

ATTRIBUTE UNCERTAINTY MODELING IN LUNAR GIS DATA

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ABSTRACT:

A novel methodology to evaluate uncertainties in lunar element abundances is presented. Contrary to most terrestrial applications, lunar GIS data cannot be verified by in-situ measurements due to the limited number of ground control points and their reduced spatial extend. This investigation evaluates the uncertainty in lunar element abundance measurements without the use of ground-checks but by statistical evaluation and comparison of datasets. We find that major elements (Oxygen, Iron, Aluminium, Titanium, Silicon and Magnesium) show distinct correlations between each other. This allows calculating the abundance of an element by deriving its value through a correlation law with another element. By using this method, we can verify remote measurements of the above mentioned geochemical components, and identify regions on the Moon where these correlation laws do not apply. These derivations can be explained by i) an erroneous measurement or ii) by an exotic mixture of elements in the lunar soil. Based on these considerations, conclusions can be drawn about the attribute uncertainty of geochemical measurements in the lunar soil. A special observation of this work was that most theoretically obtained values fit well to the measured ones. High derivations however appear mainly in the Near Side lunar mare regions where the correlation model does not fit.

1. INTRODUCTION

Our celestial neighbour, the Moon, has shifted back into the focus of scientific interest. Various spacecraft are planned to be sent to the Moon in the coming decades. The objective of these international missions is the cartography of the lunar surface, the identification of resources for in-situ resource utilisation (ISRU), and, ultimately, the return of man to the Moon (Landis, 2001). Consequently the precision of remotely sensed data needs to be considered for the choice of future landing sites. The attempt of translating the physical reality into a digital model leads to uncertainties. Since it will not be possible to eliminate those completely, they need to be represented and taken into account in any Decision Support System that is based on such GIS data. Uncertainties “*must always be a notation that provides the language for reasoning and allows decision-makers to evaluate the potential presence of errors in GIS data*” (Zhang and Goodchild, 2002). The challenge in uncertainty evaluation of remote measurements is to quantify the accuracy of this data at the local scale. In terrestrial GIS applications, this process is termed “validation”. Validation of remotely sensed data is achieved by analytical inter-comparison to ground control checks, reference data or model outputs (Justice et al., 2000). This can be done by the collection of in-situ measurements, low altitude photography by aircraft or the comparison to independent, but identical in content, satellite observations. In the case of the Moon, very little ground-control points exist which can be used to validate orbital measurements. Extrapolating this data to the whole surface of the Moon would lead to errors, since their correlation to orbital measurements is rather low, as it was shown elsewhere (Weiss et al., 2009).

We describe efforts to model attribute uncertainties in geographic data of the Moon, where no or little in-situ measurements are available. The methodology that is used,

evaluates the uncertainty by analysing correlations between orbital measurements of different elements. The uncertainty is estimated based on the deviation of the measured value from the though-correlation-expected one. The methodology was applied in a first work on the distribution of Oxygen in the lunar soil (Weiss et al., 2009). In this paper, we extend the model to six other major elements in the lunar soil: Silicon, Titanium, Aluminium, Iron, Magnesium and Calcium.

This paper is structured in two parts: In the first chapter, we will review different factors that increase the uncertainty in remote measurements of the lunar surface. We will demonstrate and discuss the problem of using the few in-situ measurements available as “ground-truth” for remote measurements. In the second part, we will present the method to estimate attribute uncertainty in lunar GIS data by using a correlation law between different elements. This methodology will be applied to estimate the uncertainty of the element measurements mentioned above. The result is a chart of the lunar surface with regions where the measured value does not fit to the theoretically derived one. We will conclude this work by studying the spatial distribution of the identified regions and the possible origin of the deriving values.

2. UNCERTAINTY IN LUNAR GIS DATA

2.1 Sources of uncertainty in lunar surface data

In GIS data, uncertainties can be categorized following their consequence, namely i) positional uncertainties, ii) attribute uncertainties or iii) temporal uncertainties. The latter play a rather minor role in the context of lunar geography; the processes that form or modify the Moon's surface are slow, and the frequency of observations low. However, temporal

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uncertainty need to be taken into consideration in the photogrammetry of the lunar surface since changes of the lightening conditions between the lunar day and night can lead to different topographical interpretations. Positional and attribute uncertainties are considered of high importance in selenographic data. The low data quantity, coverage, and scale, make it today very difficult to establish precise models of the Moon's geology and chemistry. In the coming phase of lunar exploration, much effort is focusing on the measurement of the chemical composition of the lunar surface. Uncertainties in these measurements, the attribute of the spatial data, might lead to misinterpretations and faulty decisions.

Attribute uncertainties can originate in system limitations, mission limitations or have a target specific origin. System limitations include all parameters that are related to the hardware of the remote sensing satellite: its measurement capabilities, its resolution, its temperature and the Internal Orientation Parameters (IOP) of the instrument. Mission limitations include the spacecraft's ephemeris, orbital parameters and specific events during the mission time: The satellite's altitude, orbital velocity and Exterior Orientation Parameters (EOP) influence the capability of the instrument to perform measurements on the surface. Solar Particle Events (SPE) and the Sun's relative position further influence the measured data. Third bodies' influence decreases the accuracy of the satellite's position determination, and therefore increases the uncertainties of its measurement data. Finally, the characteristics of the target can further determine the precision with which the surface is analyzed: terrain morphology, surface roughness, surface albedo, surface temperature and MASCONS can bring variations in the remote measurement's precision. Figure 1 resumes schematically the factors mentioned above.

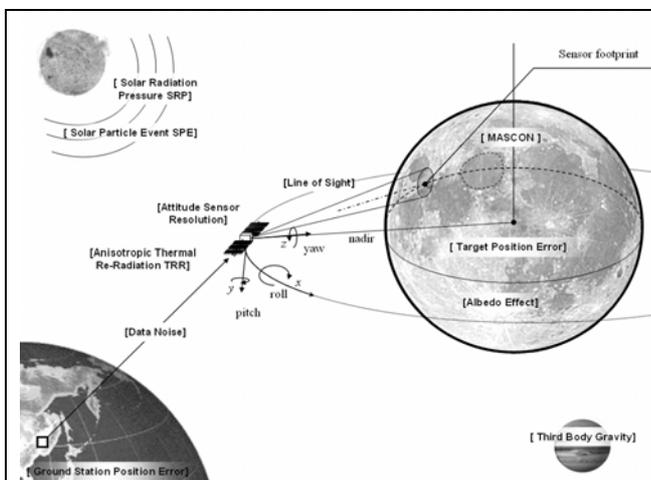


Figure 1. Parameters that influence the attribute uncertainty

Modelling the uncertainty of remote measurements as a function of the above mentioned parameters becomes therefore a complex problem. It requires a perfect knowledge of all hardware parameters, the mission's ephemeris and eventual surface influences.

An alternative is to compare the remote measurement with ground-control checks to search for potential derivations. The problem is, however, that there are very little in-situ measurements available, as it will be shown in the following section.

2.2 The dilemma of the missing ground-checks

The Moon is certainly -apart from planet Earth- the most analysed object in the Solar System. It remains, however, a largely undersampled surface: Astronauts and robots, from several US and Russian missions, brought back 382kg of Moon dust and rock (Vaniman et al., 1991). The landing sites of these missions are limited to the equatorial region of the Near Side. We dispose today of no in-situ measurement of the poles or the Far Side. The surface samples are not only limited in their spatial extend, but also in their geological context, where they were taken: Most missions aimed at (safer) landing sites in the lunar Mare regions. Actually only the Apollo 16 mission brought back samples from a site that is considered as Highland region. Figure 2 gives an overview of the different landing sites where lunar soil was returned to Earth. The number of samples and weight is given for the Apollo missions. In an earlier work it was shown that the returned samples do not correlate well with orbital measurements of element abundances (Weiss et al., 2009). This fact makes it difficult to extrapolate remote data to a local scale; both measurements do not fit together. Several reasons can be stated which might explain this divergence: The rocks that were returned by astronauts and robots did eventually not represent the bulk of the surface material. While the first manned mission to the Moon, Apollo 11, recovered a majority of lunar regolith, all consequent missions brought back increasing numbers of solid rock (Vaniman et al., 1991). The collected samples were eventually chosen since they draw the attention of the astronauts or the mission controllers. But those might represent a rather exotic lithology compared to the location. A second potential explanation is that the footprint of the remote measurements largely exceeds the exploration range of the manned missions (Vaniman et al., 2002; Berezhnoy et al., 2006). The recovered samples therefore represent only a small fraction of the area covered by the satellite's instruments.

However, Apollo 17 in-situ measurements were used to extrapolate the geological data to unsampled areas in the same region by using Clementine UV-VIS remote measurements (Jolliff, 1997). The author notes good correlations between the Iron oxide values of the Apollo samples and the spectral parameters of the Clementine data. Elphic and co-workers (1998) developed algorithms to derive the content of Iron oxide and Titanium dioxide lunar wide from Clementine spectral data. Despite these efforts, it is obvious that Apollo and Luna samples cannot serve as global "ground-truth" for the validation of orbital measurements of the lunar surface chemistry. Other techniques are needed to gather the ground-truth.

2.3 A geochemical model based on element correlation

The basic idea behind the following concept is that similar soils, which underwent similar formation processes, should exhibit similar chemical mixtures. A soil that has a specific abundance of one element should therefore have a specific mixture with other elements. The knowledge about the abundance of one element can therefore be used to derive the abundance of another element, if both correlate.

This method allows deriving the composition of a soil by knowing only some parts of its elemental composition. It furthermore allows evaluating the probability of justness of remote measurements by inter-correlating different elemental datasets. The advantage of this methodology is that it can work without Ground Control Points. Nor does it need independent datasets of the same kind (the same measurements by different satellites). Both are very limited for the lunar surface.

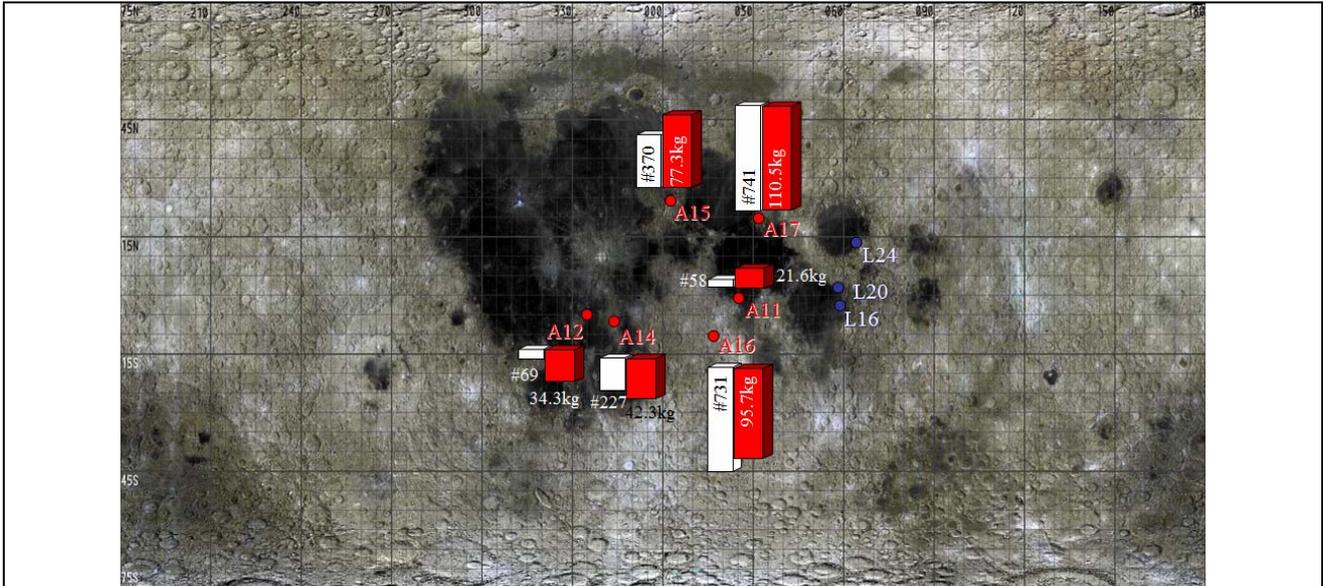


Figure 2. Positions on the Moon where in-situ samples have been returned to Earth. (A) Apollo mission and (L) Luna missions. The number of samples and the overall weight is stated in the columns.

The main condition of this approach is that there exists a correlation rule between two chemical elements. The correlation between the elements x and y can be analysed through the fitting function given in (1), with its parameters α , the intercept and β , the slope,

$$y = \alpha + \beta x \quad (1)$$

where the intercept is

$$\alpha = \left(\sum_{i=1}^n y_i - \beta \sum_{i=1}^n x_i \right) / n \quad (2)$$

The slope determines if there is a correlation between the two elements:

$$\beta = \frac{L_{xy}}{L_{xx}} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (3)$$

If β is larger than zero, then there is a positive correlation between both elements. If β is smaller than zero, then there is a negative correlation between the elements. And if β is equal to zero, then there is no or no simple correlation between both elements.

The above considerations can be applied to the measurements done by the Lunar Prospector mission (Prettyman et al., 2002). Measurements of Oxygen, Titanium, Silicon, Aluminium, Iron, Calcium and Magnesium are available in 5° data products from the PDS Geosciences Node. Figure 3 shows one of the correlation plots, namely the one of Oxygen and Iron, as measured by the Lunar Prospector. The solid line in the middle of the diagram is the regression line as determined through (1). The dotted lines show the one-sigma and two-sigma borders of

this correlation function. It was shown by Weiss et al., (2009) that Calcium shows no simple correlation to the other elements. This element was therefore excluded from the further considerations.

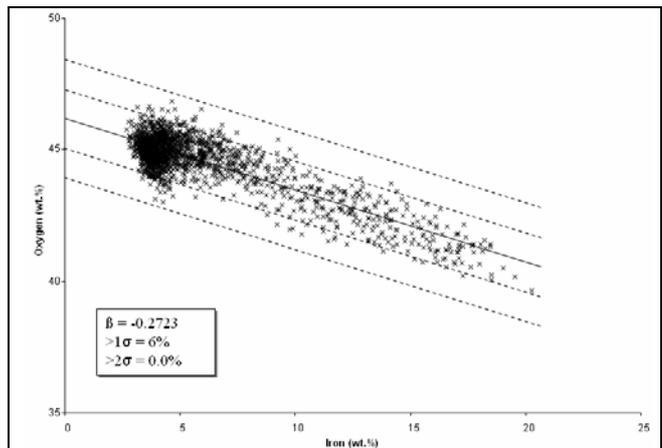


Figure 3. Negative correlation between Oxygen and Iron.

A theoretical abundance value of the above stated elements can now be calculated by using their correlation between each other. The theoretical values are then compared with measured ones at their specific position. Figure 4 shows the measured abundance of Oxygen (top) with the theoretically derived one (bottom). The yellow boxes mark surface cells that show derivations larger than one sigma between both values.

Surface cells that show a deviation of one or two sigma were flagged in the GIS following to (4).

$$\left| \frac{\alpha + \beta x - y'}{\sigma} \right| = \begin{cases} < 1 \rightarrow \text{no dispersion} \\ \geq 1 \rightarrow \text{flagged 1} \\ \geq 2 \rightarrow \text{flagged 2} \end{cases} \quad (4)$$

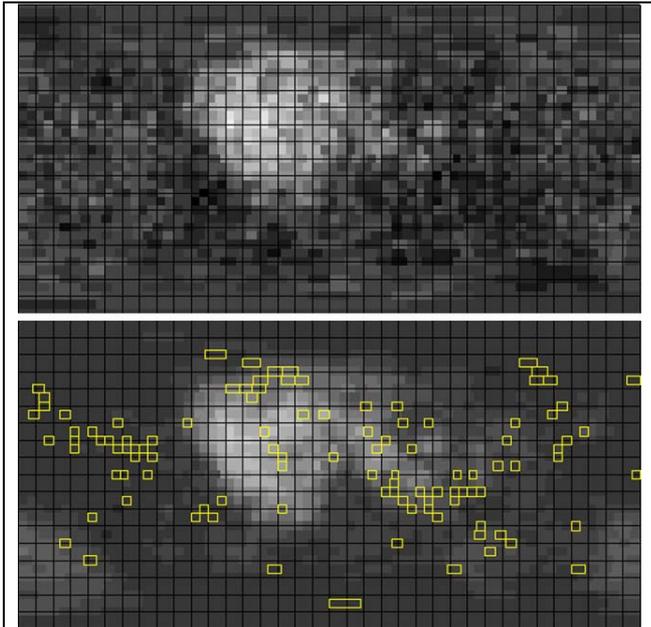


Figure 4. (Top) Oxygen content of the lunar soil as measured by the Lunar Prospector mission. (Bottom) Oxygen value as derived as a function of the measured Iron content.

All six elements (Calcium was excluded) were compared in this way with each other. Table 1 summarizes the percentage of fitting surface cells.

As a first result is that the majority of the theoretical values fit well to the measured ones. This offers the possibility to derive more precise charts of specific elements by deriving those from higher resolution data of other elements. Oxygen can, for example, be a quite precise indicator of Titanium and Iron. Iron as function of Titanium can even be predicted within one sigma in 98% of the cases. Oxygen, as one of the main ISRU elements could be derived by measuring the Iron content of the surface since in our study 94% of the calculated Oxygen values fitted to the measured ones.

In the following, however, we will study the spatial distribution of the values that do not fit and try to find possible explanation to this phenomenon.

Table 1: The input elements (left column) were used to derive the output elements (first row). The percentage shows the number of correct values within one sigma deviation.

	→ Output element						
	O	Si	Ti	Al	Fe	Mg	Ca
O		89%	93%	83%	94%	76%	69%
Si	89%		90%	72%	87%	80%	71%
Ti	92%	87%		84%	98%	80%	77%
Al	84%	74%	88%		90%	82%	71%
Fe	94%	86%	97%	90%		85%	88%
Mg	80%	83%	87%	82%	89%		82%
Ca	77%	76%	85%	72%	84%	83%	

↑ Input element

3. FROM CORRELATION TO UNCERTAINTY

3.1 Spatial distribution of outlying surface cells

In the previous chapter, a method was presented to derive element abundance values as function of a correlation to another element. It was shown that this method leads to a majority of fittings (within one sigma). However, some surface cells show large deviations between the theoretically calculated value and the measured one. These cells are defined in the following as uncertain, because their values do not follow the correlation rule. We will discuss in 3.2 different explanations for these outlying values.

It is now interesting to study the spatial distribution of these outliers. Figure 5 shows three example charts of Titanium, Iron and Aluminium. The intensity of red colour indicates the number of deviations. If the cell is marked fit, then all five input elements delivered output correlations that fitted within the one sigma limit. If the cell is marked in deep red, then four of the output values, as function of the input element, derived. Two types of cells can be identified: single occurrences of outliers and in regions clustered cells. The Iron and Titanium show a clear concentration of the outliers in the Mare regions of the Moon (especially in the Oceanus Procellarum).

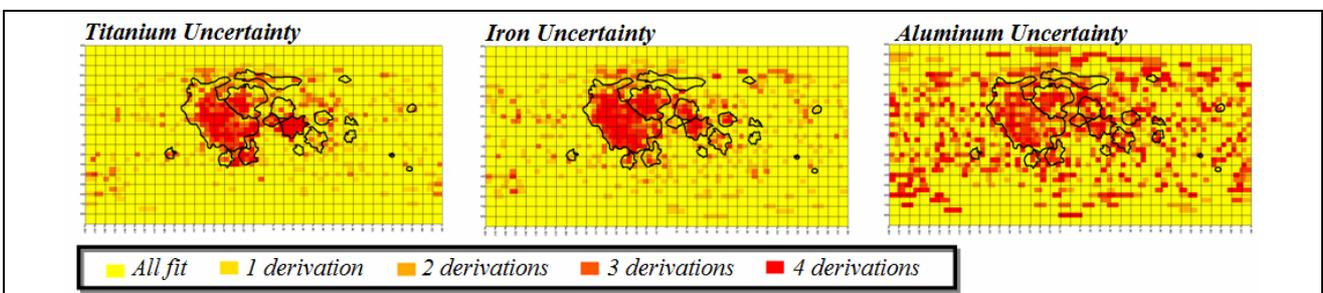


Figure 5. Uncertainty charts for Titanium, Iron and Aluminium. The charts show a concentration of the derivation of values in the Oceanus Procellarum region. This fact offers the possibility to refine the models by separating the values into two categories.

3.2 Possible explanations

We find two explanations for the occurrence of deriving abundances: i) Either the measured value is in deed erroneous or ii) the region shows an exotic mixture of chemistry due to a special formation process.

In the case of the Mare regions it is more likely that the latter case applies. The above method used the totality of the abundance measurements of the lunar surface. However, in lunar geology, there is a clear separation between the Mare regions on the Moon and the Highland regions. While our method seems to deliver good results for the Highland regions, its deriving values are mainly located in the lunar Mare.

3.3 Conclusions and further work

A method was presented to evaluate the uncertainty in lunar element abundance values by comparing different element measurements done by the same remote sensing satellite.

The paper discussed one challenge in the exploration of the lunar surface by observation methods, namely the lack of sufficient ground truth data to validate the remote measurements. The little in-situ data that was gathered by manned and robotic missions is insufficient in quantity and spatial extend to serve as model for the global surface.

A novel method was developed to derive the chemistry of the lunar surface by correlating different elements with each other. The fact that some elements show a correlation allows to evaluate the uncertainty in the data products. If the theoretical value corresponds to the measured one, then there is a high probability that the remote measured value is correct. We showed that the majority of the surface cells fit well to this rule. However, large deviations occur in the Near Side Mare regions. A possible direction of further work is therefore to separate the Mare regions from this model and to develop an own correlation law for the Mare regions of the Moon.

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