

**CHEMICAL VARIABILITY AND TRENDS IN CHEMCAM MARS OBSERVATIONS IN THE FIRST 90 SOLS USING INDEPENDENT COMPONENT ANALYSIS.** *O. Forni<sup>1</sup>, O. Gasnault<sup>1</sup>, P.-Y. Meslin<sup>1</sup>, V. Sautter<sup>2</sup>, N. Mangold<sup>3</sup>, A. Cousin<sup>1</sup>, R. Anderson<sup>4</sup>, S. Clegg<sup>5</sup>, C. Fabre<sup>6</sup>, J. Lasue<sup>1</sup>, S. Maurice<sup>1</sup>, N. Melikechi<sup>7</sup>, A. Ollila<sup>8</sup>, R.C Wiens<sup>5</sup>, and the MSL Science Team* <sup>1</sup>Institut de Recherches en Astrophysique et Planétologie, Toulouse, France, (olivier.forni@irap.omp.eu), <sup>2</sup>MNHN, Paris, France, <sup>3</sup>LPGN, Nantes, France, <sup>4</sup>USGS, Flagstaff, USA, <sup>5</sup>LANL, Los Alamos, USA, <sup>6</sup>G2R-Géoresources, Nancy, France, <sup>7</sup>Delaware State University, Dover, USA, <sup>8</sup>UNM, Albuquerque, USA;

**Introduction:** ChemCam is an active remote sensing instrument suite onboard MSL [1,2]. It uses laser pulses to remove dust and to profile through weathering coatings of rocks up to 7 m away. Laser-induced breakdown spectroscopy (LIBS) obtains emission spectra of materials ablated from the samples in electronically excited states. LIBS on ChemCam, with its narrow emission peaks and large number of channels, suits itself very well to multivariate analysis (MVA). We apply a MVA technique, called Independent Component Analysis (ICA), to analyse and to decipher the chemical trends and variability of the 90 first Sols ChemCam data. The elemental analysis is not treated here per se and is described in another paper [3]

**Sample Details :** This abstract reports on a subset of all the ChemCam data. Spectra that had obvious low signals because being too far or mis-focused, were discarded. We are left with 337 samples out of 372 for the 92 Sols. Each spectrum is divided into three wavelength ranges. We normalise each of these ranges by their total emission to correct for variation of the signal with distance. We also correct for the instrument response function. Finally, all the data were carefully recalibrated in wavelength.

**Methodology:** In spectroscopy, it is considered that the observed spectra are linear combinations of pure sources or poles that we want to estimate. To achieve this goal, we will use the ICA method instead of the well-known Principal Component Analysis (PCA). PCA calculates principal components (PCs) which are linear combinations of the variables that convey the major part of the information contained in the global dataset. Spectra are decomposed in linear combinations of the PCs. Their coordinates along the PCs (scores) can be represented to visualize similarities between spectra and to identify classes of spectra. PCA maximises the dispersion, and consequently, decorrelates the signals assuming that all the sources follow a Gaussian probability function. For a complex ensemble of data in which many signals contribute to the observed data, the Gaussian hypothesis of PCA will not be valid in all cases. The extraction of pure and statistically independent spectra from a mixture cannot be reliably obtained with the PCA.

ICA is a different technique that comes from developments in the Blind Source Separation (BSS)

research. The goal of ICA is to estimate  $h$  source signals, assumed to be stationary and independent, using  $n$  observed signals that are independent unknown mixing of the source signals ([4]). ICA, tries to transform the original representative space by searching for directions in a new space, so that the resulting vectors are independent, and not solely uncorrelated. ICA is then a method of linear transformation in which the representation is the one that minimise the statistical dependence of the components. This is achieved using a criterion, related to the information entropy theory that gives back the statistical independence assuming that the data follow a non-Gaussian distribution. As in [5] and [6] we have used the Joint Approximate Diagonalization of Eigenmatrices method (JADE) algorithm ([7]), which is an orthogonal ICA method and, like most mainstream ICA techniques, it relies on higher order statistics related to the fourth order cross cumulants to maximise the non-gaussianity of the sources.

**Results:** We clearly identify independent components that are related to individual chemical elements e.g. Al, Ca, CaO, Fe, H, K, Mg, Na, O, Si, Ti. Some of them are displayed in Fig. 1.

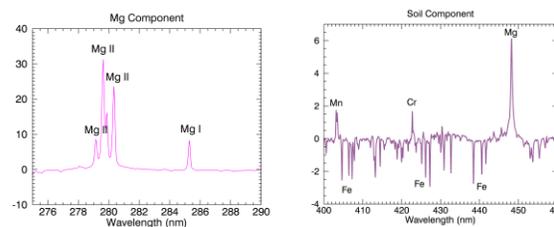


Figure 1: Example of two ICA components, Magnesium and Soil component, with their respective emission lines. Each component may include many lines of a single element (left panel) or lines of various (un-)correlated elements (right panel)

From these components, we can derive elemental relationships, which is a first step toward quantitative elemental composition. For example, we can see that Si is anticorrelated with Fe (Fig. 2). Moreover, we can infer the presence of various trends in the data. In the K vs Na plot (Fig. 3), we can distinguish three regions, the first one is represented by the pre-Rocknest data which show a relative high Na content with respect to K but with a large variability.

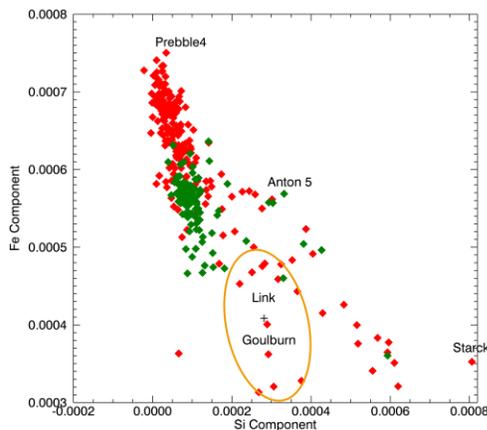


Figure 2: Silicon component vs Iron component showing their anticorrelation. Green symbols represent soils. Note the low Iron content for conglomerate (Link & Goulburn)

The second region, which is represented by a clear trend are the Rocknest rocks, which appear to have a more or less constant K/Na ratio and finally the rock Bathurst that exhibits a very high K content with respect to Na. These trends and their analyses are detailed in [8]. Soils show clearly up (Fig. 4). They are related to the presence of H on one hand and to another component, which is enriched in Mg correlated jointly with Cr and Mn and depleted in Fe as displayed in Fig. 1 (right panel). They are also depleted in Na as described in more details in [9]. When only the pre-Rocknest data are considered, conglomerates like Link or Goulburn are showing up in the same diagrams. They have the same K/Na ratio than the Rocknest rocks (Fig 3), but contrary to the later, they are very poor in Fe (Fig. 2) as it is described more extensively in [10].

**Conclusions:** ICA is a powerful and fast MVA method that allowed us to efficiently show trends and variations in the ChemCam data. We have identified different types of materials during the first 90 sols MSL campaign: (1) Pre-Rocknest rocks that show a large range of composition variation i.e. High-Fe Low-Si rocks like Prebble or Low-Fe High-Si rocks like Stark. This diversity may be explained because we are still in the landing fan. (2) Rocknest rock type that are represented by in place rocks with more or less the same composition except Bathurst which is apparently an outlier. These rocks may have a pyroclastic origin [8]. (3) Soils that are mainly characterised by high H and Mg contents (4) Conglomerates like Link or Goulburn. In this analysis other subclasses appear like the high Ca and CaO rocks perhaps Ca-Sulfates like anhy-

drite since S has been detected by the SAM instrument [11]. All these classes can be represented using classification and dendrogram techniques [12]

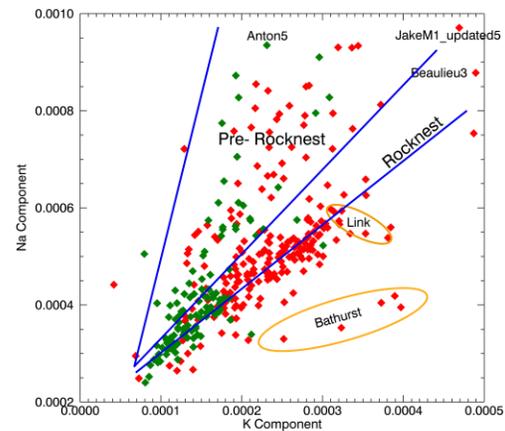


Figure 3: Potassium component vs Sodium component showing the various trends; pre-Rocknest rocks, Rocknest trend, Bathurst and Link.

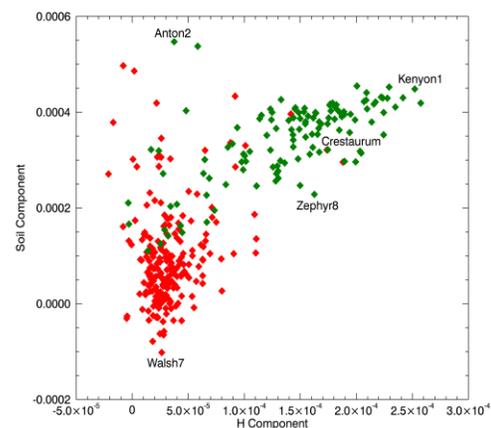


Figure 4: Hydrogen component vs Soil component showing how the soils (green symbols) are discriminated.

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