

**GRS ELEMENT MODELLING WITH CRISM SUMMARY PRODUCTS.** O.M. Kamps (o.m.kamps@utwente.nl)<sup>1</sup>, D. Hood (drhood2938@lsu.edu)<sup>2</sup>, R.H. Hewson<sup>1</sup>, F.J.A. van Ruitenbeek<sup>1</sup>, F.D. van der Meer<sup>1</sup>, S. Karunatillake<sup>2</sup> <sup>1</sup>University of Twente, ITC (Faculty of Geo-Information Science and Earth Observation), <sup>2</sup> Louisiana State University Geology and Geophysics

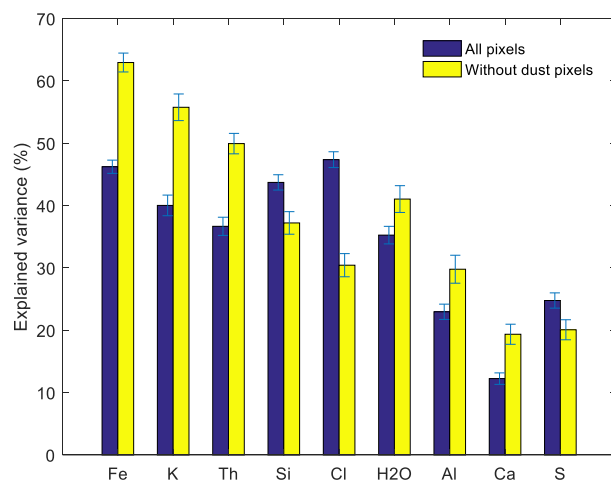
**Introduction:** The element distribution on Mars as measured with the gamma-ray and neutron spectrometers (GRS) [1], is hard to interpret. Its low spatial resolution of the dataset complicates the interpretation of the element distribution with geological processes.

A comparison between the GRS element maps [1] and global mineralogy data could give a better understanding of the processes related to the element distributions. However, differences in detection depth and spatial resolution between mineral and element datasets complicates such a comparison.

This study proposes a statistical approach that tests for a linear relation between CRISM summary products and the element data of the GRS. The benefit of this approach is that it can be statistically proven how well these datasets relate to each other, and which variance of the element data can be explained best by CRISM. By testing which summary products have most influence on the model for the different elements, it could give new insights on what geological process is behind the element distribution.

**Method:** The method used to test for linear relations is partial least-squares regression (PLSR). With PLSR the covariance between CRISM and GRS can be tested. The CRISM multispectral summary products of Pelkey et al. (2007) were used as input variables to predict the concentration of the elements: Fe, K, Th, Si, Cl, H<sub>2</sub>O, Al, Ca, and S [1,2].

**Figure 1:** Maximum explained variance for each model including and excluding dust covered pixels.



The differences in spatial resolution was resolved by averaging for each GRS-pixel the values of the summary products.

The model was evaluated using cross-validation in a monte-carlo simulation with a thousand repetitions. The error bars present the standard deviations of these repetitions.

**Results:** A PLSR-model gives several output from which the model can be evaluated. Here, we will address the explained variances of the different models, the variable importance for each element, and the results of the model presented as maps.

#### *Explained variances*

Because the CRISM and GRS instruments measure to different depths, a homogenous layer must be assumed. It was thought that in the dust covered regions this assumption would not apply because the dust is covering underlying rock. Therefore the accuracy of the model was expected to decrease for all elements. The bar diagram in Figure 1 shows the results where all GRS-pixels are included in the model (blue), and those where the dust covered pixels are taken out (yellow). The results show that the accuracy of the model does not decrease the same for all elements when the dust covered pixels are included. Instead, for the elements Si, Cl and S the accuracy of the model increases when these are included. Apparently for these elements variation of the data in the dust covered regions can well be explained by CRISM, and improves the accuracy of the model.

#### *Importance summary products*

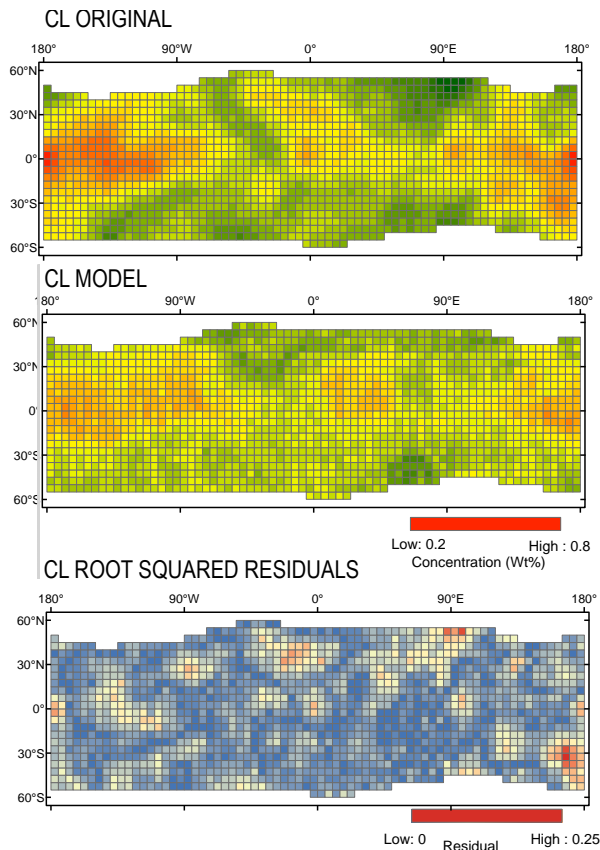
VIP scores (variable importance in projection) are used to define the importance of each variable in the model. In Table 1 it is summarized for each element which summary products have the highest impact. This includes both those with a positive and inverse effect. The summary products with a negative regression coefficient are underlined.

#### *Model accuracy*

A spatial impression of the accuracy of each model is presented as maps. Figure 2 shows the example for chlorine, the element with the most accurate model. The three maps show respectively the original, modelled and error data. This way it can be seen which regions the model predicts best and where the error is the largest.

**Discussion:** The low explained variances for the elements Al, Ca and S can be explained in two ways. (1)

The summary products do not explain the variance of all minerals of importance for that element. (2) For that element the hypothesis of homogeneity in sub surface does not apply. If the element concentration is not homogeneous in the sub-surface, within CRISM detection limits, then the modelled estimates are not representative for the layer, as measured by the GRS instrument.



**Figure 2:** Original, modelled and residual data for the element chlorine.

The regions with high residuals, could indicate if these regions represent areas with a mineralogy that cannot be detected with CRISM, or if a geological process has influenced the homogeneity of that region.

Interpreting the importance of the summary products for each model is work in progress. Both datasets are complicated but some first ideas are shared for the element chlorine.

For chlorine (Figure 2), the model was able to describe the major variance in the data (Figure 1 and 2). Among others, the summary products R770 and RBR have a high impact on this model according to Table 1. These are both products related to the dust coverage on Mars [5]. This is supported with what is seen in Figure 2, where most of the higher concentrations of Cl are in the dust covered region. The importance of the summary product BD1900 indicates that some of the vari-

ance can be explained by this product. The band depth near 1900 nm is known feature for water, either bound or unbound. With the relation to chlorine it could be that it represents hydrated salts. These relations suggest that salts are one of the components of dust on Mars. Also the product ISLOPE has an impact on the model. In literature this product is described as a feature de-

<i>Element</i>	<i>Summary products</i>
Fe	<u>BD920</u> , ISLOPE1, LCPINDEX, BD3400
K	<u>RBR</u> , BD920, <u>BDI1000IR</u> , <u>OLINDEX</u> , <u>LCPINDEX</u> , ISLOPE1, BD2210, SINDEK, BD3100, CINDEX
Th	<u>OLINDEX</u> , <u>LCPINDEX</u> , <u>HCPINDEX</u> , ISLOPE1, BD2210, SINDEK
Si	<u>R770</u> , <u>RBR</u> , <u>BD530</u> , BDI1000IR, <u>IRAC</u> , OLINDEX, ISLOPE1, SINDEK
Cl	ISLOPE1, BD1900, R770, RBR
H2O	R770, RBR, BD530, LCPINDEX, <u>HCPINDEX</u> , BD2210, <u>D2300</u>
Al	<u>BD860</u> , <u>ICER1</u> , BD2210, <u>D2300</u> , <u>BD3200</u> , BD3400, LCPINDEX, HCPINDEX
Ca	SH600, BD640, <u>ISLOPE1</u> , ICER1, BD1900, BD2210, BD3100, <u>BD3400</u> , CINDEX
S	BD1900, BD2210, <u>SINDEK</u>

**Table 1:** Important summary products per element

scribing ferric coating [3,4]. It is not yet understood how this relates to chlorine.

**Conclusions:** The results prove the significance of the linear modelling of the element concentration using CRISM products. This statistical method allows us to examine how the mineralogical data is related with element concentrations. The mapped PLSR results indicate which regions are best modelled. Of all elements, chlorine shows most covariance with the CRISM summary products. In particular, for the regions of interpreted high dust concentrations. The effect of the summary products related to dust and water suggests that hydrated salts could be a major component of the dust on Mars.

**References:** [1] Boynton, W.V. et al. (2007) *JGR*, 112, E12S99. [2] Hood, D.R. et al. (2016) *JGR*, 121, 1753-1769 [3] Pelkey, S.M. et al. (2007) *JGR*, 112, E08S14. [4] Viviano-Beck, C.E. et al. (2014) *JGR: Planets*, 119, 1403-1431.