit in March 2019 and after closing the commissioning phase, the access to PRISMA data (both archived and as new acquisitions) opened. The PRISMA web page can be found here: http://www.prisma-i.it/index.php/en/.

To register for access to PRISMA data, please visit https://prismauserregistration.asi.it/. After registration, the PRISMA documentation (e.g., PRISMA Product Specifications) is also available in the same portal for data search and download. The data has been downloaded at the L2D level from two regain Afghanistan Dashti-e-Nawar and Bolivia Salar De Uyuni.

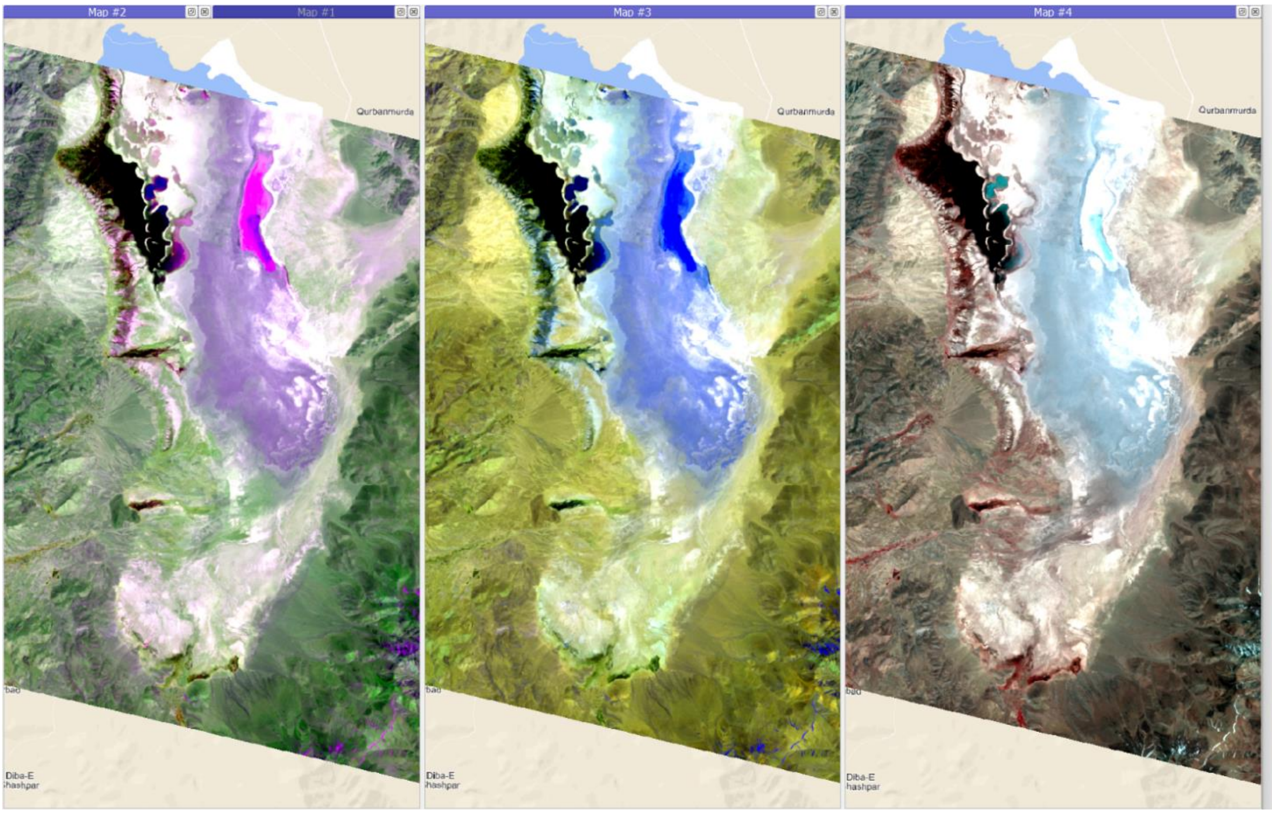

Figure 12. Prisma satellite image from Dashti-e-Nawar in three different electromagnetic spectrum bands: CIR, SWIR, and Geology bands. Made through EnMap-box software.

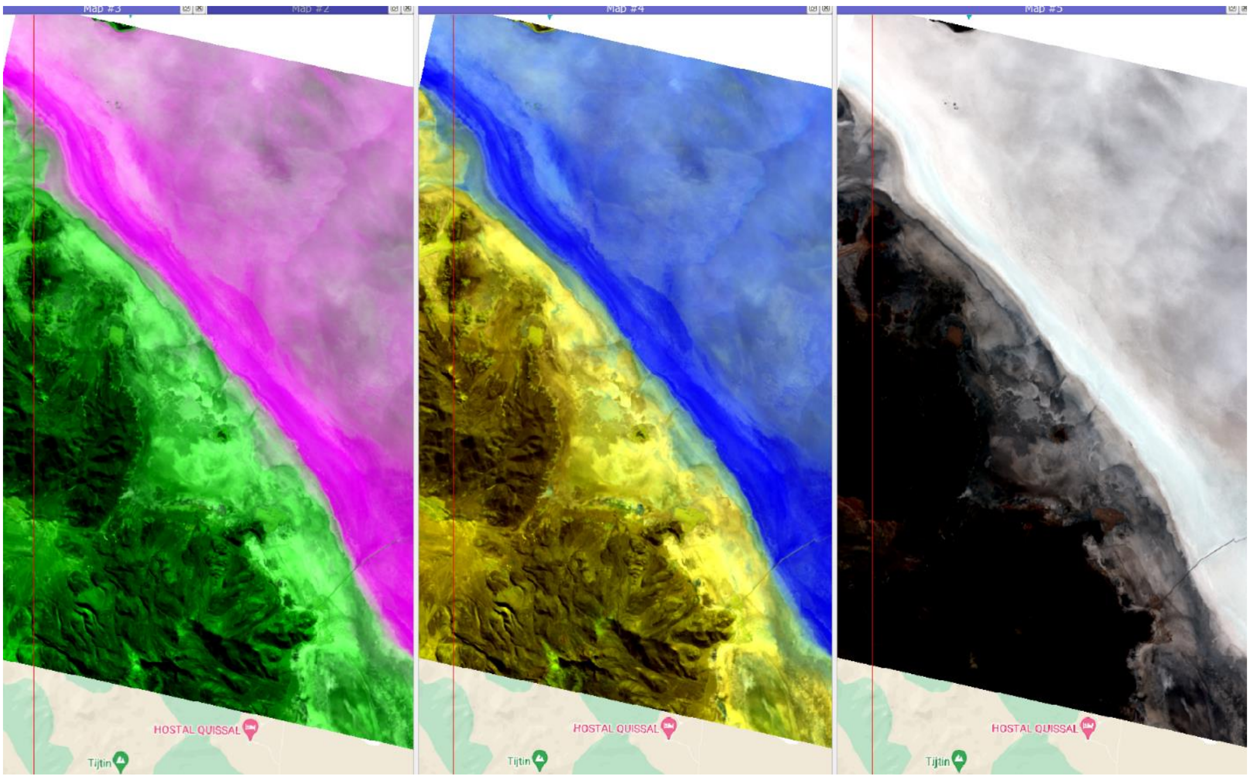

Figure 13. Prisma satellite image from Bolivia Salar De Uyuni in three different electromagnetic spectrum bands: CIR, SWIR, and Geology bands. Made through EnMap-box software.

In fig. 12 the Prisma satellite image of Dashti-e-Nawar captures the region in three distinct electromagnetic spectrum bands: CIR (Colour Infrared), SWIR (Short-Wave Infrared), and Geology bands (2202 nm, 1614 nm, 492 nm). This multi-spectral approach enables the acquisition of valuable information about the area's, geological features, and other relevant data for comprehensive analysis and interpretation. The NIR and SWIR region has multiple advantages, NIR and SWIR wavelengths aren’t visible to human eyes, but the light interacts with objects. But in the case of NIR/SWIR imaging, we can capture images of objects and see aspects that we couldn’t see in the visual range.

To examine the spectral characteristics of different types of lithium minerals, a comparison was conducted between the spectral signature of each pixel from Dashti-e-Nawar, and the spectral signature of lithium minerals obtained from Bolivia's Salar de Uyuni or "Salar de Tunupa". In fig. 13 the Prisma satellite image from Salar de Uyuni has been visualized in three different electromagnetic spectrum bands, CIR, SWIR, and Geology bands. The Salar de Uyuni is recognized as the world's largest known salt flat or playa, spanning over 10,000 square kilometres. Situated in the Daniel Campos Province in Potosí, southwest Bolivia, it is located near the crest of the Andes at an elevation of 3,656 meters above sea level. This comparative analysis aimed to identify any similarities in the spectral properties of diverse lithium minerals found in these two regions.

3.2. Overview of Methods

In this study, we analyse the spectral signature of lithium minerals by comparing it to the known spectral signature of lithium brine in the Bolivia salt flat and the spectral signature of various types of lithium minerals obtained from the spectral libraries of the United States Geological Survey (USGS), which served as a reference from spectral library (ASTER, JPL, USGS V4, and USGS V6 Convolved) ERDAS imagery software. By examining and comparing the spectral profiles of lithium minerals with established spectral signatures, this research contributes to the advancement of effective methodologies for lithium detection and exploration.

The data have been used to analyse the chemical composition of minerals by examining their spectral signatures. The spectral signature of minerals is the unique pattern of reflected electromagnetic radiation across a range of wavelengths. This signature is inflected by the chemical composition of the mineral, as well as crystal structure, morphology, and other physical properties. To analyse the chemical composition of the minerals using hyperspectral data there are many steps to do, the following steps have been done in the work.

1. Acquired Prisma L2D level spaceborne hyperspectral data.
2. Pre-process the data, to remove noise and artifacts and to correct for atmospheric and radiometric effects. This step is critical to ensure the accuracy of the subsequent analyses.
3. Identify the mineral of interest based on it is known spectral signature or by using a library of mineral spectra as a reference.
4. Extract spectral features from the data that are related to the mineral of interest. This part can be done using various statistical techniques such as Principal component analysis spectral angle mapper or spectral in mixing.
5. Validate the result of the analysis by comparing them to ground truth measurements, laboratory analysis, or other independent sources of information.
6. Analysis of the spectral feature, and extraction of spectral features to determine the chemical composition of the mineral, can be done by comparing the features to a library of known minerals spectra.

The analysis of minerals composition using hyperspectral is a bit complex process that requires good knowledge of remote sensing, mineralogy, and data analysis.

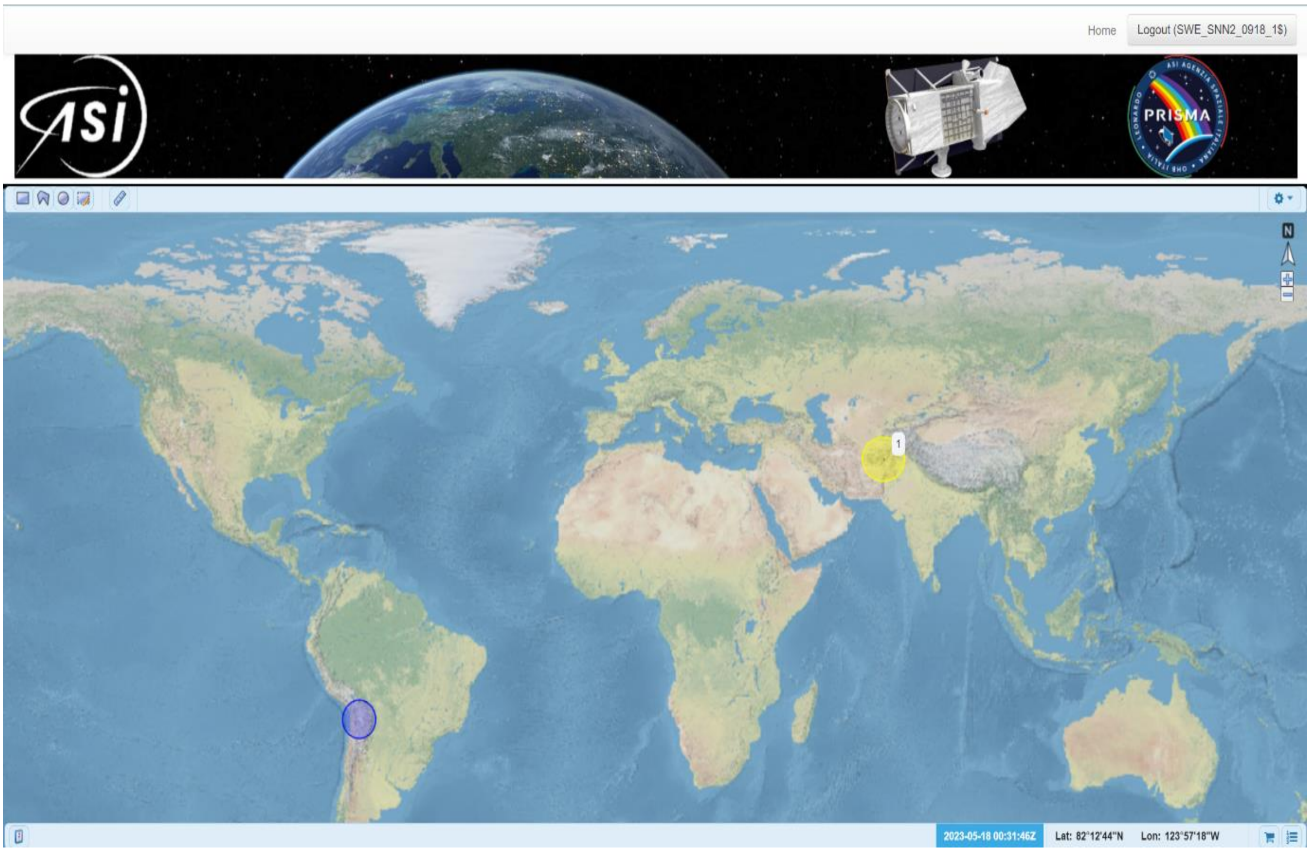

Figure 14. PRISMA product was obtained in the HDF-EOS5 format, providing surface reflectance data. The study areas are marked with yellow- and purple-coloured circles (*Mission Selection Form*, n.d.).

The study area can be seen by yellow- and purple- coloured circles over the PRISMA data aquation site in fig.14. The acquisition took place on June 15, 2022, at 12:30 AM, encompassing the Dashti-e-Nawar Caldera site and the Bolivia salt flat.

3.3. Pre-processing - Data Analysis

The analysis of hyperspectral imagery data involved several pre-process steps and analytical techniques. The data was acquired using the Prisma satellite and was obtained in a TIFF file in L2D level format. Initially, sensor information was gathered, followed by the removal of bad bands that contained unreliable or noisy band. A spectral subset, focusing on the Visible Near Infrared (VIS/INR) and short-wave infrared (SWIR) ranges, was created to enhance specific spectral characteristics of interest. Additionally, a spatial subset tool was applied to select a specific region of interest for further analysis.

To account for atmospheric effects, an atmospheric adjustment method was implemented to correct the imagery for atmospheric interference and improve the accuracy of subsequent analyses. The minimum noise fraction (MNF) technique was employed to reduce the noise and enhance the signal-to-noise ratio in the hyperspectral data.

After the pre-processing steps, the analysis proceeded in the General workstation mode. Various analytical techniques, such as anomaly detection, target detection, material mapping, and material identification, were performed on the hyperspectral imagery data. These techniques enabled the identification of unique spectral signatures, the detection of anomalies or specific targets, and the mapping and characterization of different materials within the scene.

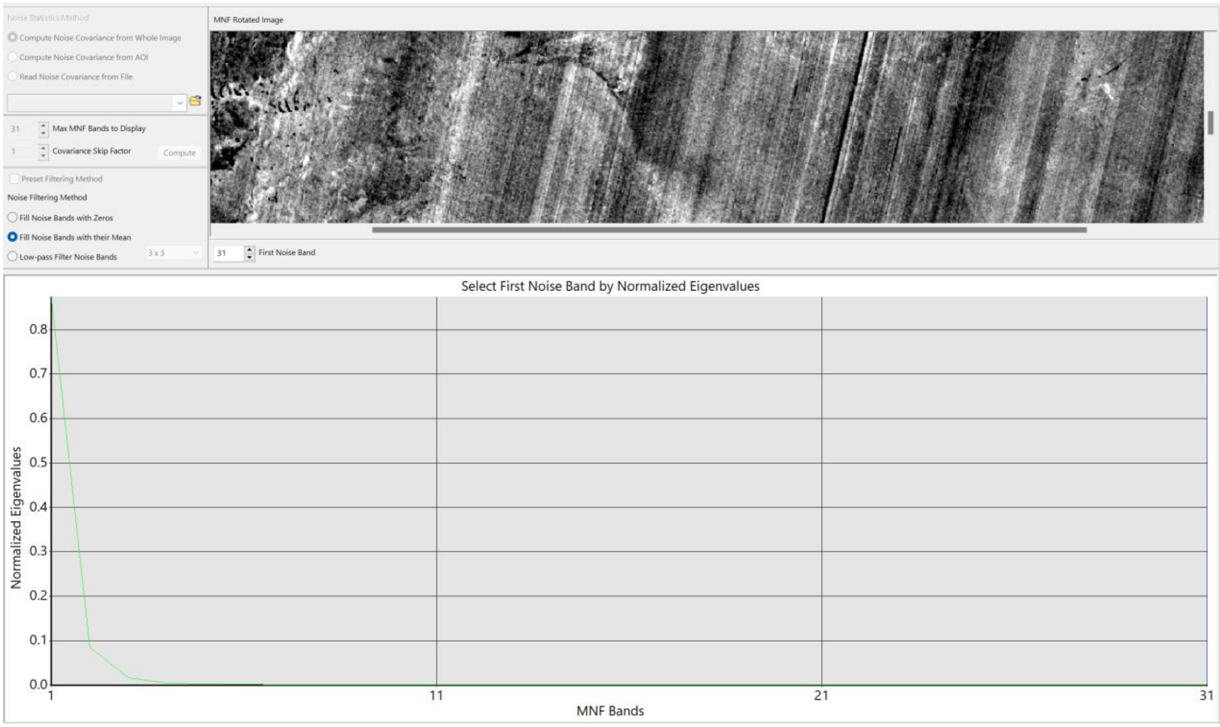

Figure 15. Minimum. noise fraction 31 bad bands, over study area Dashti-e-Nawar, was removed, the first noise band by normalised eigenvalues shows by light green colour.

3.4. Spectral Analysis Workstation

The spectral analysis workstation's hyperspectral data analysis section was used to perform the following tasks:

- Pre-processing the data involved removing noise, correcting for atmospheric effects, and converting the data into a usable format for analysis.
- Spectral signature extraction, this involved selecting a region of interest (ROI) in the image and extracting the spectral signature from that area. The spectral signature is a plot of the reflectance values of the pixels in the ROI at different wavelengths.
- The spectral signature has been extracted; it was compared to known spectral libraries of minerals to identify the mineral present in the study area of Dashti-e-Nawar.

To ensure accuracy, the mineral identification results have been validated by comparing them with reference data (USGS) spectral library (known lithium mineral signature) and field measurements study area Dashti-e-Nawar. Finally, the identified mineral can be mapped across the study area to determine its distribution.

3.5. Surface Mineral Maps

In the material Identification and Characterization Algorithm, the analysis identifies the mineral content in each pixel of the imaging spectrometer data by comparing its reflectance spectrum to a reference spectral library of minerals. In Material Identification and Characterization Algorithm spectral comparisons, the term best match is applied to the reference spectrum that has the highest measure of similarity, in the wavelength positions and shapes of absorption features, between the reference spectra and the spectrum being analysed, in this case, each pixel of imaging spectrometer data is the spectral signatures of single substance on the Earth surface.

The wavelength regions for the comparisons are locations of diagnostic features in the reference spectra. Diagnostic features are strong features, unique features, or both, arising from chemical bonds inherent in the reference material. Continuum removal, or baseline normalization, is a method applied to isolate and analyse these diagnostic features (Clark et al., 2003) and commonly has been used in laboratory infrared spectroscopy (*Spectrochemical Analysis - Ingle | PDF | Spectroscopy | Emission Spectrum*, n.d.). This is the technique that has been applied to terrestrial imaging spectrometer data as part of analyses to map the distribution of minerals by comparing remotely sensed absorption band shapes to those in a reference spectral library (Kruse et al., 1990). The continuum is an estimate of the other absorptions present in the spectrum, not including the one-off in interest (Kokaly & Clark, 1999)

In that sense, continuum removal is most often performed on absorption features.

The values of the continuum-removed spectrum (RC) are calculated by dividing the original reflectance values (RO) by the corresponding values of the continuum line (RL) for all the channels in the wavelength (λ) region of the absorption feature:

1. $RC(\lambda) = RO(\lambda) / RL(\lambda)$

The depth (D) of the absorption feature at each channel is calculated.

2. $D(\lambda) = 1 - RC(\lambda)$

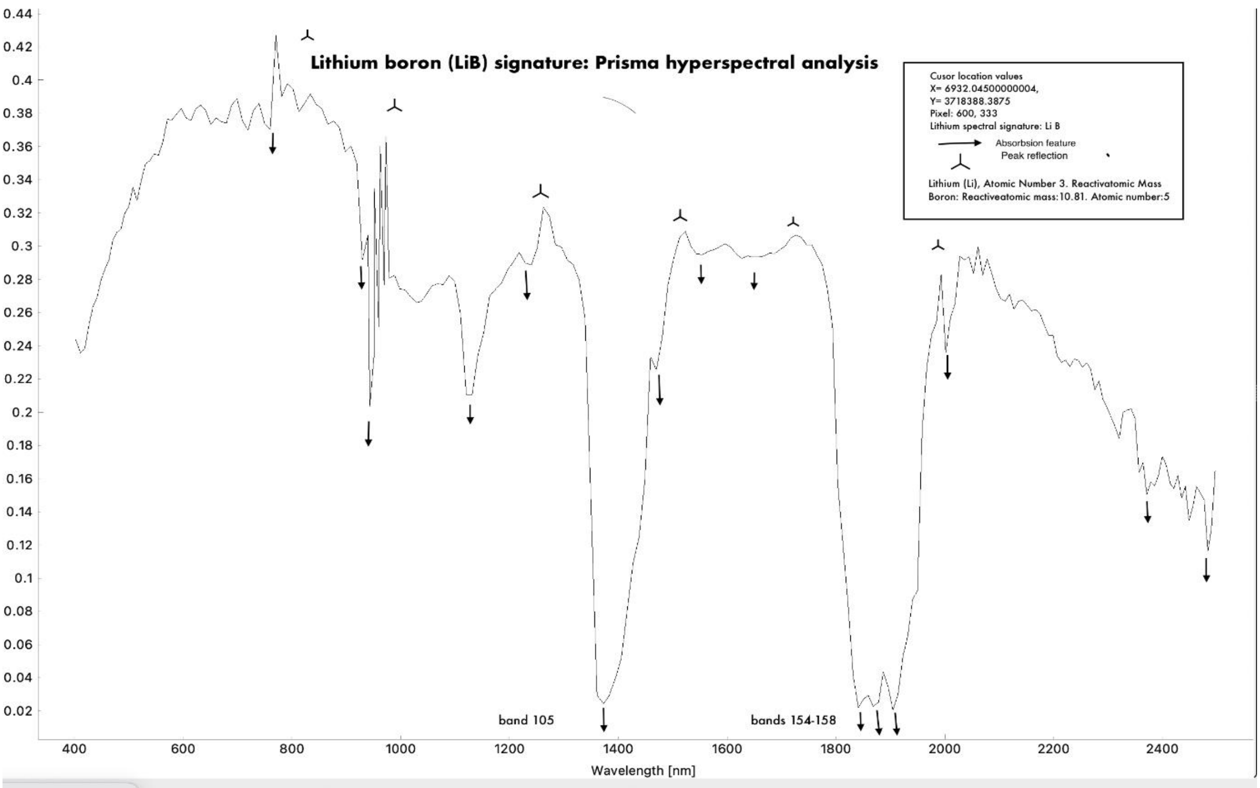

Figure 16. The spectral signature of mixed with lithium and boron shows a reflectance of 43% in the visible and near-infrared spectral region and a reflection of 30% in the short-wave infrared spectrum region. The absorption bands are observed at band 105 and bands 151-158 in NIR and SWIR region. Boron spectral signature that contains lithium made by EnMap-Box software.

An example of continuum removal applied to the Boron in brine absorption feature in a Prisma hyperspectral data, the pixel spectrum is shown in fig. 16. A continuum-removed feature can be described by several parameters, such as the absorption feature dip and the reflection spectrum. including its central wavelength position and its depth at the band center, with the first absorption in (band 105 with 1372,72 nm) and with second absorption (band 151-158 with 1841 nm and 1904,6 nm). A feature's central wavelength position, commonly termed the band center, can be characterized in several ways (Kokaly & Clark, 1999, p. 201) and here it is depicted at the wavelength of the channel at the minimum position in the continuum-removed feature (position of maximum depth).

The depth at the band center position of a feature is referred to as the band depth. Boron uses the coefficient of determination (r2) from the linear regression between a continuum-removed feature in the reference spectrum and the corresponding continuum removed region in the spectrum being analysed, as the feature fit value, a measure of the agreement between the spectral features). The r2 fit value ranges from 0 to 1, with better matches indicated by high fit numbers and perfect similarity between spectral features indicated by a value of 1.

An absorption band refers to a specific range of wavelengths within the electromagnetic spectrum, where a mineral or material absorbs energy from light. This absorption occurs due to the interaction between the incident light and the molecular or atomic structure of the mineral or material. By studying the absorption band, valuable information about the material's properties, such as concentration and physical state, can be obtained.

The depth of the absorption band is directly related to the concentration of the mineral or substance being analysed. A higher concentration of the target mineral leads to a deeper absorption band, indicating a greater absorption of light within that specific wavelength range. To determine the absorption depth, a calculation difference between the reflectance at the wavelength of maximum absorption and the reflectance at a nearby wavelength where there is no absorption must be done. This analysis helps quantify the extent of absorption occurring within the mineral or material.

3.6. Principal Components Analysis

Principal components analysis (PCA) is a commonly used technique for reducing the dimensionality of hyperspectral data sets while retaining the most important information. It works by transforming the original data set into a set of linearly uncorrelated variables, or principal components, which are ordered according to the amount of variance they explain in the data. The first principal component captures the most variance, the second captures the next most variance. The variables on which PCA would be performed are the spectral bands or channels. These bands represent the different wavelengths at which the hyperspectral sensor measures the intensity of reflected or emitted light.

PCA aims to transform the original high-dimensional spectral data into a reduced set of principal components, which are linear combinations of these spectral bands. Furthermore, PCA is an unsupervised technique used to pre-process and reduce the dimensionality of high-dimensional datasets while preserving the original structure and relationships inherent to the original dataset.

By selecting a subset of the principal components that capture the most variance in the data, one can reduce the dimensionality of the data while retaining most of the important information. PCA can be useful for a variety of applications, including data visualization, data compression, and feature extraction. In the context of hyperspectral data, PCA can be used to extract absorption-band depth and position information from spectra. This can be particularly useful for analysing and interpreting the data, as these parameters can provide valuable insights into the composition and properties of the materials being studied. However, it is important to keep in mind that the information lost in the reduction process may be important for certain applications.

3.7. Unsupervised classification

Supervised classification entails training a model using labeled data, where each data point is assigned a known class. The model learns from this labelled data to classify new, unseen instances into predetermined classes. This involves associating input features with corresponding class labels based on the provided training examples. Decision trees, support vector machines (SVM), and neural networks are examples of supervised classification algorithms. The crucial distinction is that supervised classification necessitates labelled data for both training and prediction.

In contrast, unsupervised classification operates without predefined class labels. Its goal is to uncover inherent patterns, structures, or clusters within the data without prior class knowledge. Unsupervised classification algorithms analyse input data and automatically group similar instances based on intrinsic similarities or statistical properties. Common techniques for unsupervised classification include clustering algorithms like k-means, hierarchical clustering, and Gaussian mixture models. Unsupervised classification is particularly valuable for exploratory data analysis, discovering hidden patterns, or identifying natural groupings within the data.

ERDAS Imagine software was used to perform the unsupervised classification, to map and create a visual representation of the mineral distribution. Unsupervised classification is a good approach when one does not have reference data for training the classification algorithm. An unsupervised classification is a valuable approach for exploratory analysis, pattern discovery, and understanding complex datasets. It operates without prior knowledge of class labels and identifies inherent patterns, structures, or groupings within a dataset. This approach is useful when classes or categories are unknown or ambiguous, providing insights and generating hypotheses for further investigation. Unsupervised classification can handle large-scale datasets efficiently without the manual labelling of training samples. This approach is used to identify patterns in the data and group them into classes based on their similarity. The algorithm does not require any prior knowledge of the classes and can be used to identify new classes that were not previously known.

The unsupervised classification was run, and used an ISODATA clustering algorithm, with 20 clusters. Clusters refer to groups or clusters of similar data points that are identified through the unsupervised classification process. The unsupervised classification used an ISODATA clustering algorithm to group the data into 20 distinct clusters. Each cluster represents a subset of data points that share similar characteristics or properties based on the analysis of the input data. Other techniques such as supervised classification or spectral mixture analysis may be necessary for more detailed mapping of mineral distributions. It's also important to consider the limitations of the classification method used and to validate the results using ground-truthing or other complementary techniques.

3.8. Supervised classification

The ERDAS Imagine software was utilized to conduct supervised classification for mapping and generating a visual depiction of mineral distribution. The classes included carbonate, boron, halite, and several others, with around five training samples allocated per class. The training dataset for supervised classification was developed using domain knowledge and distinctive spectral signatures specific to the area. A Maximum Likelihood classification algorithm was employed for this purpose as well.

The visual depiction of mineral distribution obtained through this process allowed for a comprehensive understanding of the spatial patterns and concentrations of these minerals. This information is crucial for various applications, including mineral exploration, environmental monitoring, and land management. Moreover, the accuracy of the supervised classification results was enhanced by the careful selection and allocation of training samples based on domain knowledge and the distinctive spectral characteristics specific to the study area.

3.9. Quantitative analysis of spectral profile

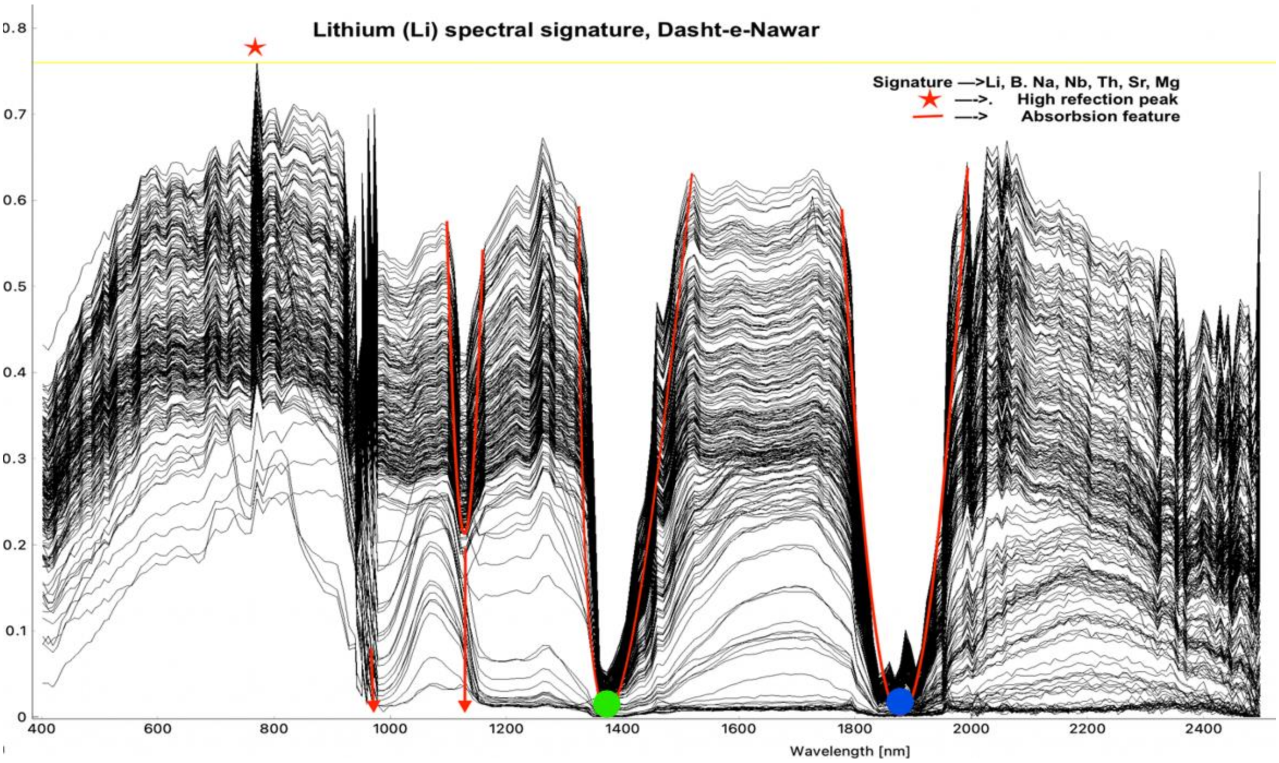

Figure 17. Two different lithium spectral signatures, boron, and borax, exhibit distinct characteristics. The boron absorption shows a high reflection of 76% at a wavelength of 1372.72 nm in the NIR region band (105), which is marked with green. In the SWIR region bands (151-158), marked with blue, at a wavelength of 1841-1872-1904 nm, there is a 65% reflection, indicating a high concentration of lithium in these pixels. On the other hand, the borax signature exhibits a 35% reflection and absorption in both the NIR and SWIR regions, which helps differentiate between these two mineral signatures. Used and done through spectral library EnMap-box software.

Once the position, depth, and asymmetry of the absorption band have been analysed, statistical methods are employed to determine if there are significant differences between the spectral features of different minerals. These statistical techniques aid in distinguishing and classifying various substances based on their unique absorption characteristics. As for a reference supporting this technique, one relevant study is "Hyperspectral remote sensing of plant biochemical properties" by Curran, et al. (2001), published in the Journal and Biological Sciences. This paper explores the use of hyperspectral remote sensing to assess plant biochemical properties, including the analysis of absorption bands and their relation to various parameters. Spectral profiling is a technique that uses the spectral signature of features in the study area to identify and distinguish different minerals. The spectral signature is essentially the pattern of light reflected or emitted by an object at different wavelengths, which is unique to each object or mineral. This pattern can be captured by sensors onboard satellites and used to create spectral profiles for different features on the Earth's surface.

Spectral profiling involves selecting areas of interest on an image and reviewing the spectral information of all bands, which can be seen in fig. 15. This allows analysts to compare the spectral profiles of different features and identify patterns or differences that can be used to distinguish one feature from another. The spectral profiles can also be used to quantify the physical properties of the features, such as their reflectance. This information is essential for accurate interpretation and analysis of the spectral data. Spectral profiling is a powerful tool for a range of applications, including remote sensing, environmental monitoring, and geological exploration.

SECTION 4

4. Results

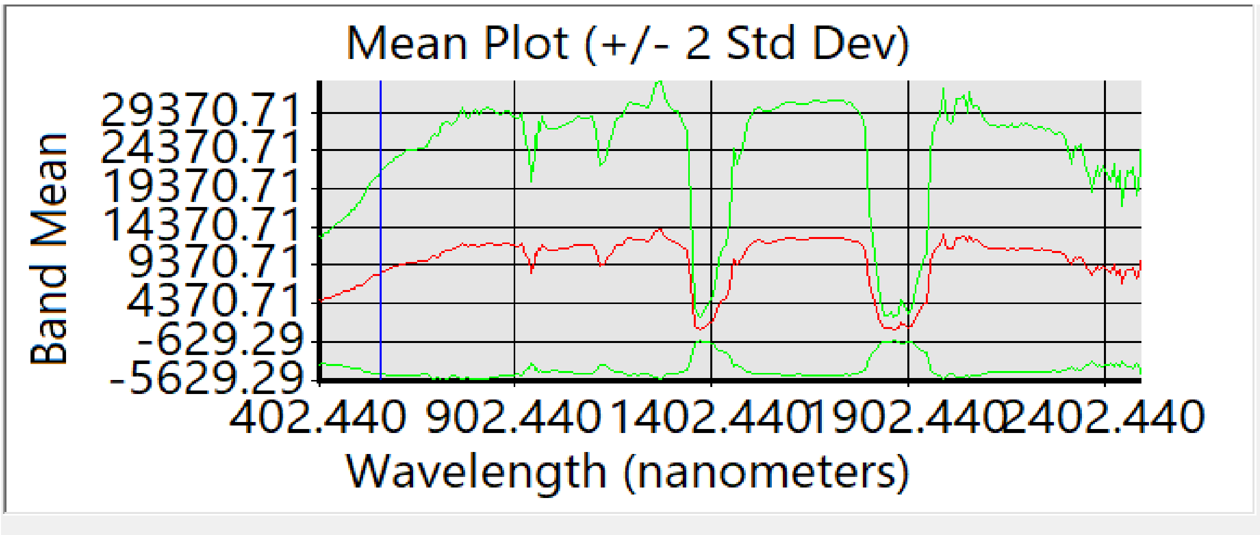

Figure 18. Lithium and non-lithium, spectral signature from study area Dashti-e-Nawar, in different reflectance. Top green line is lithium signature of the study area with high reflectance, red line is lithium signature with medium reflectance, and bottom green line is the non-lithium signature.

The lithium signature in brine deposits, "Dashti-e-Nawar," is shown in fig. 18. The figure displays the reflection levels of both lithium and non-lithium signatures, which are categorized as high, medium, and low. The difference between and fig. 17 and 18 is shown in terms of lithium minerals and non-lithium minerals. In fig. 17, all the signatures represent lithium minerals because they exhibit the same absorption feature at the same electromagnetic wavelength. On the other hand, fig. 18 displays three different spectral signatures, with two of them representing the signature of lithium minerals, and one representing the signature of non-lithium minerals. This distinction is based on their differing absorption features and reflections.

According to the obtained results by Prisma data, there is a good comparison of the lithium signature from study area Dashti-e-Nawar and the lithium minerals spectral signature from the standard laboratory (USGS). In the graphs below Figure 20, the spectral profile is a critical component of hyperspectral data, and it contains valuable information that can be used to identify minerals, materials, and map or classify different materials or minerals, lithium and nonlithium, collect data remotely.

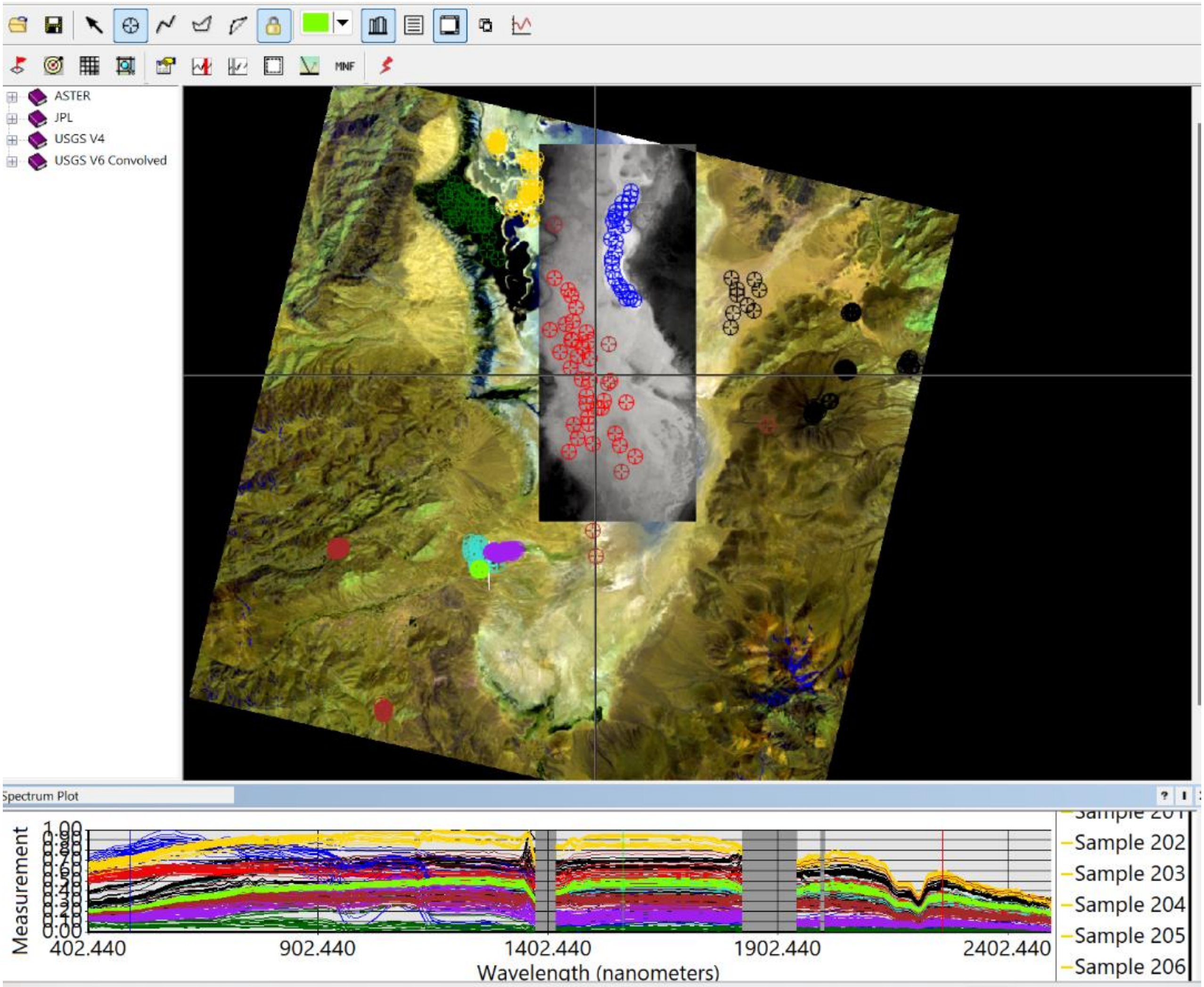

Figure 19. Shows the spectral analysis workstation used over the study area of Dashti-e-Nawar. Multiple pixels were sampled to identify lithium minerals. The red-coloured circles indicate the signature of lithium boron minerals, while the blue-coloured circles also exhibit the Borax signature. Made through ERDAS Imagine software.

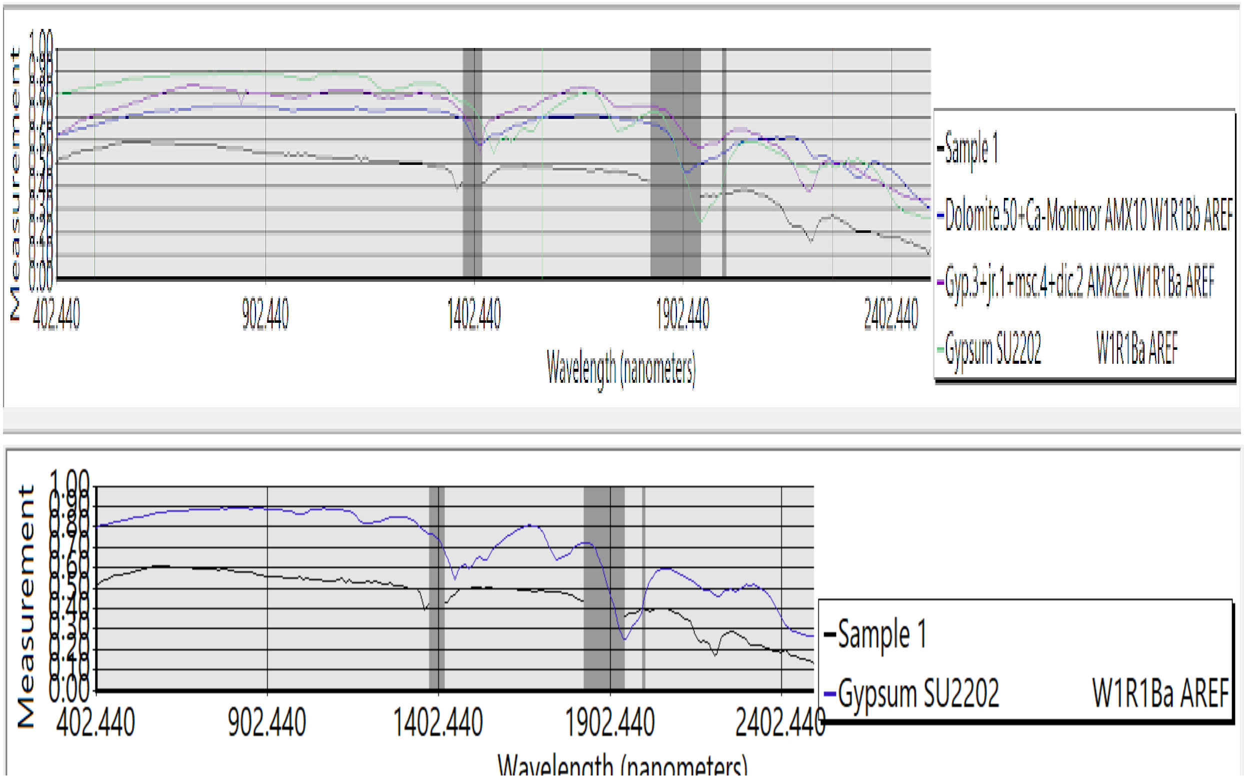

Figure 20. Spectral signature of Lithium (Li) sample 1, and Gypsum SU2022 from USGS, Gyp-3- and Dolomite 50+Ca-Montimor spectral library, have been analyzed through ERDAS Imagine software.

The spectral signature of Gypsum from USGS spectral library, and lithium (Li) from Dashti-e-Nawar sample 1 have the same pattern and match their absorption bands. These three types of minerals have been found over the Dashti-e-Nawar dry lake, shown in fig. 20. The spectral signatures of Lithium sample 1 from the study area and Gypsum, obtained from the USGS spectral library, possess unique characteristics, enabling their differentiation from other minerals based on their distinct spectral response at various wavelengths.

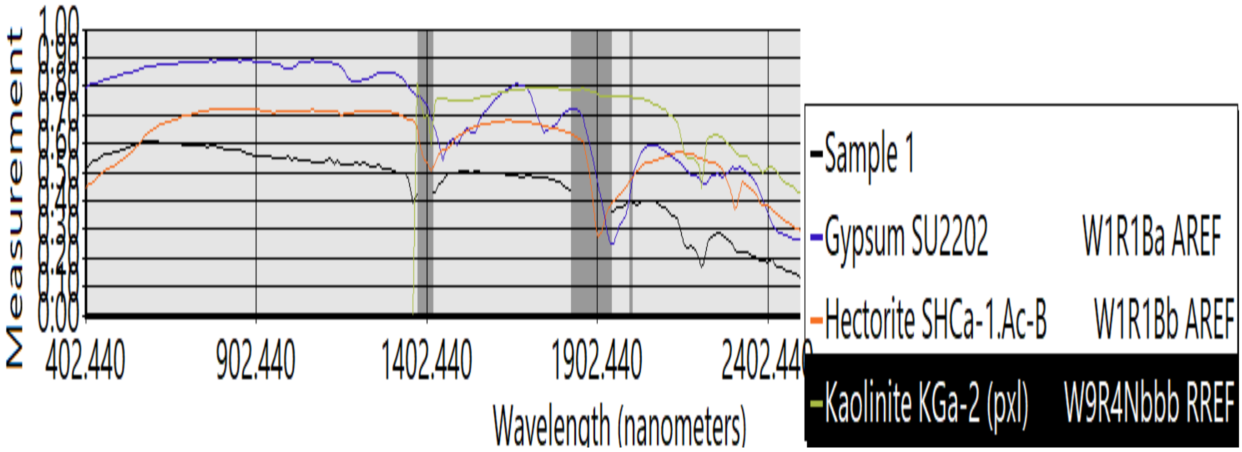

Figure 21. Spectral signature of Lithium (Li) sample 1. Gypsum SU2022, Hectorite, and Kaolinite spectral library. Analyzed through ERDAS Imagine software.

The presence of Gypsum and Hectorite in Dashti-e-Nawar is significant for lithium production because Gypsum is often associated with lithium brines. Therefore, identifying Gypsum using hyperspectral data can help in identifying areas with potential lithium deposits. In fig. 21 the lithium mineral signature can be seen, the light-green coloured pattern represents Kaolinite, the red coloured pattern represents Hectorite, the purple-coloured pattern represents Gypsum, and the black-coloured pattern represents Sample 1, lithium signature from Dashti-e-Nawar. This can potentially save time and money during exploration and can also reduce environmental impact by focusing on specific areas with high potential for lithium deposits. In addition, the identification of other minerals and materials in the area can provide a more comprehensive understanding of the geology and mineralogy in the study area.

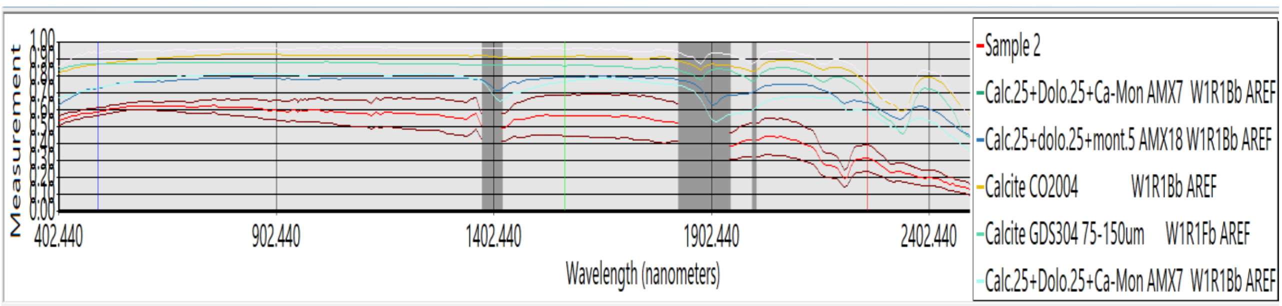

Figure 22. Spectral signature of Calc and Calcite from USGS spectral library and sample 13 and 14 are lithium (Li) signature from Dashti-e-Nawar that has the same absorption feature in the same wavelength calc. This information examined that Calc-silicate rock minerals also occur in Dashti-e-Nawar dry lake. Done through ERDAS Imagine software.

Interestingly, the spectral signatures of lithium minerals from Dashti-e-Nawar in fig. 22 show a similar absorption feature in the same wavelength as Calc. This analysis suggests the presence of Calc-silicate rock minerals in the Dashti-e-Nawar dry lake. The spectral analysis was conducted using the ERDAS Imagine software, which enables the examination of spectral characteristics and the identification of mineral compositions. This finding contributes to our understanding of the mineral diversity and potential lithological variations in the Dashti-e-Nawar area.

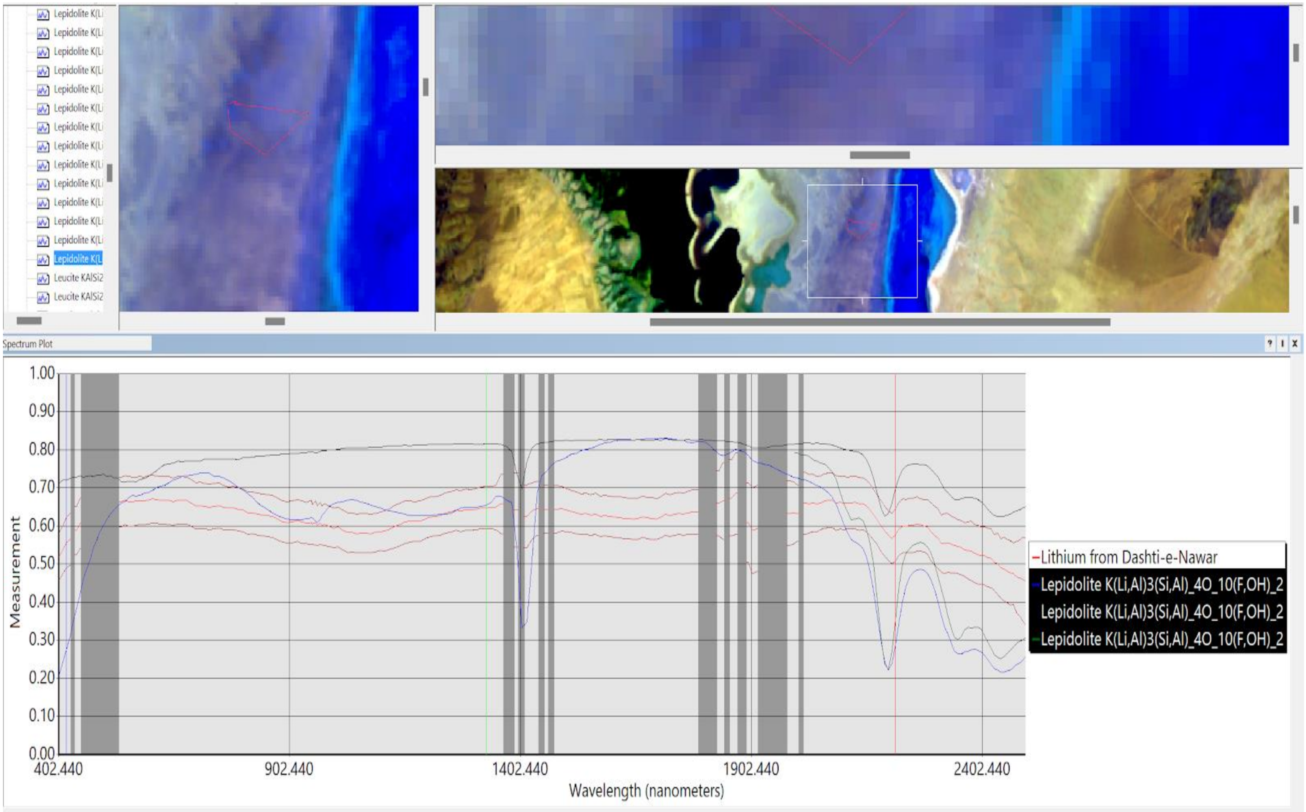

Figure 23. The spectral signatures of three different lepidolite minerals from reference data the USGS spectral library and one sample from the lithium with lepidolite mineral signature from Dashti-e-Nawar show similar absorption features in the NIR and SWIR regions. Done through ERDAS Imagine software.

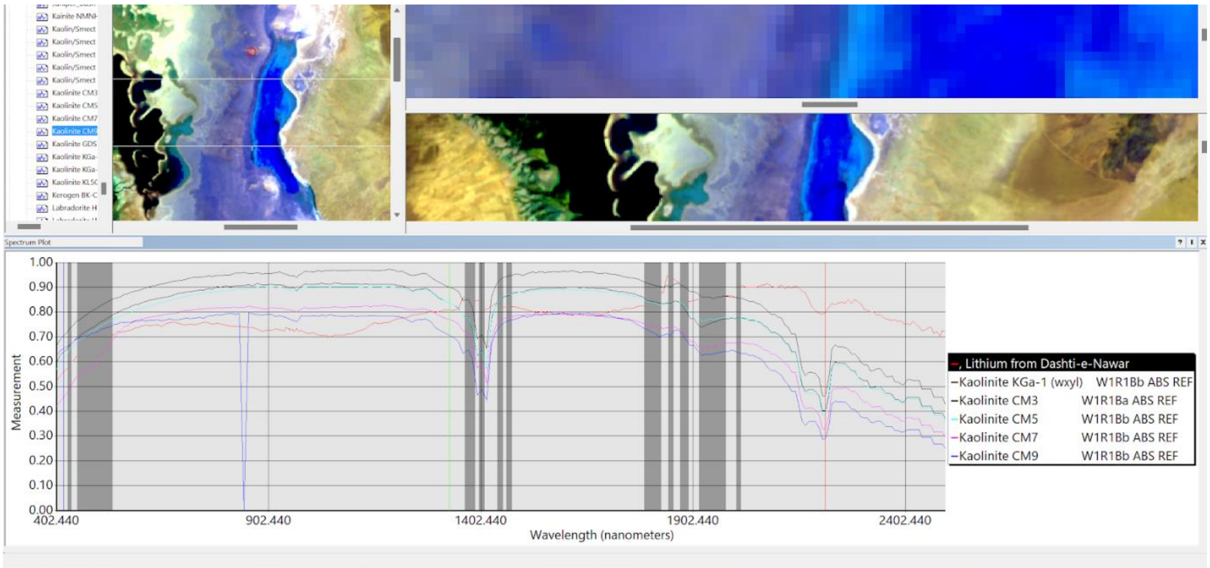

Figure 24. The spectral signatures of five different kaolinite minerals from the USGS spectral library and one sample from the lithium with Kaolinite mineral signature in Dashti-e-Nawar show similar absorption features in the NIR and SWIR regions. These kaolinite minerals are found with dry thermal spring deposits over Dashti-e-Nawar dry lake. Done through ERDAS Imagine software.

The spectral signatures of three different lepidolite minerals, along with one sample exhibiting the lithium with lepidolite mineral signature from Dashti-e-Nawar is presented in fig. 23. The spectral analysis conducted through the ERDAS Imagine software reveals that these samples exhibit similar absorption features in the near-infrared (NIR) and shortwave infrared (SWIR) regions. This finding indicates the presence of lepidolite minerals in the Dashti-e-Nawar region and suggests their similarity to the reference data.

On the other hand, in fig. 24, it displays the spectral signatures of five different kaolinite minerals, alongside one sample exhibiting the lithium with Kaolinite mineral signature from Dashti-e-Nawar. Through the utilization of the ERDAS Imagine software, it is observed that these samples exhibit comparable absorption features in the NIR and SWIR regions. The presence of kaolinite minerals in the Dashti-e-Nawar area is associated with dry thermal spring deposits. These findings provide valuable insights into the mineral composition and characteristics of the study region, highlighting the presence of kaolinite minerals alongside lithium mineralization.

The spectral analysis and comparison of these figures using the ERDAS Imagine software contribute to our understanding of the mineral diversity and distribution in Dashti-e-Nawar. By identifying and analyzing the spectral signatures of various minerals, we gain insights into their presence and potential lithological variations in the region.

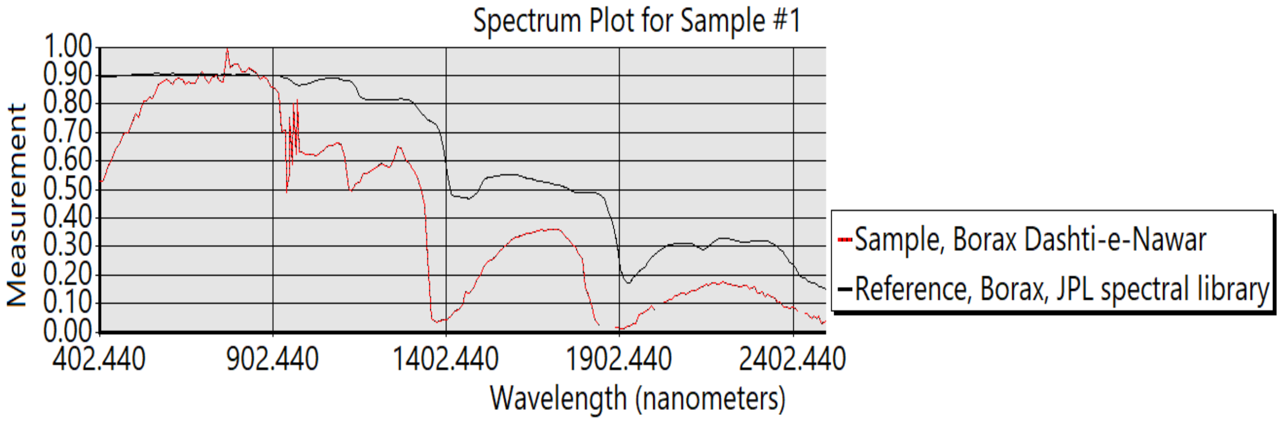

Figure 25. Two Borax spectral signature, red colour is from Dashti-e-Nawar, and black colour is Borax signature from reference data, JPL spectral library. Done through ERDAS Imagine software.

By comparing the spectral signatures in fig. 25, it can be observed that the Borax signature from Dashti-e-Nawar exhibits similarities to the reference data in terms of its spectral characteristics. This suggests the presence of Borax minerals in the Dashti-e-Nawar region, which aligns with the known mineral composition in the area.

The utilization of the ERDAS Imagine software enables the identification and comparison of spectral signatures, facilitating the analysis of mineral content and the characterization of specific mineral signatures. This information is valuable for understanding the mineral diversity and distribution in Dashti-e-Nawar and can assist in further exploration and mapping efforts in the region.

4.1. Mapping and classification

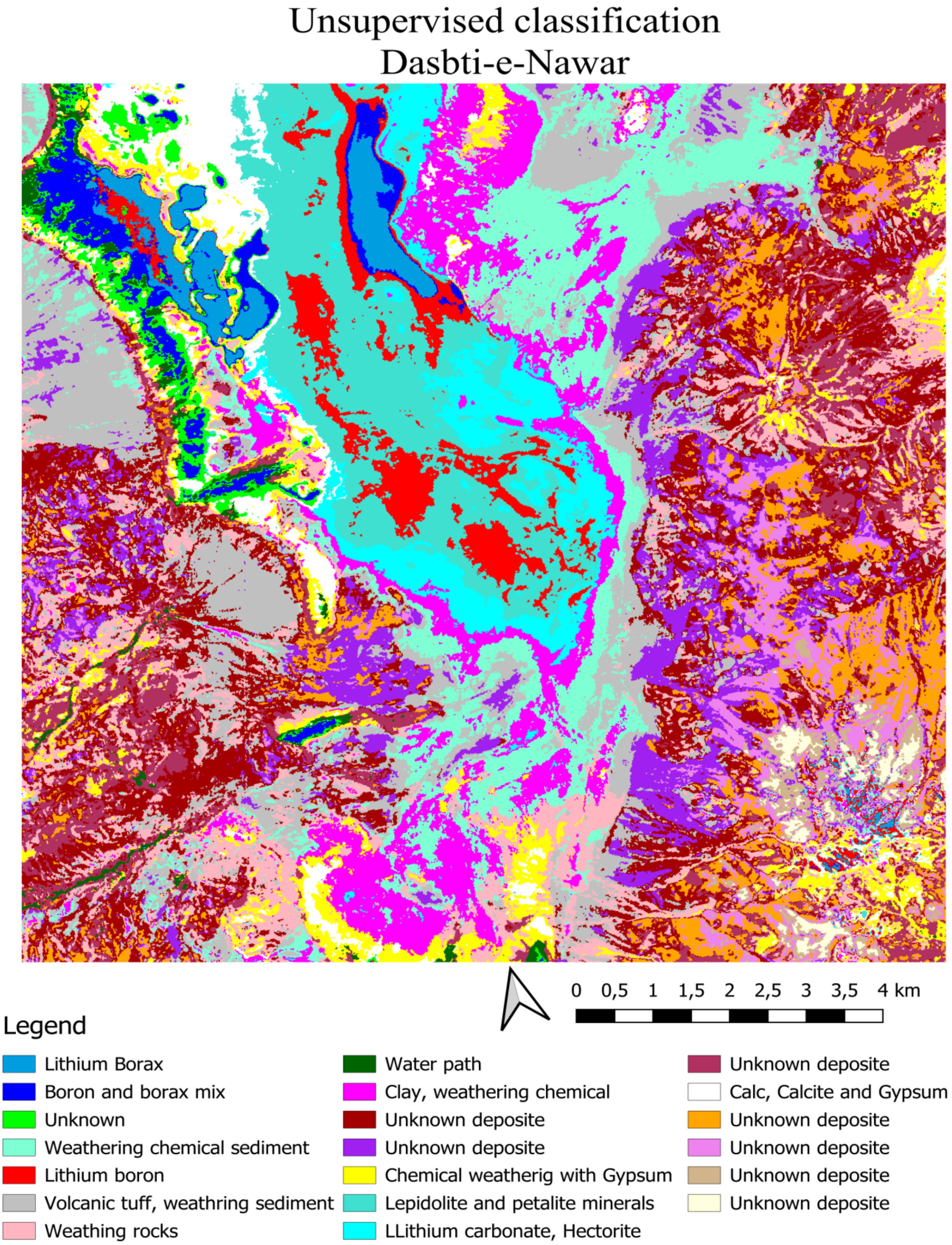

Figure 26. Principal Component Analysis (PCA) Unsupervised Classification Study area Dashti-e-Nawar, legend with yellow colour is the Borax lithium mineral area, done through ERDAS Imagine software, (21/03/23).

Table 4. The following is the calculation of the lithium mineral deposit area above the Dashti-e-Nawar brine lake, based on the unsupervised classification information.

Row	**Name**	**Colour**	**Pixel**	**Area (km^2)**
1	Borax	Blue	11462	10.3
2	Boron and Borax and some other minerals mixed	Dark Blue	12659	11.5
3	Lithium chloride, LiCl	Cyan	56762	51.1
4	Boron	Red	24462	22.0
5	Cale and calcite, $CaCO3$	white	39255	35.3
6	Volcanic tuff and weathering sediments	Gray	27507	24.8
7	Weathering chemical clay associated with lithium	Rose colour	59071	53.2
8	Clay and weathering sediment	Pink	67643	60.9
9	Lithium carbonate, $Li2CO3$	Light blue	102743	92.5
	Total area:			361.6 (km^2)

Spectral profiles have been used to map and classify the concentration of lithium materials in the study area. By analysing the spectral profiles of different materials, it is possible to create maps that show the distribution of different objects in the study area. Based on spectral profile/spectral library, PRISMA data could then be used to create maps and statistics regarding the area covered by Lithium deposits. Fig. 26 shows the unsupervised classification (PCA) from the study area Dashti-e-Nawar. Based on the unsupervised classification map, the legend presents the different minerals and elements over Dashti-e-Nawar, each marked with a significant colour. The calculation of the area covered by different minerals according to the unsupervised classification result and the statistics of the area covered by different minerals are given in Table 4.

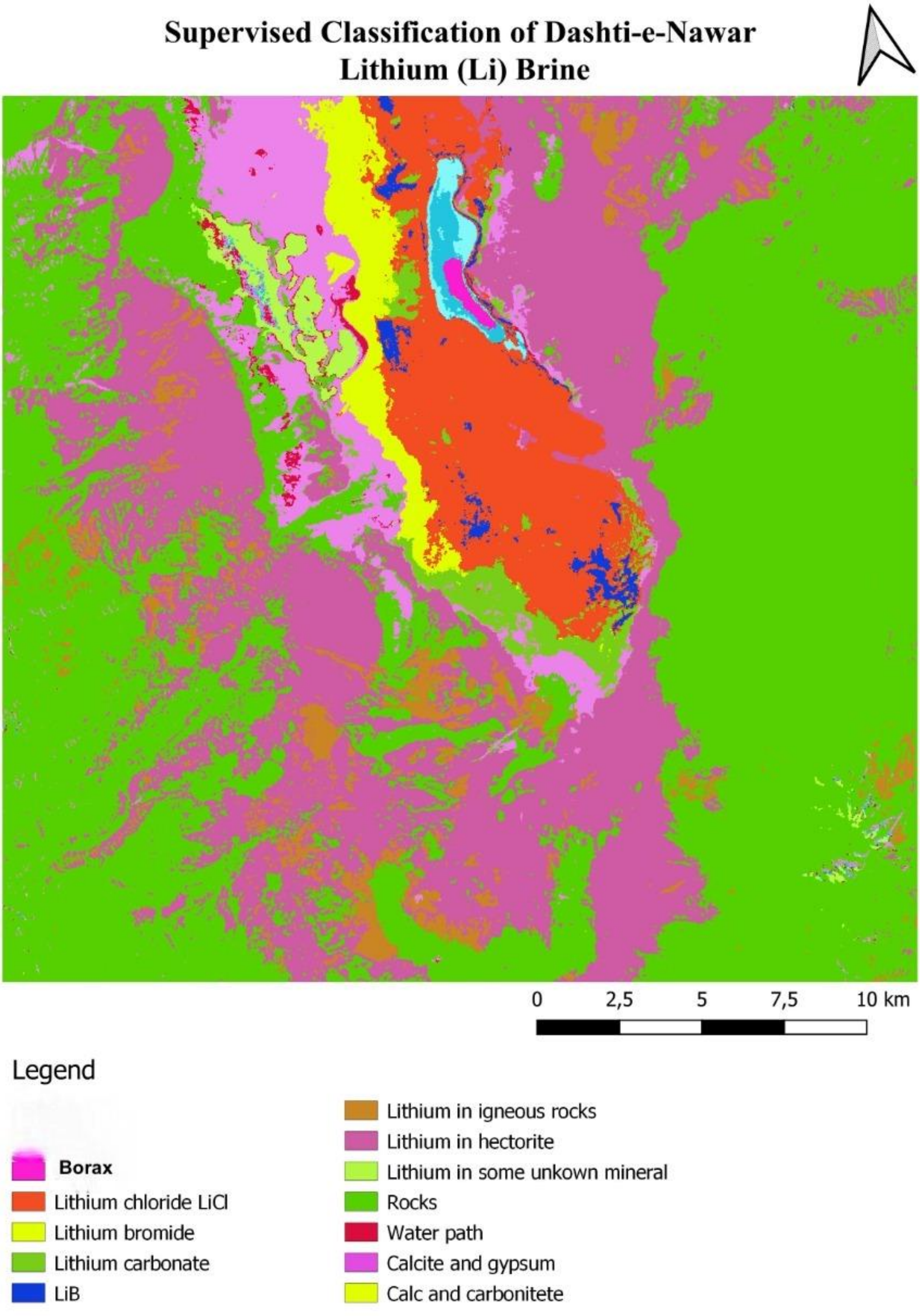

Figure 27. Supervised classification of the study area, shown 12 different classes over the Dashti-e-Nawar playa. Analyzed through ERDAS Imagine software.

The satellite imagery data from Dashti-e-Nawar was collected for the study. The data underwent pre-processing to remove noise, correct atmospheric effects, and enhance its quality through radiometric calibration and image registration. Representative training samples were selected and accurately labeled to represent the spectral characteristics of each class. Relevant features and spectral bands were then extracted, including the use of principal component analysis (PCA) to reduce dimensionality. A classification algorithm was trained using the selected training samples and extracted features, and subsequently applied to classify the entire dataset, assigning class labels based on spectral characteristics and learned rules. In fig. 27 the result of the process is shows with the different classes over the Dashti-e-Nawar playa.

Additionally, Principal Components Analysis (PCA) was performed over the areas of Dashti-e-Nawar to identify important pixels related to the identification of lithium spectral signature. PCA, a common data reduction technique for hyperspectral data, focused on bands with the most relevant information for describing the lithium signature. The first absorption feature, band 105 at the NIR region with a wavelength of 1372.72 nm, and the second absorption feature, bands 151-158 with wavelengths from 1841 to 1904 nm, contributed the most to the first principal component. The analysis was conducted using ERDAS Imagine software.

This study demonstrates the potential of utilizing Prisma hyperspectral data, with its high spectral and spatial resolution, to identify mineral deposits. The combination of advanced analysis techniques such as spectral library matching, along with the capabilities of the PRISMA satellite, provides valuable insights into lithium mineralization and other geological features.

4.2. Comparing the spectral signature of Dashti-e-Nawar Li-brine to other areas

The last part of the analysis in this thesis aimed to examine whether the spectral signature for lithium observed in Dashti-e-Nawar could be applied to detect lesser-known lithium deposits. To answer this question, two other dry salt areas, Namaksar-e-Herat, and Chahār Burja in Afghanistan were investigated, and the results indicated a positive outcome. These areas were chosen for several reasons, firstly because they are known for their geological characteristics that are conducive to the formation of lithium deposits. They are located in regions with similar geological settings to Dashti-e-Nawar, making them potential areas for the occurrence of lithium mineralization.

The selection of these areas was based on a combination of geological knowledge and remote sensing data analysis. Geological studies and exploration activities in the region provided insights into the presence of salt flats and potential lithium-rich areas. Additionally, remote sensing techniques, including satellite imagery and hyperspectral data analysis, were employed to identify spectral signatures associated with lithium minerals in these areas.

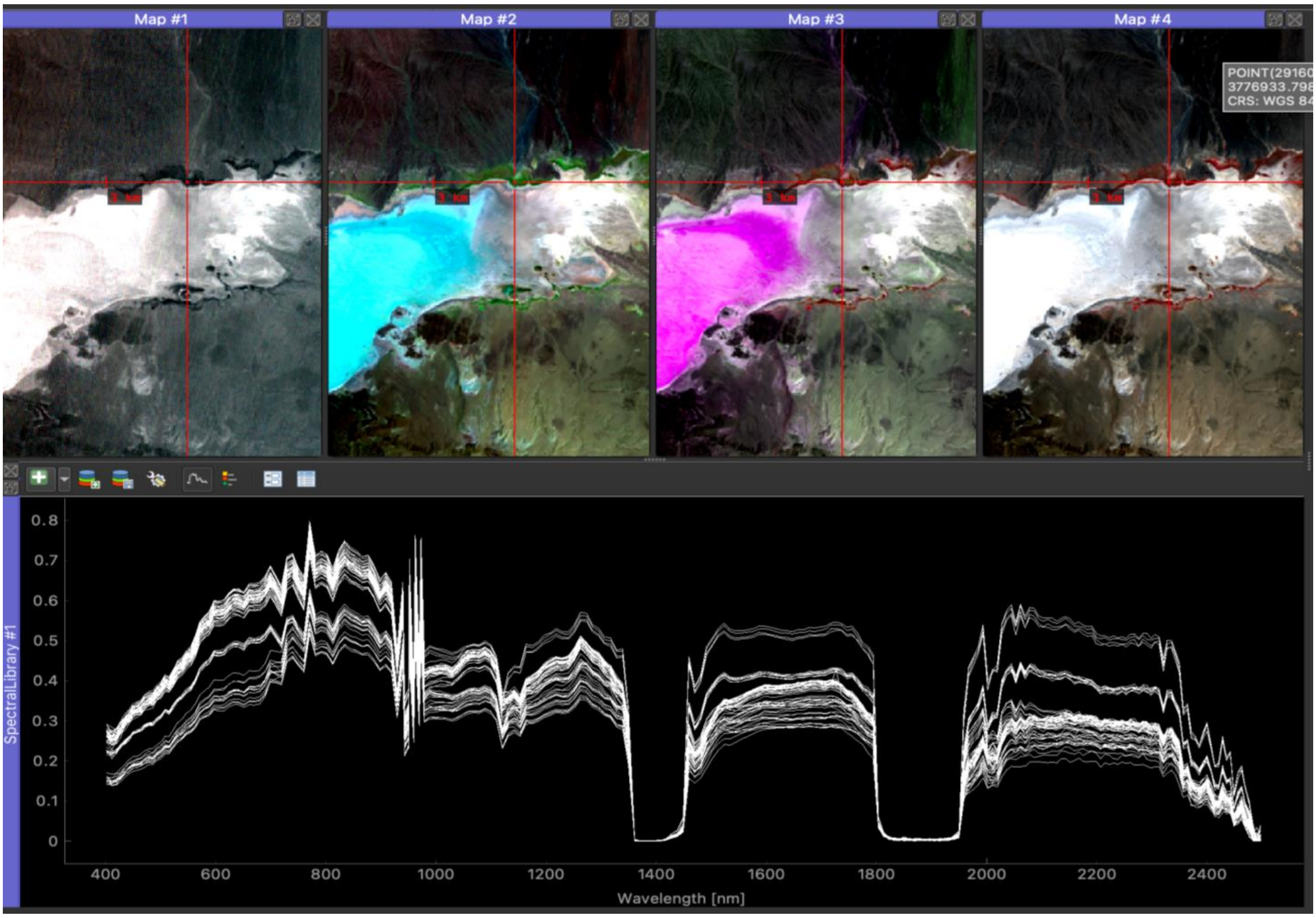

Figure 28. Prisma L2D level data over the Namaksar-e-Herat at the Southwest Afghanistan. Analyzed through EnMap-box software.

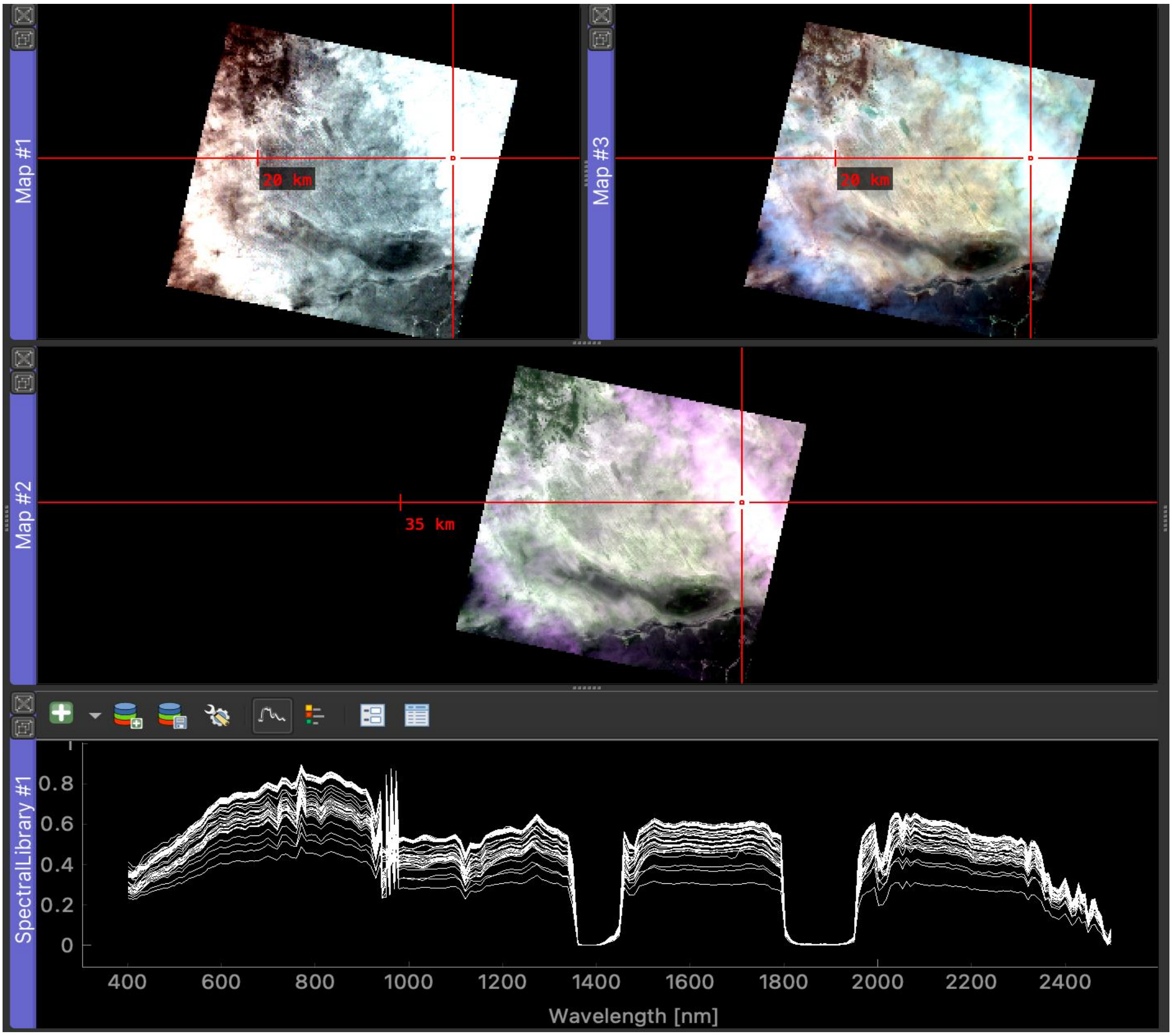

Figure 29. Prisma hyperspectral, L2D level data over the Chahār Burjak, Southeast Afghanistan. Analyzed through EnMap-box software.

The analysis of lithium signatures in the brine has revealed a consistent pattern, especially when the sediment and minerals present are similar. The signature of each element or mineral is influenced by its unique chemical and physical composition, which contributes to the observed spectral characteristics. Fig. 29 and 30 provide visual representations of the lithium signature in brine, demonstrating a consistent pattern and absorption features. These figures highlight the similarities in the spectral response of lithium minerals in different areas, indicating the presence of lithium-rich deposits.

Furthermore, fig. 29 showcases Prisma L2D level data over Namaksar-e-Herat in Southwest Afghanistan, while fig. 30 displays Prisma hyperspectral, L2D level data over Chahār Burjak in Southeast Afghanistan. Both datasets were analyzed using EnMap-box software, allowing for the examination and interpretation of the spectral information present in these regions.

These figures and the consistent lithium signature observed emphasize the potential for lithium mineralization in Namaksar-e-Herat and Chahār Burjak, indicating the presence of valuable lithium deposits in these areas of Afghanistan. Such findings contribute to our understanding of lithium resources and aid in the identification and exploration of potential lithium-rich regions.

SECTION 5

5.1. Discussion

The presence of lithium brine was verified through the analysis of mineralogical, geochemical, and USGS spectral library data, confirming its distinctive spectral signature. A comparison of mineral spectral signatures between Dashti-e-Nawar and Bolivia revealed both similarities and differences in the spectral response of different lithium minerals, enabling the identification of regions rich in lithium.

The combination of remote sensing and geoinformation enabled the location and mapping of lithium in the Dashti-e-Nawar dry salt flat. The integration of remote sensing, geoinformation, and advanced analytical techniques offers valuable insights into the distribution and behaviour of lithium in geological environments. Absorption-band parameters can be utilized to estimate the composition of samples from hyperspectral data and spectral library reflectance data, providing valuable information for data analysis. PCA and absorption-band parameters can be employed to identify areas with high potential for lithium ore extraction. PCA aids in identifying similarity patterns and trends in the data, while surface mineralogical information contributes valuable insights.

This study highlights the effectiveness of the PRISMA hyperspectral data in identifying lithium mineralization in brine evaporative sedimentary basins. The absorption band in the VNIR region at 1372 nm, 1841 nm, and 1904 nm is ideal for detecting lithium minerals. Each mineral has unique spectral characteristics such as reflectance and absorption band in specific regions of the electromagnetic spectrum, from visible to near-infrared (VNIR) and shortwave infrared (SWIR) in

Prisma data. Based on the spectral signature analysis the spectral signature of lithium minerals in the study area, typically have narrow absorption features (1372,72 nm), electromagnetic spectrum, band 105 in the near-infrared NIR region, and broad absorption features in (from 1841nm to1904,6 nm) of electromagnetic spectrum with band 151-158 in the shortwave infrared (SWIR) region, making them distinguishable from other minerals.

The spectral signature for lithium that was identified in Dashti-e-Nawar was used to detect other lithium deposits in salt flat and land located, ssuch as, ccontinental areas, desert areas, and dray salt lakes in the world, including for example Bolivia brine, Abe-e-Istada and some other area in Afghanistan. Additionally, this signature may be applied to detect less-known lithium deposits from similar sedimentary environments. However, it should be noted that the effectiveness of the signature may vary due to technical factors, for instance, differences in sensors and atmospheric conditions, as well as natural factors, like changes in surface structure.

These factors should be carefully considered when applying hyperspectral data for mineral “lithium” exploration in different regions. To detect the presence of lithium minerals in target areas by creating a spectral signature or fingerprint-based on their unique spectral characteristics. These signatures are then compared to the spectral signature of known lithium exploration areas, such as those in Bolivia, and with the USGS standard spectral library samples database to identify the presence of lithium minerals in the target area “Dashti-e-Nawar” in Afghanistan. By comparing the spectral characteristics of minerals in the target area to those of known lithium deposits, it was possible to determine whether lithium is present and to estimate the quantity and quality of the lithium deposits.

Hyperspectral data can detect the unique spectral characteristics of lithium-brine deposits and enable non-destructive and efficient mapping of these deposits in target areas such as Dashti-e-Nawar, Bolivia, and other dry salt lakes in Afghanistan or elsewhere on the land surface. Using hyperspectral imaging can identify the location and extent of lithium deposits without the need for extensive ground sampling, drilling, or excavation, which can significantly reduce exploration costs and minimize environmental impacts. Combining multiple classifiers into a single predictor can help to improve the accuracy and performance of lithium exploration. By integrating remote sensing data with geological information, such as mineral prospectivity, it is possible to target new lithium deposits better and improve the efficiency of exploration efforts.

The application of hyperspectral remote sensing in lithium brine at Dashti-e-Nawar deposits faces challenges, including the difficulty in distinguishing different lithium mineral types due to their similar characteristics and limited availability of hyperspectral imagery covering longer wavelength regions. For example: relevant to carbonate minerals, such as hydrothermally derived lithium carbonate (Li_2CO_3) associated with base-metal mineralization and sodium chloride (NaCl) rich in calcite minerals resulting from supergene deposition or enrichment of mineral deposits by solutions moving downward through the rocks or sediments. Furthermore, the generalization of these approaches to other types of lithium deposits, such as lithium in igneous and metamorphic rocks, can contribute to the establishment of remote sensing as a fundamental tool in lithium exploration. As remote sensing technologies continue to improve, it is likely that they will play an increasingly important role in the discovery and characterization of lithium deposits around the world.

5.2. Conclusion

Using hyperspectral data to target Li mineralization with the launch of the Prisma missions, there is an unequivocal exponential growth. Nonetheless,

However, considering the market demand for this raw material, we expect that many other studies will flourish in the near future all around the globe. In general, past application studies relied on four distinct approaches: geobotanical mapping, lithological mapping, mineral alteration mapping, and Li minerals discrimination. Different types of satellite products with distinct characteristics were employed as well as diverse image processing algorithms ranging from simple logical or mathematical operations (band ratios) to more evolved and complex algorithms like PCA.

Overall, the objectives and the research questions addressed in this review were successfully accomplished/answered:

1. Can PRISMA hyperspectral data be used to detect lithium?

The reviewed publications show that it is possible to identify the spectral features of brine intrusions and to discriminate the Li-bearing in evaporite brine from the host sedimentary rocks. The proposed approach to directly identify Li minerals/Li evaporite brine was confirmed in other areas of the globe. To some extent, the alteration mapping approach works to target Li evaporite brine, although it is more promising in highly altitude areas such as in the Dashti-e-Nawar region of Afghanistan.

2. Which wavelength bands are most effective in detecting lithium?

This study emphasizes the efficacy of PRISMA hyperspectral data in identifying lithium mineralization within brine evaporative sedimentary basins. The analysis reveals that specific absorption bands at 1372,72 in the visible to near-infrared (VNIR) and 1841nm to 1904 nm in shortwave infrared (SWIR) regions are particularly effective in detecting lithium minerals. Each mineral exhibits distinct spectral characteristics in terms of reflectance and absorption bands within these specific regions of the electromagnetic spectrum. Notably, the spectral signature of lithium minerals in the study area is characterized by narrow absorption features at 1372.72 nm in the near-infrared (NIR) region (band 105) and broad absorption features spanning from 1841 nm to 1904.6 nm in the shortwave infrared (SWIR) region (bands 151-158)

3. Can the spectral signature for lithium observed in Dashti-e-Nawar be applied to detect lesser-known lithium deposits? The spectral signature for lithium observed in Dashti-e-Nawar can be potentially applied to detect lesser-known lithium deposits in similar sedimentary environments. By creating a spectral signature or fingerprint-based on the unique spectral characteristics of lithium minerals, it becomes possible to compare and match these signatures with the spectral signatures of known lithium exploration areas. This allows for the identification of the presence of lithium minerals in target areas and the estimation of the quantity and quality of the lithium deposits. However, it is important to consider that the effectiveness of the spectral signature may vary due to technical factors (such as sensor differences and atmospheric conditions) and natural factors (such as changes in surface structure) that can influence spectral characteristics.

The objective of this study was to identify and map lithium minerals in the Dashti-e-Nawar brine lake using Prisma hyperspectral data, specifically Prisma L2D level data. Spectral signature analysis was employed to detect lithium and non-lithium elements, including boron, by examining their distinct absorption features and reflectance. The results demonstrated a favourable comparison between the lithium signature in the study area (Dashti-e-Nawar) and the reference data from the USGS spectral library. Additionally, the presence of gypsum, calcite, and hectorite in association with lithium brines suggested a high potential for lithium production. Boron and borax were predominantly found in the lake and surrounding mountain areas and their distribution was classified and mapped accordingly. The concentration of lithium minerals was analysed based on their unique spectral signatures, and unsupervised classification was utilized to calculate the extent of mineral and element deposits.

In conclusion, hyperspectral data proved to be a valuable tool for identifying and exploring minerals, particularly lithium minerals crucial for renewable energy and battery technologies. However, further research is necessary to validate the results using ground truth data and assess the economic feasibility of extracting lithium from the brine lake. This study aimed to enhance our understanding of the applicability of hyperspectral imaging for detecting lithium-brine minerals or mineralization in the Dashti-e-Nawar playa, located within Ghazni, Afghanistan. Specifically, the project aimed to determine the effectiveness of PRISMA hyperspectral data in detecting lithium minerals, including Green Elements such as lithium carbonate ($Li2CO3$), lithium chloride ($LiCl$), boron (B), and borax.

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