

# Regional diamond exploration under cover

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Kimberlites sample and transport exotic minerals from the mantle during their violent eruption to the surface. Weathering and transport of these indicator minerals (most importantly chromite, diopside, garnet, ilmenite, and olivine) gives the explorationist a trail to follow, which hopefully leads back to a kimberlite source. These mantle minerals are relatively rare, comprising less than 1% of surface material, which explains why explorationists collect dozens of sacks of soil and surface material which are then concentrated before the search for minerals starts. Individual mineral grains are usually less than 2 mm in diameter and some alter into other minerals during the weathering phase. The Aster satellite integrates reflected and emitted long wave infrared (LWIR) signals over a  $90 \times 90$  m pixel - which may be regarded as a large-scale geochemical sample. Mantle minerals have diagnostic spectra in the LWIR and their abundances may be mapped even under moderate vegetation and transported cover. This is done using a simple linear spectral mixing model. Kimberlite weathering products and indicator mineral maps estimated from space provide the explorationist with a cost-effective tool for regional diamond exploration.

## INTRODUCTION

Before the Argyle lamproite, now a Tier 1 diamond mine in Australia, was discovered, it was thought that diamonds occurred only in ultrabasic volcanic rocks called kimberlites which erupted from the mantle and transported diamonds to the surface.

Diamonds are not the only passengers. Chromite, chrome-diopside, garnet (pyrope [A1] and eglogitic), picro-ilmenite, and olivine are minerals from the mantle which are also transported to the surface. These minerals have very distinct LWIR spectra, even when resampled to the five thermal spectral bands of the Aster satellite.

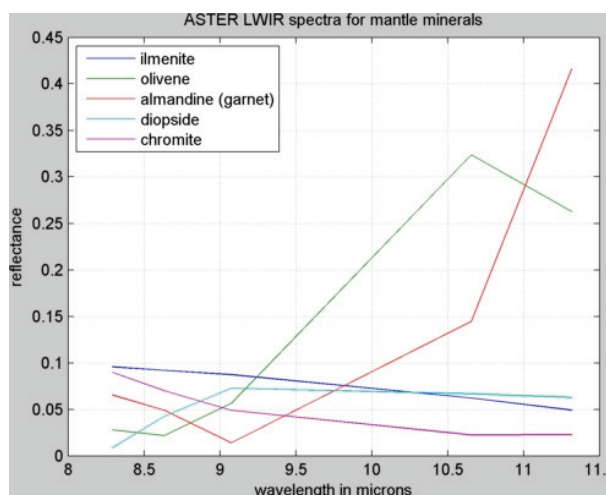


Figure 1. LWIR spectra of some common kimberlite indicator minerals, resampled to Aster bands.

Aster has been collecting five bands of LWIR data at 90 m spatial resolution both day and night since 2000 and is still functioning, well past its sell-by date. The five bands measure reflected and emitted thermal energy at 8.29, 8.63, 9.08, 10.66 and 11.32  $\mu\text{m}$ . A database of over 3 million images exists and these images have been free since 1 April 2016. They are a useful database for explorationists.

Images are downloaded as  $60 \times 60$  km scenes, and we mosaicked four such scenes from two overflights of the Orapa area of Botswana. The westernmost pair of scenes were imaged on 7 May 2000 while the eastern ones were collected on 10 May 2001. All scenes are from early winter and as the area is arid semi-desert, standing pools of water were not a problem. There was no cloud cover.

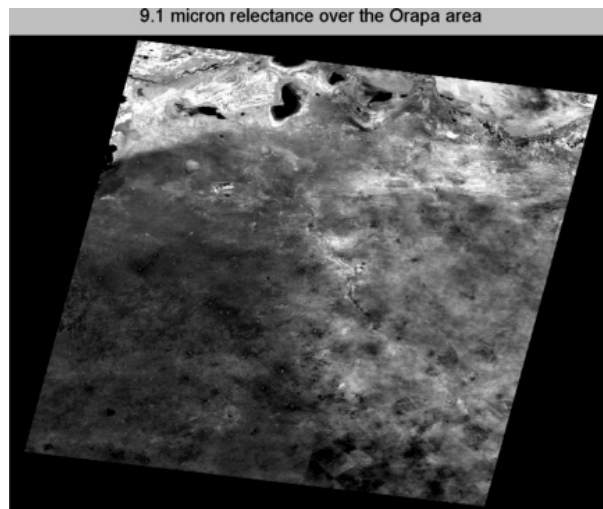


Figure 2. Reflected 9.1  $\mu\text{m}$  mosaic of four scenes over Orapa. The spatial extent is  $140 \times 140$  km.

## METHOD AND RESULTS

The data was compensated for atmospheric effects and the signal was decomposed into temperature and emissivity components using a proprietary technique described by Pendock (2016). It is this emissivity property of rocks that allows them to be mapped under cover, either transported regolith such as windblown sand or vegetation. For examples (see Pendock, 2016) while buried paleochannels, a potential source of alluvial diamonds, have been mapped using Aster LWIR data (see for example Thakur *et al.*, 2016).

As we know what spectra we are looking for, target detection algorithms seem the obvious processing strategy. Correlation of kimberlite weathering products and indicator mineral spectra with image pixels is the simplest such paradigm. Each image spectrum was correlated with the five mantle mineral spectra and the largest response for each pixel was retained. All five minerals feature in this simple classification of the scene.

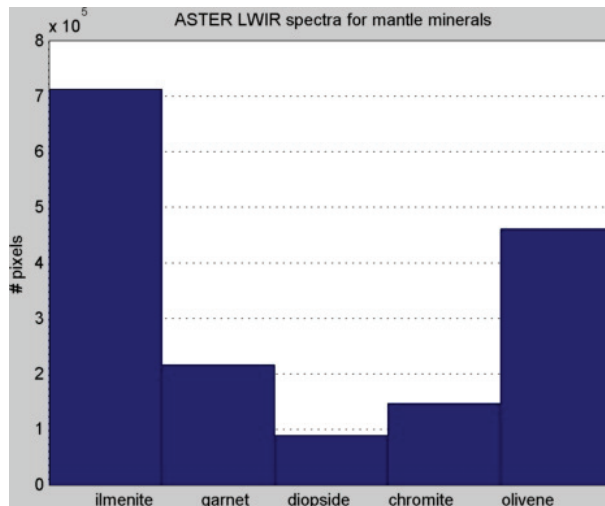


Figure 3. Classification by assigning the label of maximum correlation mantle mineral to each pixel.

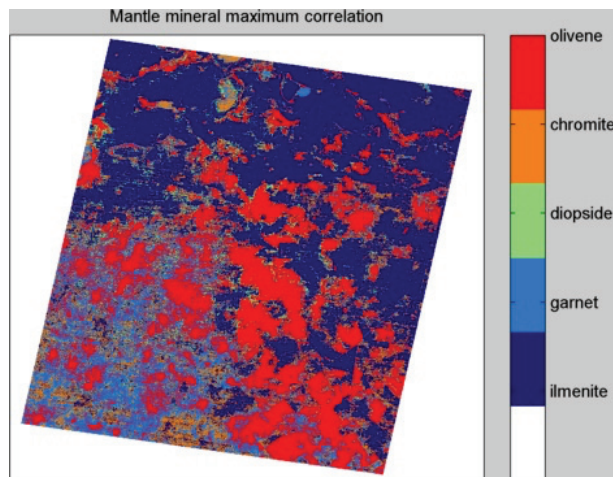


Figure 4. Maximum correlation classes.

Excluding pixels with a maximum correlation  $< 0.5$  gives a more realistic interpretation. Of course these correlations simply indicate possible presence of mantle minerals which occur in tiny amounts in the scene, if at all. While their contribution may be small, mantle minerals, like chili in a bowl of pasta, can make their presence felt due to their unique spectral fingerprints.

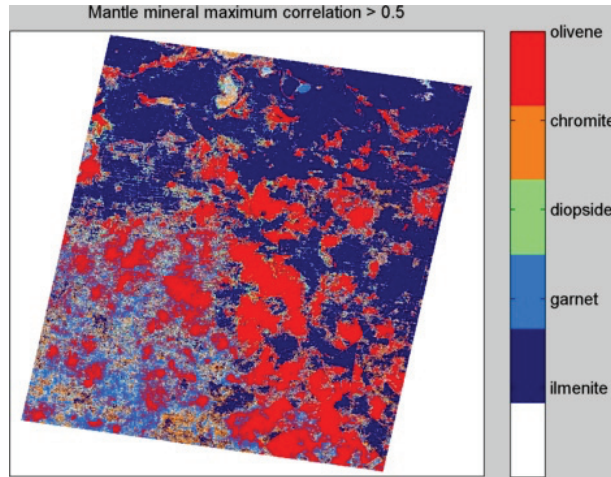


Figure 5. Maximum correlations  $> 0.5$ .

Given the relatively large spatial size of each pixel (90 m), plus the presence of an unknown background mineral (calcrete-derived carbonates, quartz, and iron oxides in the case of Orapa), a linear mixing model is arguably more realistic. If each pixel is decomposed into a non-negative linear combination of the five mantle mineral spectra, we achieve a spectral unmixing result.

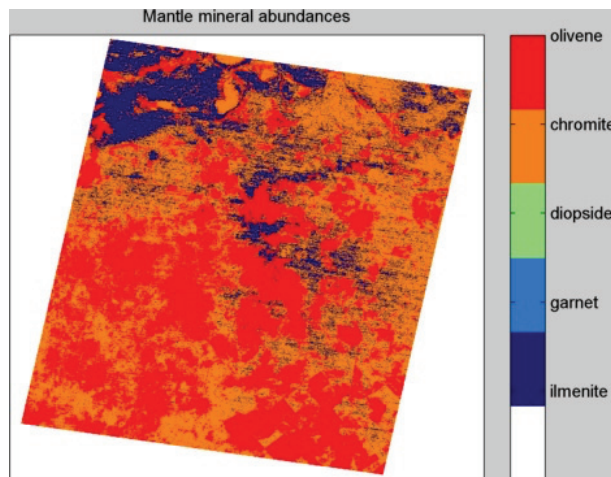


Figure 6. Linear spectral unmixing result.

Only three mantle minerals feature in this interpretation, which is in effect a supervised classification of the scene. In practise we implement an unsupervised classification by finding a set of spectral endmembers (typically around 16) with sparse abundances that explain the variation present in the scene and account for the spectral response of background minerals, vegetation, and other features of the regolith.

These spectral endmembers may be interpreted by comparing them to a spectral library measured in a laboratory. One benefit of this approach is that there is no unique spectrum for a mantle mineral as the reflected spectra are functions of grain size and texture.

The American Johns Hopkins University spectral library of 324 minerals contains 14 garnet spectra and 29 olivine spectra (Salisbury, 1991). Choosing a single target spectrum may lead to missing the source if we are blinded by preconceptions.

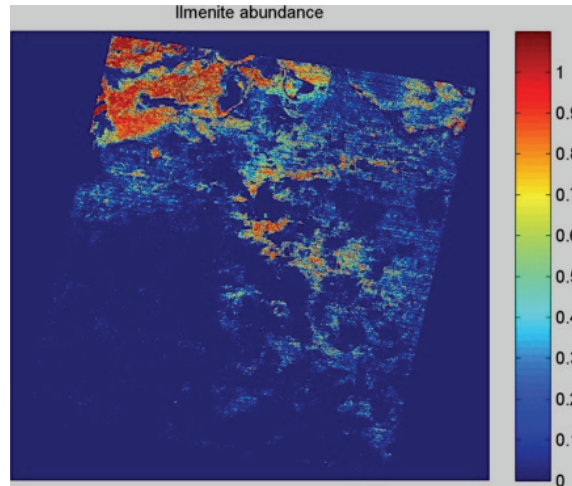


Figure 7. Ilmenite spectral abundances.

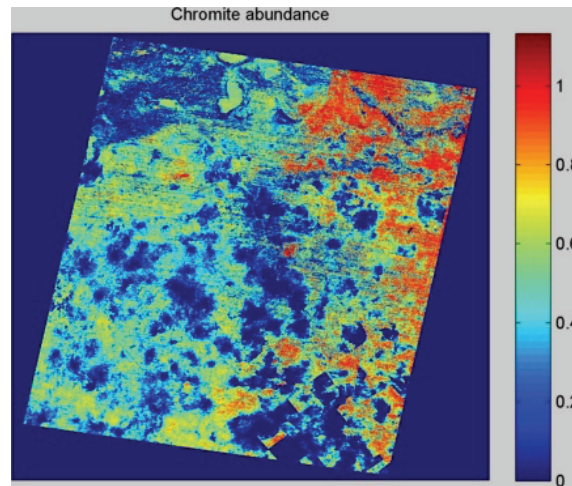


Figure 8. Chromite spectral abundances.

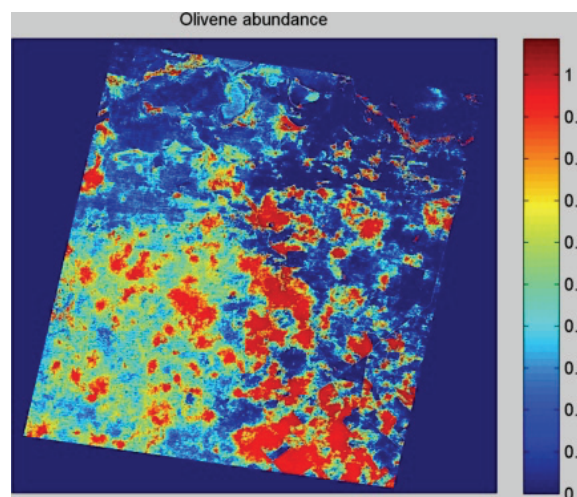


Figure 9. Olivine spectral abundances.

Figures 7-9 are likely wildly optimistic as to the actual amounts of indicator minerals present, but thresholding the largest olivine abundances and overlaying them on Google Earth along with the locations of 79 kimberlites in a database from the Botswana Geological Survey shows good spatial correlation between olivine abundance and kimberlite location. The internet link to this data is included as a reference.

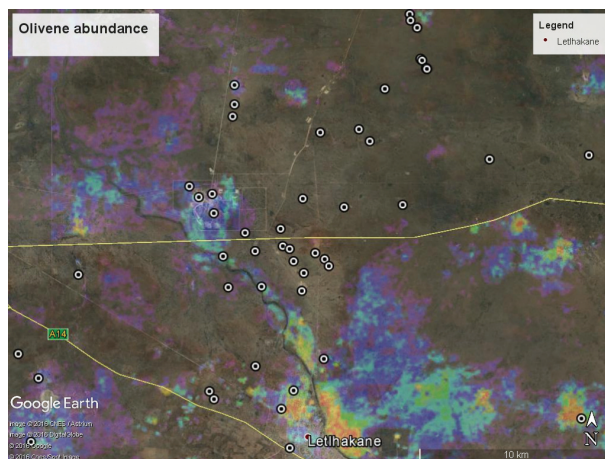


Figure 10. Olivine abundances correlate well with kimberlite locations, represented as white open circles.

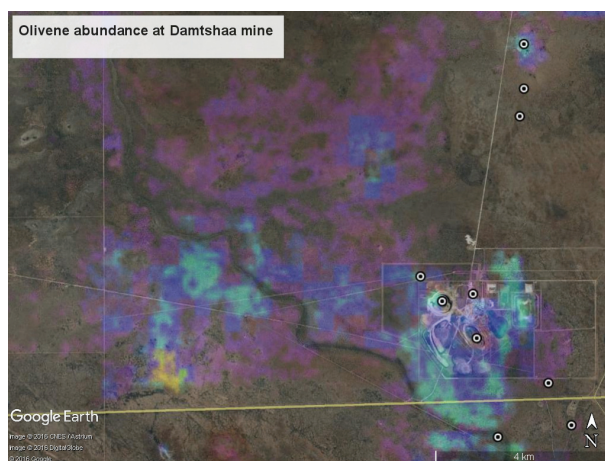


Figure 11. Olivine abundance around Damtshaa mine (kimberlites BK09 and BK12).

The Damtshaa mine, here represented by two kimberlite pipes, and its dumps are evident on the image above, so is the olivine abundance contributing anything useful? Yes, as the scenes were collected three years before the mine opened. Now it is well known that olivine rapidly weathers to serpentine, which is exactly what we observe in a shortwave infrared (SWIR) spectral decomposition of the same Aster image over the Orapa mine dumps.

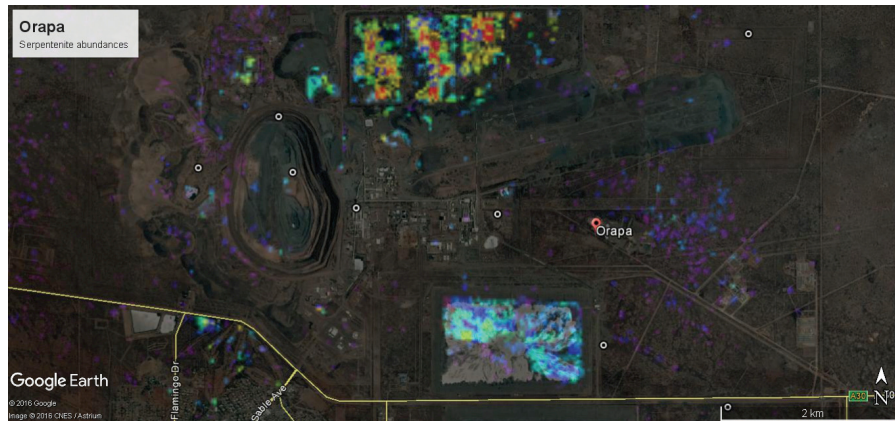


Figure 12. Serpentine (weathered olivine) over the Orapa AK01 mine dumps.

When the Aster images were collected, Damtshaa mine was just a few holes and trenches.

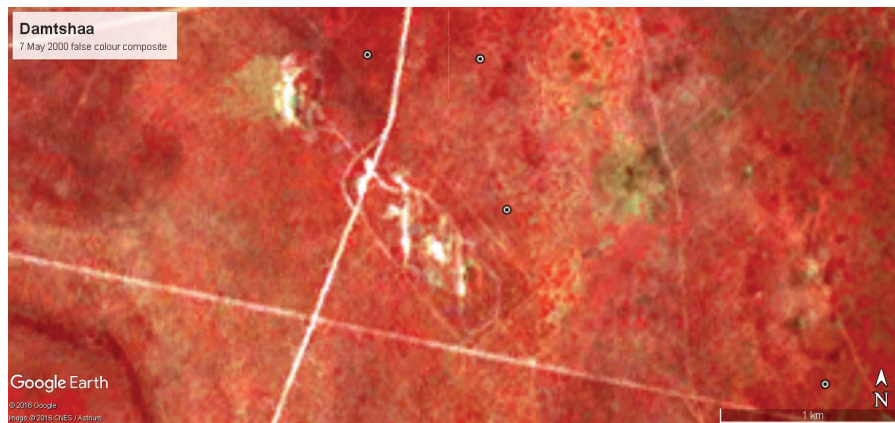


Figure 13. False colour 15 m spatial resolution Aster visible near-infrared image over Damtshaa mine BK12 to the northwest and BK09 to the southeast.

Decomposition of the scene into sparse linear combinations of 16 thermal spectral endmembers yields three spectra interpretable as 'olivine'.

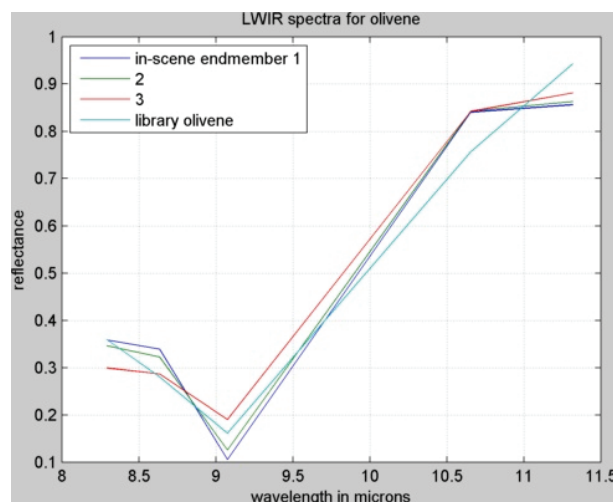


Figure 14. Three potential in-scene olivine endmembers.

Each endmember has an associated spatially sensible abundance. Sensible in that each has a contiguous geographical context.

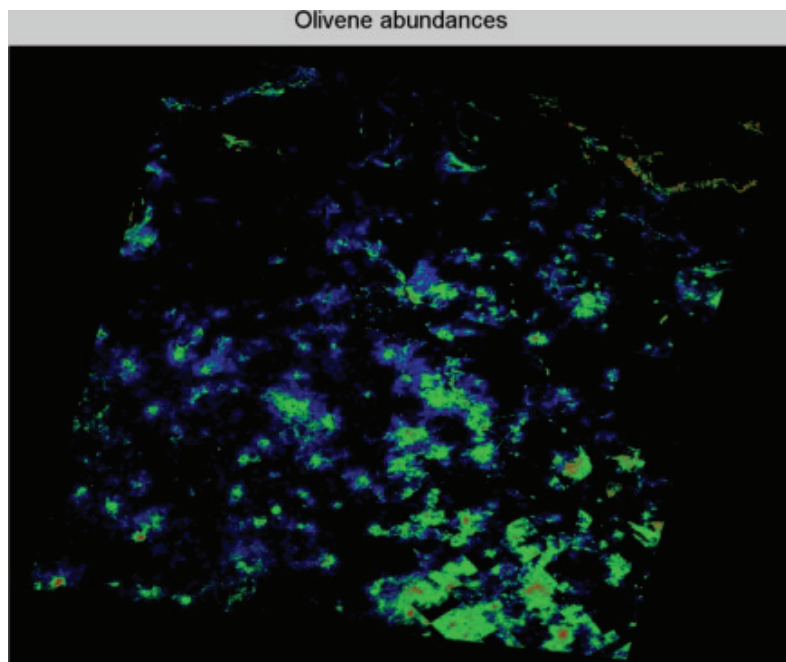


Figure 15. Corresponding abundances for three olivine in-scene spectral endmembers.

One olivine endmember does a good job of mapping Damtshaa mine. It comprises barely 0.35% of the scene, which confirms another benefit of spectral unmixing over target detection through correlation – quantification of the amount of an endmember present in a pixel.

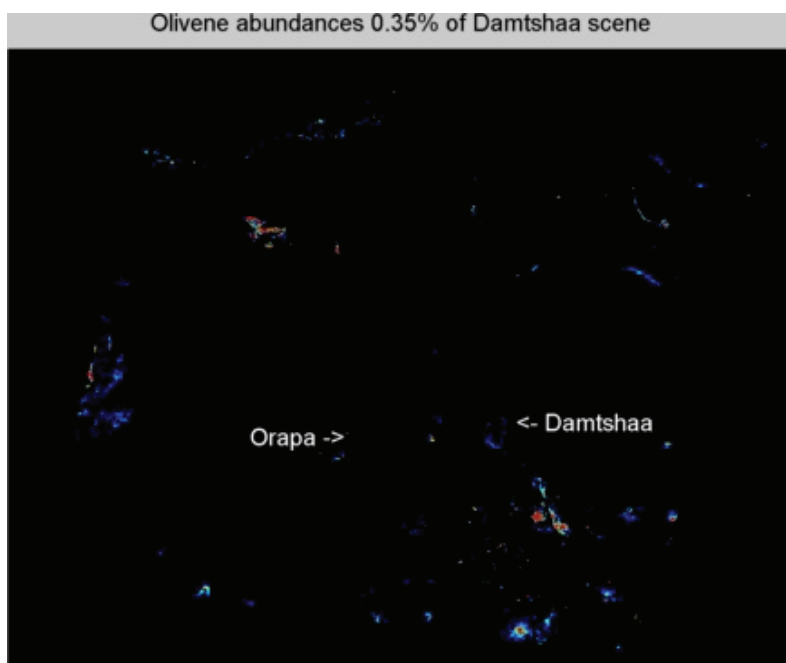


Figure 16. Abundances of one olivine signature are relatively sparse. Colour indicates amount present.

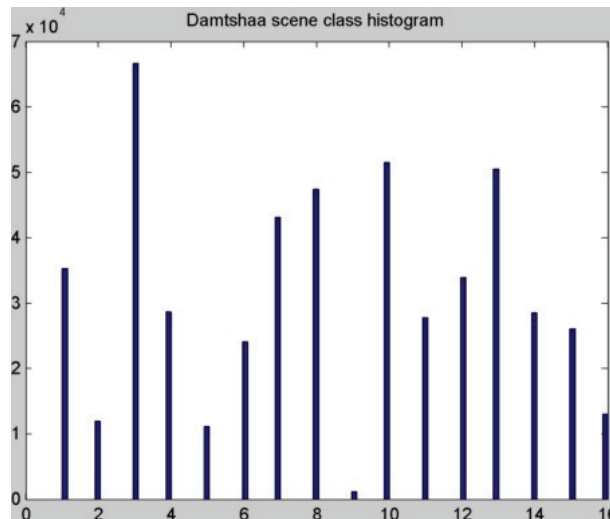


Figure 17. Histogram of thermal abundances.

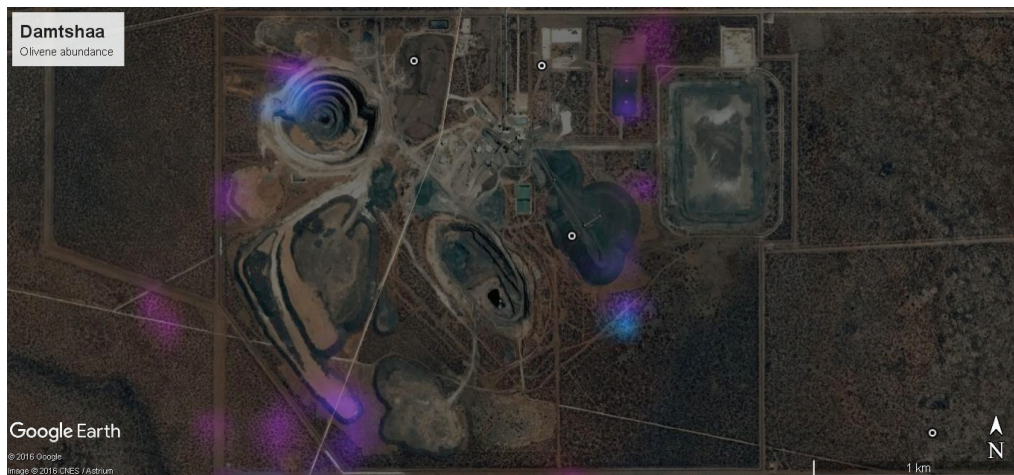


Figure 18. The same endmember abundances at Damtshaa mine (BK12 and BK09).

The abundances for endmember 9 may comprise less than 0.35% of the scene yet map the soon-to-be-developed mine at Damtshaa as well as the established Orapa mine, which was already in production when the satellite images were collected. As such, it is a useful target generator which may be integrated with other exploration data-sets.

## CONCLUSIONS

Kimberlite weathering products and some indicator minerals can be rapidly and inexpensively mapped using Aster LWIR imagery. Remote satellite geochemistry is a cost-effective addition to the toolbox of the modern diamond exploration professional.

The relatively poor spatial resolution of 90 m makes Aster imagery problematic for detailed exploration as kimberlite diameters are typically measured in the hundreds of metres, with kimberlitic dykes even smaller in cross-section. However airborne systems are currently available with two orders of magnitude more spectral bands than Aster and spatial resolution in the metres. The first explorationists to deploy such systems in environments where cover impedes traditional remote sensing methods (northern Canada, Angola) will likely be richly rewarded.

## REFERENCES

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Neil Pendock has over 30 years' experience developing algorithms and software for image processing and the analysis of remote sensing and geophysical data. He obtained a PhD in Applied Mathematics from the University of the Witwatersrand in 1984 and was employed by Wits from 1987-1999 in the Department of Computational and Applied Mathematics. From 2004-2009 he was a visiting lecturer, Department of Computational and Applied Mathematics and has been a postgraduate external examiner (PhD and BSc honours) for the last decade.

Neil consulted exclusively for the Anglo American Group of Companies (Anglo American Corp, AngloGold Ashanti and De Beers) from 1985 until 2010 and since then has consulted for a number of other international mining companies. His most recent project was developing the hyperspectral core scanning software for Terracore and Geospectral Imaging ([www.geospectral.co.za](http://www.geospectral.co.za)).

Neil developed the software for the De Beers HyMap airborne hyperspectral scanner in the 1990s. This revolutionary instrument was used to produce mineral maps used in exploration for kimberlites, gold and base metals worldwide. He also developed software for the processing and interpretation of airborne gravity and magnetic gradiometer surveys.

Dr. Pendock publishes widely in the fields of remote sensing, geophysics and mineral exploration.