USE OF OPTICAL REMOTE SENSING ANALYSIS TECHNIQUES TO MEASURE MODAL MINERALOGY USING X-RAY ELEMENTAL PHASE MAPS. J. W. Nettles[1] and M.B. Wyatt, Brown University, Providence, Rhode Island. [1]jeffrey_nettles@brown.edu.

Introduction: In the course of a petrographic analysis of rocks, the determination of mineral modes is a standard and important set of information. Modes can be determined in several ways, each with different levels of precision and accuracy, including visual estimation, point counting, and the use of the electron microprobe. When the microprobe is used, programs such as FeatureScan are used to step across a thin section at user-specified intervals, and to assign a classification to each point analyzed according to counts of X-rays with wavelengths within user-specified ranges, or "windows." While programs such as these are capable of acquiring many more analysis points than point counting, for example, they have the shortcoming that their output is typically simply a table of modes. If a problem with the analysis is discovered, the program must be re-run, potentially requiring the use of additional probe time.

Elemental X-ray maps are also traditional petrographic tools, but these are in many cases used qualitatively to show zoning patterns, concentrations of elements, etc., rather than as a source of quantitative information. [1] used X-ray maps as quantitative tools, and used software written for remote sensing analysis in order to calculate mineral modes. They used the software program ENVI to combine a set of X-ray map images into a single image cube, and used ENVI's classification routines to calculate modes. [2] used freeware image processing tools to accomplish the same task.

In this abstract we further advocate the use of remote sensing tools for the petrographic analysis by demonstrating the use of endmember selection algorithms commonly used in remote sensing analyses (the "spectral hourglass" processing flow) to select image endmembers in an X-ray map data cube. We also use another remote sensing technique, a hue-saturation-value (HSV) merge of the color information of relatively low resolution X-ray map classification images onto higher resolution backscatter electron (BSE) images, in order to show that the X-ray map images do not have to be taken at extremely high resolution in order to be useful. This means that the use of remote sensing techniques for calculation of mineral modes can be relatively easy to acquire, using minimal probe time, and can produce accurate results.

Methods: We acquired elemental X-ray phase maps for a chondrule in LEW86134 (L3.0) using standard techniques. The elements for which phase maps were acquired are Fe, Mn, Cr, Ti, Ca, K, Cl, S, P, Si, Al, Mg, and Na. Each phase map was combined into a single image cube in the manner of [1] (Figure 1).

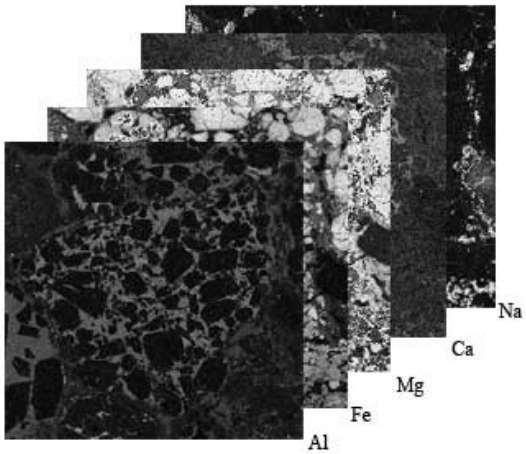

Figure 1. Example of five out of ten X-ray phase maps acquired for a chondrule found in LEW86134. All ten phase maps were combined into a single image cube in the manner of [1].

After combining the phase maps, the spectral hourglass processing flow was applied. This processing flow has two major parts (the two halves of the hourglass): 1) using the image data itself to select endmembers, and 2) classifying the entire image cube in terms of those endmembers. Endmembers are selected by using interrelationships in the data to select the most spatially and "spectrally" pure pixels that can be used to explain the rest of the cube. In the context of these discussions, "spectrally" refers to a plot of X-ray count vs. the wavelength of Kα emission of each element analyzed for each pixel in the image. The maximum noise fraction (MNF) transform is used to spectrally reduce the data, transforming it into a dataspace whose axes best describe the most amount of spectral variation in the data, and to segregate noise from signal within the data to the extent possible. Once the most spectrally pure pixels are found using the MNF transform, the pixel purity index (PPI) is used to find the spatially pure pixels. The PPI algorithm randomly projects unit vectors onto the data in the MNF dataspace, marking each time a pixel is on the ends of the unit vector. After thousands of projections, the PPI algorithm can estimate the probability that a pixel is a spatially pure pixel, since those pixels will be at the ends of a data cloud in the MNF data space. The last step of the first half of the spectral hourglass is the identification of endmembers by the analyst using n-dimensional plots of the purest pixels identified by the MNF and PPI routines. Endmembers for the LEW86134 chondrule is shown in Figure 2.

The second half of the spectral hourglass flow is the use of image endmembers to classify all the pixels in the image cube. There are many choices for classification routines, and

the decision about which is appropriate to use depends on the data itself. In our work, we chose the minimum distance classifier, which classifies pixels based on their distance from the mean of each set of endmember pixels (all the pixels with the same color in Figure 2). This is opposed to other classification schemes, such as the parallelepiped algorithm, which classifies pixels based on the range of endmember pixel sets. If endmember pixels have overlapping ranges, as in the upper left corner of the image in Figure 2, the parallelepiped classifier does a relatively poor job, resulting in many unclassified pixels (Table 1). The minimum distance classifier resulted in no unclassified pixels. The results of both classification schemes are shown in Table 1. Once every pixel is classified, the analyst must assign meaningful phase names to each of the endmember groups. The final step is to simply count the pixels in the image cube that were assigned to each phase, which is the modal mineralogy.

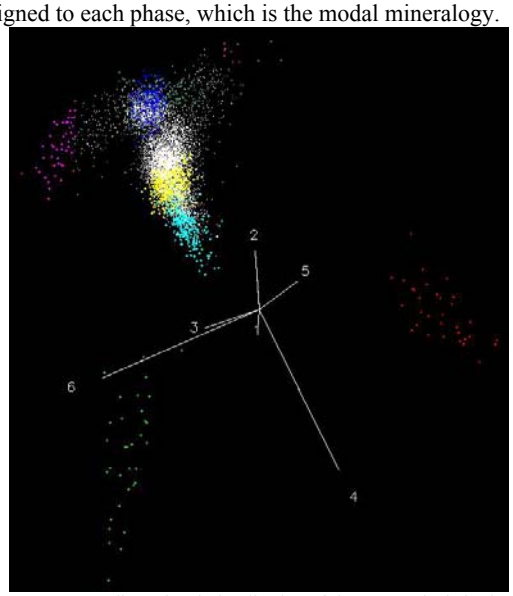

Figure 2. N-dimensional visualization of the purest pixels in the image cube, and the selection of endmembers (colored points). Because this is a screencapture of a 2D projection of a 6D plot (see axes in image), it can be difficult to see that all endmembers are nicely separated and thus easy to identify. The clouds on the right and lower left of the image are the best examples.

Results: Modal mineralogy estimates from two different classification schemes are shown in Table 1. The minimum distance classifier did not fail to classify any pixels, and is the best choice of classification algorithm for our particular dataset. Figure 3 is an image showing the distribution of pixels of each class. The color information from the minimum distance classification image, which was at relatively low resolution (512x512) was projected onto a higher resolution BSE image. This allows the information from a low resolution dataset to be combined with a high resolution dataset, preserving attributes of both.

Conclusions: This work has shown that it is possible to use x-ray elemental maps to quickly and accurately calculate mineral modes. Compared to programs such as FeatureScan, our method has the benefit of allowing analysts to assess the validity of their results and to redo calculations without the need to acquire more probe time. It can also be used with x-ray maps of relatively low resolution and combined with higher resolution BSE images that are often used for reconnaissance purposes in electron microprobe analysis schemes. Commercial, off-the-shelf software (of which there are free versions available) can be used to perform many of these analyses. Also, the analyst is not limited to simply calculating modes with their X-ray maps. Grain size and shape measurements, for example, are possible under certain conditions using image analysis techniques. For these reasons we advocate that analysts consider X-ray maps as a dataset that complements their other thin section data and is capable of being mined for a wealth of mineralogic and petrologic information.

Table 1. Modes for a LEW86134 chondrule.

	Minimum Distance		Parallelipiped	
	# Pixels	Abundance	# Pixels	Abundance
Metal/Sulfide1	45	0.2%	34	0.1%
Metal/Sulfide2	160	0.5%	95	0.3%
Matrix	4611	15.7%	1363	4.6%
Olivine	14767	50.3%	3592	12.2%
Pyroxene	6360	21.7%	3505	11.9%
Veins1	165	0.6%	93	0.3%
Veins2	1091	3.7%	520	1.8%
Veins3	2137	7.3%	328	1.1%
Unclassified	0	0.0%	19806	67.5%
		100.0%		100.0%

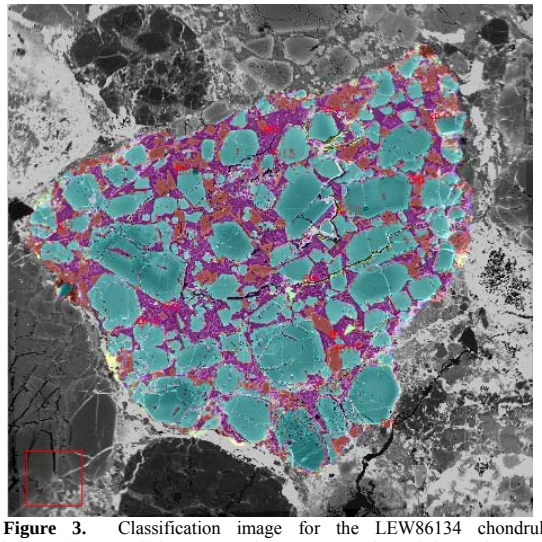

Figure 3. Classification image for the LEW86134 chondrule. Blue/green colors are olivine, Maroon is pyroxene, and purple is matrix.

References: [1] Hicks T.L., Taylor G.J., Fagan T.J., Krot A.N. and Keil K. (2002) *LPSC XXXIII*, Abstract # 1055. [2] van Niekerk D. (2003) *LPSC XXXIV*, Abstract #2015.