ESG IMPROVEMENTS THROUGH SENSOR-BASED SORTING FOR LITHIUM PEGMATITE ORES

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HIGHLIGHTS

- Applicability of SBS on various lithium pegmatite ores
- Improved energy and water usage by coarse gangue rejection with SBS
- Reduction on waste generation with by-products concentration with SBS

ABSTRACT

The clean energy transition presents a direct impact on the increasing demand for critical metals, amongst these is lithium. At the same time the minerals industry faces the need for improvement, and must meet growing sustainability targets and evolving standards of ESG policies. Therefore, it is necessary to develop process routes that make it possible to address the aforementioned demands. The present work demonstrates the applicability of sensor based sorting (SBS) technology for the processing of lithium pegmatite ores. For this, a test methodology commonly used in the initial stages of evaluation, which provides a better understanding of the separability between the most common lithologies in lithium pegmatite ores, is presented. This work offers a framework on which to evaluate the sortability of lithium pegmatite ores with a focus on achieving ESG goals. Using a multi-sensor platform approach provides flexible solutions to decrease the carbon footprint of existing processing routes.

KEYWORDS: ESG, Multi-sensor sorting, Lithium, Sustainability, Critical Minerals, Decarbonization.

1. INTRODUCTION

The global energy transition places a higher demand on the mining and minerals processing industry. For instance, the transition by automotive manufacturers to electric vehicles (EV's) is associated with an almost six-fold higher requirement on minerals inputs when compared with conventional vehicles (IEA 2021). Similarly, off-shore wind generation requirements command nearly nine times the mineral input compared to current gas-fired power stations (Michaux 2021; IEA 2021). Considering these growing demands on the mining and minerals processing industry, significant efforts need to be made to support this expanding sector in a sustainable and environmentally conscious way.

Major mining companies are aligning environmental, social and governance (ESG) commitments to their portfolios as they address the sustainability and social impact of their investments. In this context, stakeholders demand more ESG-oriented policies. The way mining organisations allocate the capital expenditure across their assets could have a decisive effect on their competitive advantage over the next decade. According to Stoch and Desai (2022), miners need to convince their investors on how they are positioning their assets for the long term.

According to the Deloitte report authored by Davidse *et al*., 2016, energy is one of the biggest expenses for mining companies, constituting approximately 30% of total cash operating costs. The most direct and impactful portfolio is one that focuses on energy-management related projects that have clear economic returns. At the same time, the reduced grade of the available mineral resources demand for processing more tons of material. This results in a significant increases on the total energy consumption. The minerals industry is currently tackling this challenge by developing new comminution technologies, improving process controls, and also implementing waste rock removal at coarser grain sizes. Coarse gangue rejection is also known as preconcentration and consists on of eliminating material without valuable metal content, prior to high energy intensity grinding stages. The preconcentration stage can be implemented in the form of many different technologies, which can be selected based on the technology's capabilities, orebody suitability and economic viability (Valery, et al., 2020). Ballantyne, *et al*. (2018) assessed the energy efficiency of preconcentration through SBS for a gold and chromite ore, thus concluding that energy savings are in the order of 6% to 11%. Esteves, *et al*. (2023) proposed the evaluation of SBS for the preconcentration of a polymetalic ore, thus resulting in a reduction of: 44% on specific water usage (m^3/t), 34% on specific energy consumption (kWh/t) and 43% on fine waste generation.

In addition to the energy usage, the waste generation is also an important challenge in mining. Considering the number of catastrophic tailings dam failures experienced in recent decades, the risks are not only environmental but also increasingly deadly (WISE 2023). In this sense, Valenta *et al.*, 2023 considered several strategies aimed at improving resource efficiency, whilst reducing mine waste generation. Reprocessing, desulphurisation, dry stacking, preconcentration, sand co-production and in-situ recovery are pointed as alternatives to mitigate the waste impacts while minimizing the disposal hazards. Also highlighted in their study is importance of understanding the site-specific characteristics when defining suitable technologies and/or alternatives at different mining operations.

Water is rapidly becoming a scarce resource in many parts of the world. It will be important to develop processes that require less water and reduce the amount of fine slimes waste material which is store in tailings dams.

Existing and future mining projects will have to address ESG targets which will require implementing new flowsheet designs and new or improved technologies to develop Climate-Smart processes.

2. BACKGROUND

As one of the most critical metals to the EV market, the demand for lithium is growing exponentially. This paper focuses on preconcentration techniques for lithium ores which will impact portions of ESG aspects.

Lithium is primarily found in two major sources, lithium brines and hard rock pegmatite orebodies (Drobe 2020). The largest lithium deposits are encountered in brine sources, which are basically saltwater deposits in the form of lakes, salars and geothermal brines mainly encountered in Chile, Argentina, Bolivia, USA, and China (Morh *et al*., 2012). Although lithium brine sources correspond to approximately 87% of lithium reserves, it is suggested that the environmental, safety risks and occupational health hazards associated with lithium brine extraction can be much larger than for lithium bearing pegmatite ores (Agusdinata, *et al*., 2018). In addition to this, it is also suggested that salars are paleolakes structures with rich microbiological ecologies that contains memories of past life on Earth, which could be disrupted by the intensity of mining activities (Bonelli & Dorador, 2021).

Alternatively, over the past six to eight years there has been a marked increase in interest in hard rock lithium deposits. The lithium minerals are usually encountered in pegmatite deposits which can present large mineralogical variations. More than one hundred minerals are listed from the Tango Pegmatite deposit, including native elements, sulphides, oxides, phosphates, carbonates, borates, and silicates (Garret, 2004). Some of the lithium minerals encountered include; spodumene, lepidolite, petalite, cookeite, elbaite, rossmanite, holmquistite and others, while accompanying minerals and rocks types include basalt-gabbro, mica, quartz, feldspar, albite, muscovite, calcite, schist and dolomite (Garret, 2004). This vast diversity in lithium pegmatite mineralised deposits, will require different ore-specific concentration flow sheets.

This study only considers Li-pegmatite ores within the context of mineral beneficiation (as explained in Tadesse *et al*., 2019), not lithium extraction or the formation of lithium compounds (e.g., carbonate, sulphate or hydroxide) (as explained in Gao *et al*., 2023). Conventional mineral beneficiation techniques for Li-pegmatite ores include dense medium separation (DMS), froth flotation and magnetic separation (Tadesse *et al*., 2019; Kundu *et al*., 2023). Both DMS and froth flotation require the introduction of process water as a medium to facilitate the separation. In almost all instances where process water is introduced, tailings, or some form of fines slurry wastes are generated. DMS and froth flotation are applied on relatively fine feed material (e.g., ≤4mm being typical for Li-pegmatite ores). Sensor based sorting (SBS), as implemented in various applications (Robben and Wotruba, 2020), presents the opportunity to reject barren waste and/or very low-grade lithium material prior to size reduction for DMS, froth flotation and magnetic separation.

In this sense, Äijälä (2018) proposed a multi sensor approach, including color, NIR, laser and XRT sensors for the estimation of a sorting index that represents an estimation of rock dilution for lithium pegmatite ores. The test was performed at bench scale and a SBS test program was recommended. More recently, Filippov, *et al*.,2022, proposed the evaluation of optical sorting for the preconcentration of a lithium pegmatite ore in Portugal, thus concluding that the coarse-grain texture of the lepidolite allows for gangue liberation at coarse sizes. It was suggested that the optical sorting also allows for the production of a feldpspar-quartz product with suitable characteristics for the ceramic industry. Esteves, *et al*., 2022, proposed a multi sensor approach for different lithium pegmatite deposits encountered in Brazil. Although it was concluded that a combination of laser, XRT and color sensors could be applied to separate spodumene and petalite, the possible separation results were not evaluated in terms of grades and recoveries. In relation to this multi sensor approach, Peukert, *et al.*, 2022, also indicated that greater sensor fusion offers the potential for an improved ore classification and sorting efficiency.

3. OBJECTIVE

A diverse selection of lithium pegmetite ore samples from different deposits around the world were provided for this study. Since numerous case studies featuring SBS have been presented in literature for other minerals, the authors believed it would be pertinent to present the methodologies developed to assess the amenability of lithium pegmatite ores to SBS. It is also important to demonstrate that different sensor technologies are required to treat different ore bodies, due to the diverse nature of lithium pegmatite minerals. Experience has shown that a “one size fits all” approach is not suitable for all lithium ore types. This paper also aims to demonstrates the opportunity to remove a significant portion of coarse waste material SBS. This will result in energy, water and therefore cost savings which could incentivize mining companies to consider such alternatives.

4. MATERIALS AND METHODS

Twelve tonnes of ores originating from different lithium pegmatite deposits across three continents, were submitted for *Amenability Testing*. Although all deposits are characterized as lithium pegmatite orebodies, they represent different lithium occurrences and mineralization that can be encountered in various regions across the globe. In this sense, the lithium bearing minerals do vary, as do the main contaminates (gangue) present. By testing different mineral compositions, it is possible to obtain a broad understanding of how different sensor technologies can be utilized to process lithium pegmatite ores, in a general and global perspective.

Spodumene, cookeite, lepidolite and petalite are the main lithium bearing minerals considered in this study. The other lithologies commonly associated with lithium deposits are described in Table 1.

Table 1 - Properties of minerals occurring in lithium pegmatite ore

Mineral / Rock	Description	Specific Density	Li_2O (%) theoretical
Feldspar	X $(Si, Al)_4 O_8$ X = K, Na Ca	2,5 to 2,8	
Quartz	SiO2	2,6 to 2,7	
Schist	Metaphorphic	2,7 to 3,2	
Mica	$X_2Y_{4}–6Z_8O_{20}(OH, F)_4$ X= K, Na or Ca Y = Al, Mg or Fe Z = Si or Al	2,8 to 3	
Amphibolite	Metamorphic	2,9 to 3,6	
Gabbro	Igneous	2,7 to 3,3	
Spodumene	Li Al(Si2O6)	3 to 3,2	8
Petalite	Li Al(Si4O10)	2,3 to 2,5	4,9
Cookeite	$LiAl_5Si_3O_{10}(OH)_8$	2.58 to 2.69	2,86
Lepidolite	$K(Li,Al)_3(Al,Si,Rb)_4O_{10}(F,OH)_2$	2.8–2.9	7,7

4.1.SBS: AMENABILITY TEST

The *Amenability Test* (AT) is performed as an initial evaluation for determining the sorting applicability. The test requires calibration samples that are used for characterisation and settings development. The calibration samples are scanned with different sensors and the sensor response is then used to develop a separation setting for the application. The setting and sensor response can be used to simulate materials separation to obtain an initial assessment of the sorting task. The test procedure is summarized in Figure 1.

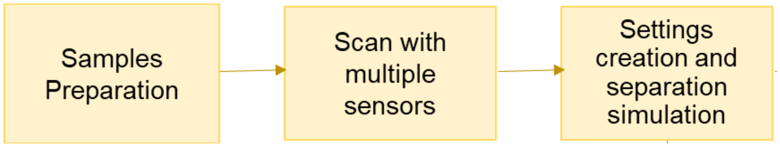


Figure 1 - Flowsheet of *Amenability Test* (AT) methodology

The first stage for the test is to prepare the samples, which can be defined as *Calibration samples (CS)*. The setting adequacy relies on the quality of the initial assessment of the CS, which consists of groups of different rocks according to pre-determined/known characteristics, such as grade range or lithology. The table below provides some examples of calibration samples specifications. The size fractions for the calibration samples should be in accordance with the size ranges of material to be sorted. The amount of CS can be defined in terms of a minimum amount of mass or quantity of particles.

Table 2 – Calibration samples (CS) examples

CS examples	**Size fraction**	**Amount of rocks**
High-grade sulphides	- 25mm +10mm	10kg / 50 pieces
Low-grade	- 25mm +10mm	10kg/ 50 pieces
Waste rock type 1 e.g. schist	-75mm+25mm	30kg/ 50 pieces
Waste rock type 2 e.g. andesite	-75mm+25mm	30kg/ 50 pieces

Table 2 shows an example of CS for a copper project. In this example, the copper mineralization consists of chalcopyrite and the high-grade samples are mainly composed of massive sulphides. The medium grade material is chalcopyrite inclusions entrained in gangue material, the low-grade material is very disseminated sulphides and, the, waste material is mostly gangue. The samples are generally handpicked by a geologist, and thus, all the individual particles provide similar characteristics according to the categorization.

The next test stage consists of scanning the CS with multiple sensor technologies. For the proper evaluation of surface characteristics, it ~~might~~ may be necessary to provide proper surface preparation of the samples, which can include washing prior to scanning. The sensor responses are used to create a customized sorting setting, as defined by the test targets. Complex separation applications require more than one sensor to identify and distinguish between different minerals or rock types: For example, XRT can identify the atomic density of dense sulphide minerals locked within a rock, and laser reflection properties are utilised to identify quartz. This quartz-vein gold sulphide type deposit can thus be effectively sorted by utilising the XRT/laser sensor combination. However, not all applications ~~may~~ have this multi-sensor requirement, as this study will show. The setting is used to simulate what would be the separation decision for each calibration group. Figure 2 shows the separation simulation for the different copper calibration samples presented in Table 2. The x axis represents a threshold for the sensor and the y axis represents the material separability. The analysis can be performed for different sensor selections. In the presented example, by selecting a threshold of 0.4, the following materials are recovered: 90% of the high grade, 39% of the mid grade, 14% of the low grade and less than 1% of waste. This could be used as an operational point with a focus on material upgrade, in this case favouring the recovery of high grade material while minimizing low grade and waste material. When increasing the threshold, (moving from left to right) the recovery begins to increase. Conversely, by decreasing the threshold (moving from right to left) the upgrade is favoured over recovery. In summary, the results generated by AT can be used to evaluate separability of different materials, such as to select the best sensor/s for the separation.

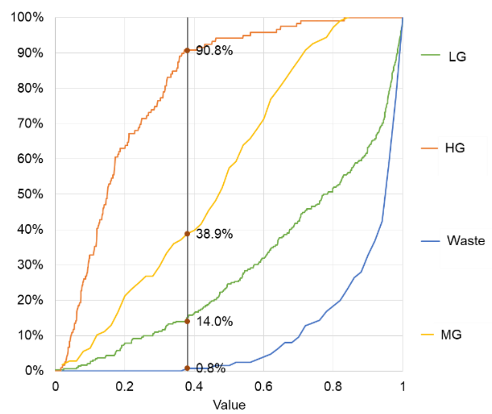


Figure 2 - Separation setting example for AT

4.2. SENSOR TECHNOLOGIES

Various different sensors have been applied in SBS for ores over the years, these include transmissive technologies such as x-ray transmission (XRT), surface based technologies such as near infrared (NIR), x-ray fluorescence (XRF) and colour detection. This study specifically examines the sensor technologies which have most recently been applied to the testing and commercial processing of lithium pegmatite ores.

4.2.1. Near Infrared (NIR) spectroscopy for minerals

Near infrared (NIR) is a spectroscopic technique which relies on the unique absorption of light in the NIR range by molecules. This absorption occurs as a result of the interaction between photons and the molecules of the specimens being observed. Specific wavelengths cause molecules to oscillate whilst the remaining radiation is reflected and detected by a camera unit and/or other detectors. This measured response provides a spectral signature which can uniquely identify the minerals responsible for the absorption (Robben 2010).

Various authors define the NIR wavelength range differently nevertheless this range can be anywhere from 780nm – 2500nm (Clark 1999; Robben and Wotruba, 2010; Robben 2017). Importantly are the known-absorption bands of various molecules within the wavelength range which make the identification of certain minerals possible. Figure 3 shows two spectra of Li-Pegmatite specimens for Lepidolite and Muscovite.

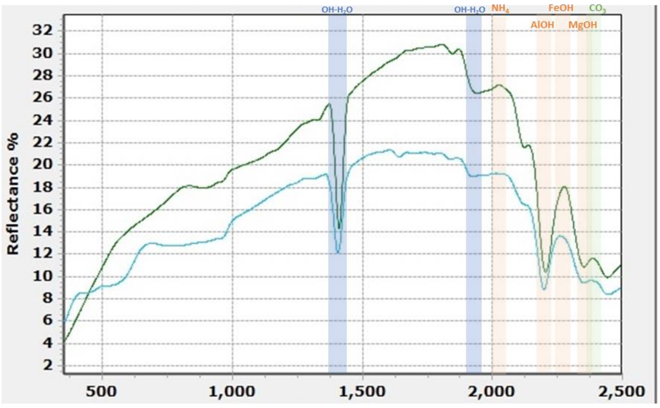


Figure 3: Spectral plot of muscovite (green) and lepidolite (blue) from a field spectrometer (Courtesy of Spectral evolution)

We see the major behavioural bands where we expect the interaction of various molecules also shown in Figure 3. Not all minerals are active in the NIR wavelength range, iron (Fe) has shown to have strong absorption in the NIR range, which could provide some indication of why sulphides are difficult to detect within this range. However, minerals that have some structural presence of H_2O, OH^-, NH_4, and carbonates (CO_3) have all demonstrated strong NIR detectability (Shanker, 2015).

Differences between the two spectra at one or several points within these absorption bands allow for the mathematical distinction between the spectra and provide a separation criteria for sensor based sorting.

4.2.2. Dual Energy X-Ray transmission (De-XRT) for minerals

The working principle relies on the absorption of x-rays transmitted through objects. The density, molecular structure and thickness of the objects all contribute to whether the radiation is partially or completely absorbed. An x-ray source is located on one end of the object, whilst detectors also such as scintillators are located on the opposing end. Photons are radiated with a defined intensity and these travel through the material and are transmitted on the opposite side, where they are measured by the detectors. The difference between the incidental radiation and measured radiation is equal to the absorption, which allows conclusions about atomic density of the measured material to be made.

The dual energy principle is used to compensate for differences in material thickness. A sandwich board detector provides the possibility to measure the transmitted radiation on two energy levels. Such a detector essentially consists of two detectors separated by a thin metal film, allowing for two measured values. High energy (HE) and Low energy (LE). Depending on the belt speed, and hardware selection of the x-ray tube and detectors, a certain pixel resolution can be achieved. The information from the scanned objects is translated to a scatterplot of pixels displayed on two axis. Each pixel consist of a HE transmission and LE transmission values which are plotted on a scatterplot similar to Figure 4.

Figure 4 demonstrates the visual interpretation of De-XRT principle with two distinct curves showing high and a low dense materials. Heavy elements are expected on the upper curve, while elements with a lower densities can be found on the lower curve. In this diagram an area of interest is defined, which allows a mapping of every single pixel recorded and thereby allocation it to a material class for the purposes of sorting.

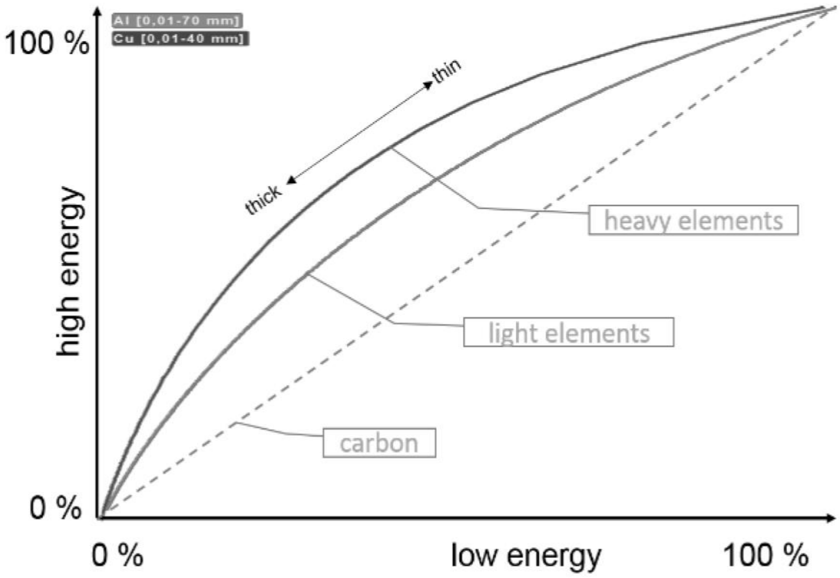


Figure 4: Visual interpretation of De-XRT where the x- and y-axis show percentage of transmitted radiation of the LE and HE detectors, respectively.

In the context of this paper, material was scanned on a conveyor belt at 3m/s with the source (x-ray tube) located below the belt and the detectors above. The signal processing of each pixel is classified according to the area of interest defined in the DE-XRT diagram and on this bases each scanned object can then be displayed as a classified "False colour image" as shown in Figure 5.

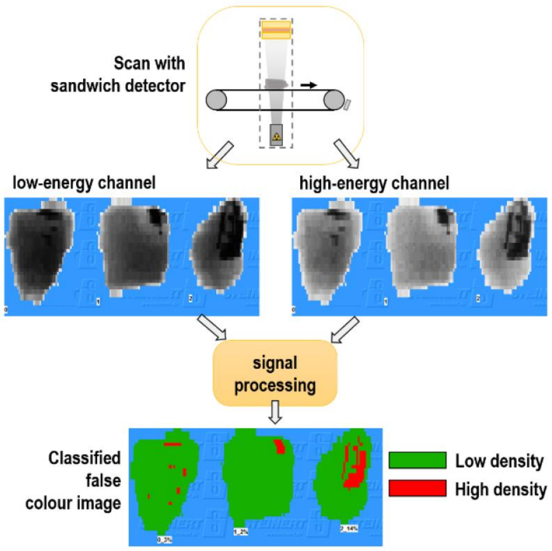


Figure 5: De-XRT signal interpretation

4.2.3. Visible light separation (VIS) techniques for minerals

Optical colour sorters have been employed across various industries such as; food processing, recycling and minerals processing. The visible light spectrum is located between the ultra-violet (UV) and infrared (IR) range (400nm- 700nm). Similar to other surface based detection principles, colour sorting relies heavily on the cleanliness and visibility of the materials surface in order to provide an accurate measurement of the colour characteristics. The principle works on the red green and blue (RGB) colour cube with three main primaries and an evolution of these as demonstrated in Figure 6. The model works by adding the three primary colours together to achieve different colours. Each measured pixel of a camera denotes a particular point on the cube and depending on that position a particular colour is recognised. The resolution of the detecting camera plays a critical role in determining how many different colours can be recognised.

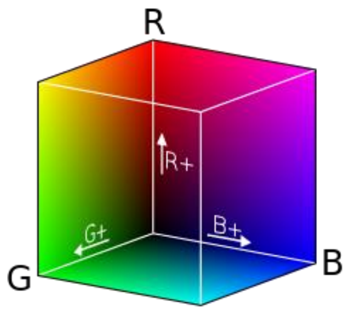


Figure 6: RBG colour cube (www.javatpoint.com/introduction-to-color-spaces)

Light illuminates the surface whilst a camera placed at a specific position away from the object detects the various colours and plots these at various points on the RGB scale. Calibration samples are usually scanned in this case as well allowing for a reference scale to be developed, similar to the scale presented in Figure 2. This scale is generally used as a measurement against which sorting material is compared against. Depending on the colour scale for a specific group of material against the developed calibration scale, this material can either be “ejected” or “dropped” in the sorting operation, whilst the sensitivity can be adjusted in accordance with the threshold previously described for Figure 2.

Laser scattering, brightness also fall within the context of VIS technologies however utilizing a visible laser line and camera detection system. Based on the surface characteristics of certain minerals such as quartz, the translucent appearance of the crystalline structure allows for a significant scattering or dispersion of a laser beam when focused on its surface. This response can be detected by a camera/s and interpretated as a criteria for separation. Figure 7 shows 4 particles from a lithium pegmatite ore body with different degrees of surface oxidation and presence of quartz and feldspar.

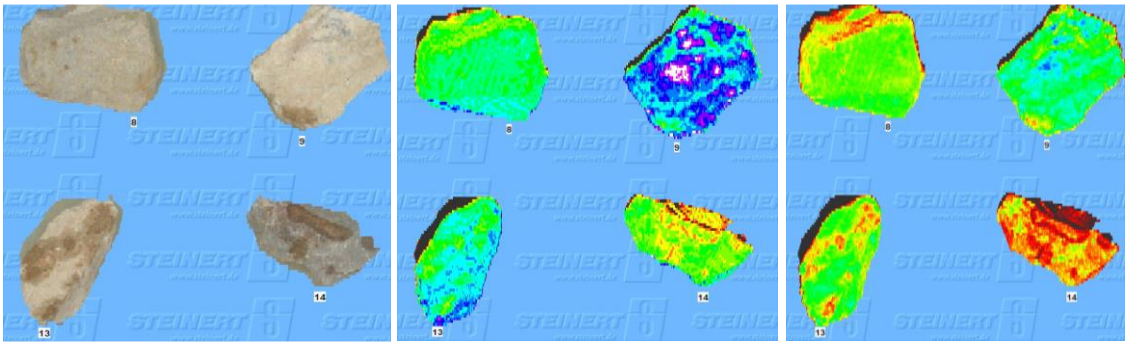


Figure 7: (LEFT) Colour camera image (MIDDLE) Laser width. (RIGHT) Laser brightness

4.2.4. Effect of particle presentation

In addition to the physical properties, particle presentation also has a direct effect on the sensor classification. While XRT is a transmissive technology, NIR, laser and colour camera only perform surface measurements of the particles.

Figure 8 shows a rock with cookeite and petalite crystals. In the case of surface detection, it is important that the crystals are shown towards the direction of the sensor, so they can be seen and detectable.

In the case of XRT, the surface characteristics are not a measurement parameter, since it is a transmissive detection. However, the direction of the particle can have an effect on the measurement. This can be better understand in terms of the x-y-z axis. By taking XRT scans across these different axis' this can result in variations in the absorption patterns, depending on the structure of the mineralization. This is a result of the variations on the crystal position in terms of the direction of the measurement. Based on that, it can be concluded that particle presentation is directly affected by all sensors measurements and need to be properly take into account during test work.

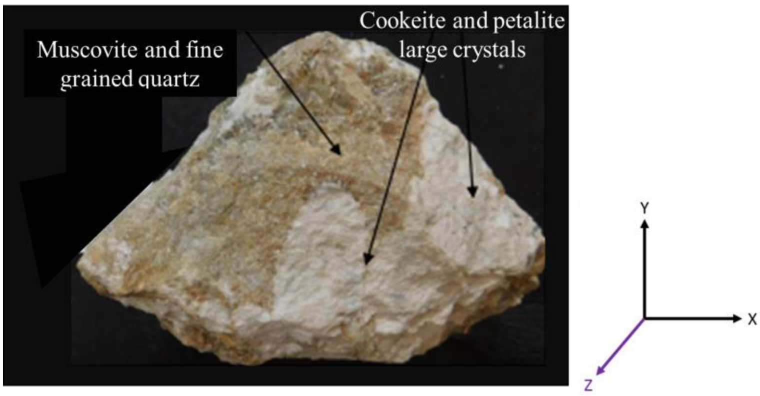


Figure 8 – Particle with cookeite and petalite large crystals

5. RESULTS AND DISCUSSION

CS from the different lithologies were submitted for AT. The samples were scanned using the following equipment:

- Steinert KSS XT CLI: XRT, colour camera, laser and induction
- Steinert KSS NR CLI: NIR, colour camera, laser and induction

The AT was performed to generate separation settings that were later applied in a separation test. The sensors used were XRT, laser, colour and NIR. The obtained results are shown in the next sections.

5.1. XRT + LASER + COLOUR

Figure 9 shows the colour and XRT images for different lithologies commonly encountered in lithium pegmatite ores. For the XRT image, darker tones indicate a higher absorption pattern, while lighter colours are associated with lower absorption. The XRT absorption is related to the atomic density of the particles. In this sense, light colours should be associated with smaller atomic densities for a particle.

The lithium minerals found are mainly composed by light elements, such as Li, Al and Si. In this sense, lighter shades are observed for the lithium minerals thus indicating a low absorption pattern. Although some of the lithium minerals present higher specific densities, such as spodumene, in the XRT pattern they are detected as low-density material. This is due to the fact that XRT measurement is based on atomic density, rather than the specific density.

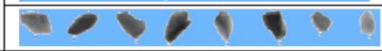
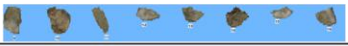
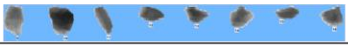
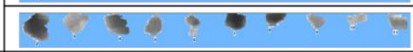
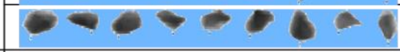
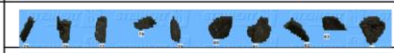
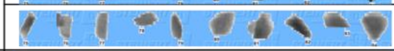
Sample	Sensor Image	Sensor
Feldspar		Color
		XRT
Petalite		Color
		XRT
Spodumene		Color
		XRT
Mica		Color
		XRT
Schist		Color
		XRT
Quartz		Color
		XRT
Amphibolite		Color
		XRT
Gabbro		Color
		XRT

Figure 9 - Images obtained through the colour sensors and XRT.

The difference in the absorption pattern of the samples can finally be utilized to simulate the separability. The curves shown in Figure 10 show the separation curves obtained for XRT sensor. The x-axis indicates the separation criteria, which can be adjusted for greater recovery or purity. The y-axis indicates the separability of the samples, as a percentage. For example, an adjustment of the XRT threshold at 0.6 provides the rejection of approximately 100% of Feldspar, Schist, Mica, Amphibolite, Gabbro, and virtually no rejection of Quartz, Petalite, and Spodumene. Selecting this threshold, allows to generate a material with high content of petalite, spodumene and quartz, while other lithologies are almost completely rejected.

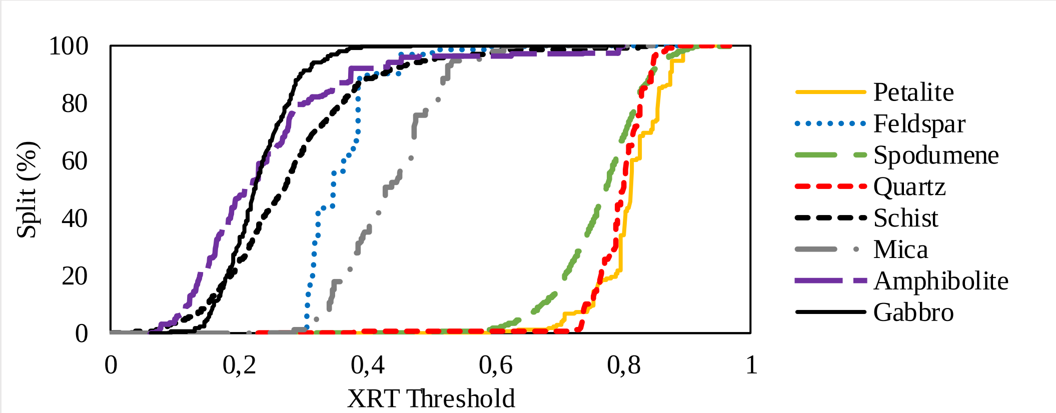


Figure 10 - Separation chart for XRT sensor.

In a different approach, the colour camera is capable of detecting different shades among the samples. In addition to that, the laser detects both shape and surface properties. The laser and colour sensors were combined to generate a separation curve, shown in Figure 11. The interpretation of the curve can be done on the same way as for the XRT. For example, a threshold of 0.95 results in a rejection of over 90% for Quartz, Feldspar, Schist, Amphibolite and Gabbro, with a rejection around 20% for Spodumene and Petalite, and virtually no rejection for Mica.

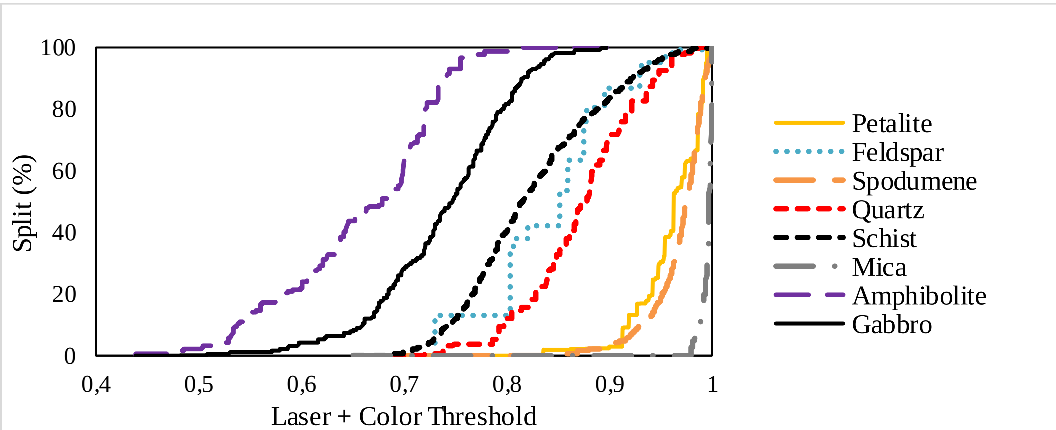


Figure 11 - Separation chart for colour separation.

This separation criteria can be adjusted to higher values, resulting in higher purity and lower recovery of lithium minerals. Conversely, the use of smaller thresholds results in higher recovery of lithium minerals with reduced contamination, especially by quartz. Based on the graphs evaluation, it can be concluded that it is possible to achieve different separation objectives by using either laser, colour or XRT sensors. The XRT sensor provides good separation of the lithium minerals from mica, shale, schist, feldspar, amphibolite and gabbro. The laser and colour combination presents a better separation between lithium minerals and quartz. In this sense, the best results can be achieved as a combination of the three sensors, depending on the ROM and lithologies. However, in the cases presented here, it is possible to reject all contaminating lithologies, generating a concentrate of spodumene and/or petalite with high purity. Both separation criteria can be combined and adjusted to maximize lithium purity and/or recovery, according to the defined separation objectives.

Based on this multi sensor approach, 6t of sample were tested at different size ranges, multiple feed grades and ore compositions. Table 3 summarizes the characteristics of the test material.

Table 3 - Characteristics of lithium pegmatite ore separated with multi sensor approach

Characteristic	**Unity**	**Min**	**Max**
Particle Size	mm	6,0	100,0
Feed grade	Li2O%	1,0	5,5
	Fe2O3%	1,0	3,5
Product grade	Li2O%	1,2	5,9
	Fe2O3%	0,4	0,8
Waste grade	Li2O%	0,1	2,9
	Fe2O3%	2,9	11,9

The relation between mass pull, Li_2O recovery and Li_2O upgrade are shown in Figure 13 and Figure 12. Another quantitative measure of assessment is the upgrade or enrichment rate, this is the ratio between the product grade after SBS is applied and the original feed grade. Based on Figure 13 and Figure 12 it is possible to note that operating at smaller mass recoveries favours higher upgrades, which can mean an elevated upgrade rate. On the other hand, operating at elevated mass recoveries generating higher Li_2O recoveries, up to 90%. The two graphs (Figure 13 and Figure 12) can be utilized to determine an optimized operating envelope that takes into consideration the aforementioned factors. The generated data can also be utilized for economic and sustainability evaluations of different operational points in a project.

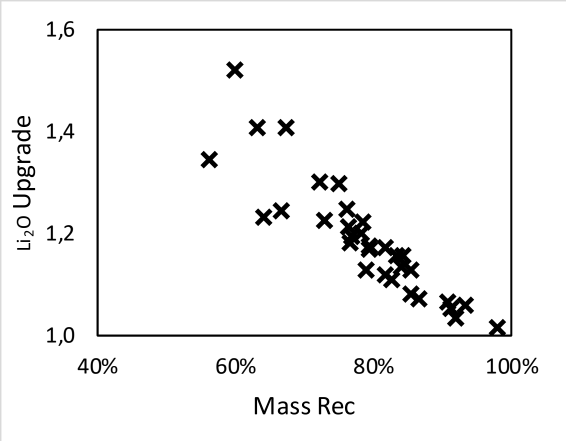


Figure 13 – Relation between mass pull and Li_2O upgrade with multi sensor separation

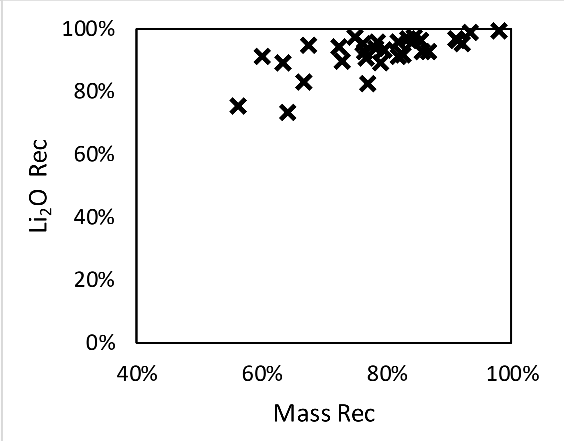


Figure 12 - Relation between mass pull and Li_2O recovery with multi sensor separation

For example, a defined operational range can be selected to increase the feed grade of a beneficiation plant, thus making low grade deposits viable. Another possibility would be to upgrade concentrate material generated at coarser fractions (> 6,5mm). In this sense, Table 3 indicates the possibility to achieve Li_2O grades up to 5.9%. This grade is at the level of final product concentrate of brines and spodumene (Drobe, 2020). This potentially indicates the possibility to apply SBS for obtaining a final product at this size, with the advantages of eliminating DMS, grinding and flotation stages. Other outcomes include a significant reduction of iron content in the product (concentrate).

A very consistent trend can be observed in the results across various orebodies and tests. This is a result of the multiple possibilities generated by sensor combination.

5.2.NIR

Although Spodumene is the more commercially viable lithium bearing minerals, not all lithium pegmatite orebodies contain appreciable amounts of spodumene. Furthermore, in some instances appreciable atomic density differences are simply not present in the ore to allow for sorting using XRT. For this reason, an approach to a petalite rich orebody has also been explored.

Tests were conducted using a Near Infrared sensor sorter with Hyper Specral imagining (NIR-HSI). All work was conducted on a conveyor belt system at 3m/s at equipped with a line scanner with a spectral resolution of < 3nm.

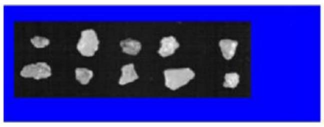


Figure 16: Sample scans - NIR image

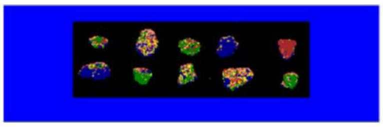


Figure 15: Classified false colour image

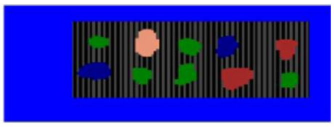


Figure 14: Classified valve mirror image

Samples from a Li-bearing Pegmatite orebody formed part of the bulk sorting campaign. The lithium minerals included; petalite, amblygonite, cookeite as well as some Li-containing Muscovites. Quartz and Feldspar formed the balance of the orebody. Figures 14, 15 and 16 represent the NIR images and classifications of the scanned samples. Figure 15 shows the classified false colour image per pixel identified in each sample. This demonstrates on a granular level the classification of each object. On this basis appropriate boarders can be set as well as prioritization of minerals in order to provide the final valve mirror image in Figure 14

In Figure 15 each pixel follows down a decision tree path until the entire object is classified as a single mineral type shown in Figure 14. The de facto criteria for sorting is either to "eject" or "drop" a sample, in order to carry out this sorting operation the valve mirror images are required to classify a whole sample as one or another mineral. For characterisation purposes however, we look to the false colour images in Figure 15 for the mineralogical classification. For this reason, the NIR sorting system can also provide a quantified analysis of the various minerals classified as demonstrated in Figure 17

Feldspar	48 px	11,0 %
PetaliteCookite	111 px	25,4 %
Quartz	99 px	22,7 %
Muscovite	109 px	24,9 %

Feldspar	644 px	23,8 %
PetaliteCookite	835 px	30,8 %
Quartz	408 px	15,1 %
Muscovite	600 px	22,1 %

Figure 17: (LEFT) - False colour image of pixel classification. (RIGHT) - Valve mirror image of object classification

The requirements for the testing campaign was to concentrate as much lithium (Li_2O) in approximately 30% of the mass as possible with a clear focus on achieving as high an upgrade as possible. The results of the bulk testing campaign are presented in Table 4

Table 4: Feed grade of bulk samples tested along with achieved upgrade rates through NIR-HSI sorting

	Sample 1	Sample 2	Sample 3	Sample 4
Feed grade (mg/kg)	0,94	0,96	0,66	0,73
Upgrade rate (*x times*)	1,3	1,4	1,2	1,5
Upgrade rate (%)	32%	36%	22%	51%

The average grade of the samples was 0,82% Li_2O and upgrade rates from 22% to 50% were achieved. Working within the confines of the mass pull requirements, we see the impact of mass pull on recovery, demonstrated in Figure 19. Increasing the mass pull would provide the opportunity to increase the Li_2O recovery, however conversely given the waste grades presented in Figure 18 this would also result in the dilution of the product.

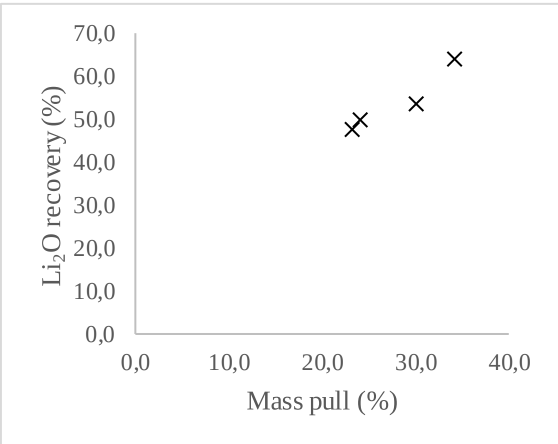


Figure 19: mass pull vs LiO_2 recovery

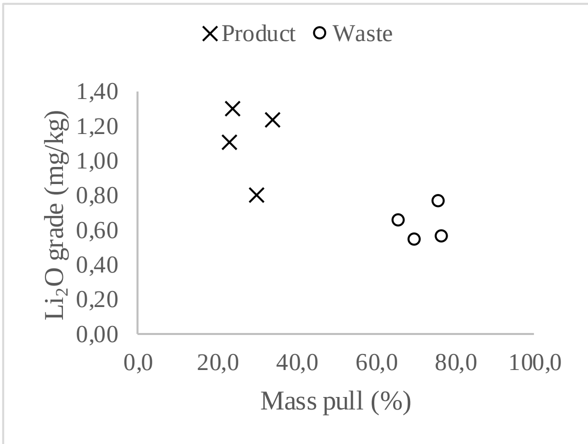


Figure 18: product and waste grades at varying mass pulls

Fe_2O_3 grades were also evaluated, however, the orebody demonstrated no more than 0,40% Fe_2O_3 on average with the highest measured value in one sample at 2,81and an standard deviation of around 0,32%. As such Fe_2O_3 was not considered as pertinent to the NIR findings. With the reported average grades of lithium bearing pegmatite orebodies being anywhere between 1,5 - 4,0 % Li_2O the opportunity to achieve economically viable grade of Li_2O become increasingly important.

6. CONCLUSIONS

Lithium ores vary in their compositions from ore body to ore body. Pre-beneficiation thus requires adaptable techniques to detect multiple characteristics of materials in order to separate lithium-bearing rock and waste material.

A total of approximately twelve tons of different lithium ores from Southern Africa, South and North America were tested at different size ranges, multiple feed grades, and ore compositions. The Li-minerals consisted of cookeite, petalite, spodumene and lepidolite. Waste rock minerals varied from feldspar, quartz, schist, gabbro, muscovite, basalt, and amphibolite. The separation results indicate that the multi sensor approach allows for consistent results at different mineral compositions. This was observed in the relations between mass recovery, upgrade factor and Li_2O recovery. Based on the results, it can be concluded that different sensor solutions need to be applied to maximize the separation results of ores with multiple mineral compositions.

To summarize, beneficiation of coarser size fractions provides several factors enhancing a mine’s processing efficiencies, energy/water reduction, cost savings and at the same time improving the ESG performance. The more waste rock that is removed before the mill, the more energy is saved, feed-grade improved and controlled, which vastly improves the downstream wet processing of Lithium. Waste rock sorting also provides an opportunity to utilize additional separation stages to produce clean waste rock fractions as secondary products. From the sorting results achieved for other lithologies, it is possible to generate by-products such as high purity quartz or feldspar using different sensor combinations. Some mines have already embarked on a zero-waste mining program which utilize flexible multi-sensor sorting programs to produce sellable products for all their material mined. Finally, the high grade and coarse lithium mineral concentrate achieved through SBS can potentially progress directly to the lithium conversion process, without the need for other wet downstream process.

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