

PROGNOSIS OF TiO₂ ABUNDANCE IN LUNAR SOIL USING A NON-LINEAR ANALYSIS OF CLEMENTINE AND LSCC DATA. V. V. Korokhin¹, V.G. Kaydash¹, Yu. G. Shkuratov¹, D. G. Stankevich¹, and U. Mall², ¹Astronomical Institute of Kharkiv V.N. Karazin National University, 35 Sumskaya St., Kharkiv, 61022, Ukraine, dslpp@astron.kharkov.ua. ²Max Plank Institute for Solar System Research, 2 Max Plank St., Katlenburg-Lindau, 37189, Germany.

Introduction: Lunar Soil Characterization Consortium (LSCC) data give a unique opportunity to study direct links between spectral characteristics and the chemical/mineral composition of lunar soils [1,2]. These links can be used for a prognosis of the composition of the lunar surface with spectrophotometric observations of the Moon (e.g., Clementine UVVIS data [3]). Usually multiple linear regression (MLR) is used for this prognosis. In particular [3], it is assumed that abundance P linearly correlates with the spectral parameters:

$$\log P = w_0 + \sum_{q=1}^6 w_q a_q, \text{ where } w_0 \text{ and } w_i \text{ are the}$$

weight coefficients, a_i are the following spectral parameters: reflectance $A_R = A(750 \text{ nm})$, color-indices: $C_{BR} = A(415)/A(750)$, $C_{IR1} = A(900)/A(750)$, $C_{IR2} = A(950)/A(750)$, $C_{IR3} = A(1000)/A(750)$, and bend $D = A(750)A(1000)/[A(900)]^2$ (this set provides higher correlation with composition parameters in comparison with the initial UVVIS reflectances [3]). Logarithm is used to avoid negative values of P . Weight coefficients are found using the minimal least-squares method for the LSCC data.

Such a technique gives good results for some components, e.g., pyroxene and maturity degree [4,5]. This is not the case for titanium. Although MLR prediction map demonstrates more or less realistic distribution of TiO₂ over the lunar surface [3], but the following problems exist: the map is too noisy; the abundance for maria is too low (maximum 6%, while some LSCC samples contain as high as 10% TiO₂); the abundance for highlands is overestimated; histogram for mare regions indicates a unimodal distribution of TiO₂ concentrations (see Fig. 1b), whereas sample data show a strongly bimodal distribution of TiO₂ concentrations (see Fig. 1a).

This discrepancy suggests several possibilities: the bimodal distribution of TiO₂ in the sample collections is an artifact of sampling as was noted by Gillis et al. [6]; or the assumption on linearity of the relationships between optical and composition parameters is not adequate. The last assumption is confirmed by the correlation diagram given in Fig. 1 [7]: plots for low-TiO₂, high-TiO₂ maria, Apollo-14 and 16 highland samples do not lay on the same line and form separated groups.

There is another method for TiO₂ prognosis, developed by Lucey et al. [8]. However it also gives a unimodal distribution. Gillis et al. [6] have revised this method suggesting two classes of lunar surface. One of them corresponds to Appolo-11, Luna-16, and Luna-24 samples. The other one is a characteristic of the rest of samples. As result, the TiO₂ concentrations distribution became bimodal. Unfortunately,

the classification proposed by Gillis et al. is too difficult for using and is applicable for mare regions only.

Nonlinear regression approach using artificial neural networks: We suggest an alternative nonlinear method for the TiO₂ prognosis. There is a computation technique which allows finding empirical relations in statistical systems with any number of parameters without restrictions on the character of these relations. This is the artificial neural networks (ANN) approach [7].

To take into account the different behavior of TiO₂ correlations with the optical parameters for maria and highlands we use a system of two ANNs: the 1-st one (6 inputs and 4 outputs) serves for a morphological classification of points in the Clementine mosaics and the 2-nd one (10 inputs and 1 output) carries out a prediction using the optical parameters directly from Clementine data and information about classes from the 1-st ANN. The classifying ANN provides a “soft” classification. For each pixel, 4 parameters corresponding to low-Ti, high-Ti mare, Apollo-14 and Apollo-16 sites are calculated in 0 ... 1 range. The structure (1 hidden layer with 3 neurons is used) and parameters of the ANNs are defined to make the ANNs moderately nonlinear and to produce the results with a histogram similar to the LSCC one. Both the ANNs are trained by the LSCC dataset.

In Fig. 2 results of this prognosis are shown. Noise in the ANN prognosis map became significantly lower in comparison with MLR. Correlation diagram for LSCC data (see inset in Fig. 2) shows that points corresponding to the different classes (plotted by different colors) lay on the same diagonal line. The correlation coefficient between predicted and measured values is very high (0.99). The histogram of TiO₂ distribution (Fig. 1c) is similar to that in Fig. 1a. Such results given by the system of two weakly nonlinear ANNs allow a conclusion that correlation between optical parameters and abundance of TiO₂ inside of classes is nearly linear, but the character of these relations is different depending on class.

According to the new TiO₂ map, broad mare areas in Procellarum and Mare Imbrium and also the whole Mare Tranquillitatis show maximal TiO₂ content on the lunar surface (~8.5-9% at 8-km resolution). Northern maria, like Frigoris and NW part of Procellarum, belong to the low-Ti mare subclass with TiO₂ content ~3-4 wt.%. We also confirm the compositional difference of Mare Serenitatis and Mare Tranquillitatis by the TiO₂ content. The South Pole – Aitken basin clearly shows up on the map with intermediate 5-6% TiO₂ content. The TiO₂

content for highland regions varies in the <2% range.

Conclusions: (1) Algorithms and software based on the artificial neural networks (ANN) technique have been developed for prognosis of chemical and mineralogical composition of the lunar surface using Clementine UVVIS maps and LSCC data. (2) Using the ANN technique allows us to study empirical links between spectral characteristics of lunar soils and composition parameters without any restrictions on the character of these relations. (3) A new nonlinear method for prognosis of TiO₂ abundance based on the ANN approach is proposed and a new map of TiO₂ distribution over the lunar surface is constructed. (4) The method reliably reproduces the statistical distribution of LSCC data for mare basalts. (5) Our results could be useful for the strategy in analysis of lunar data obtained with spacecrafts especially for Chandrayaan-1 and Lunar Reconnaissance Orbiter missions.

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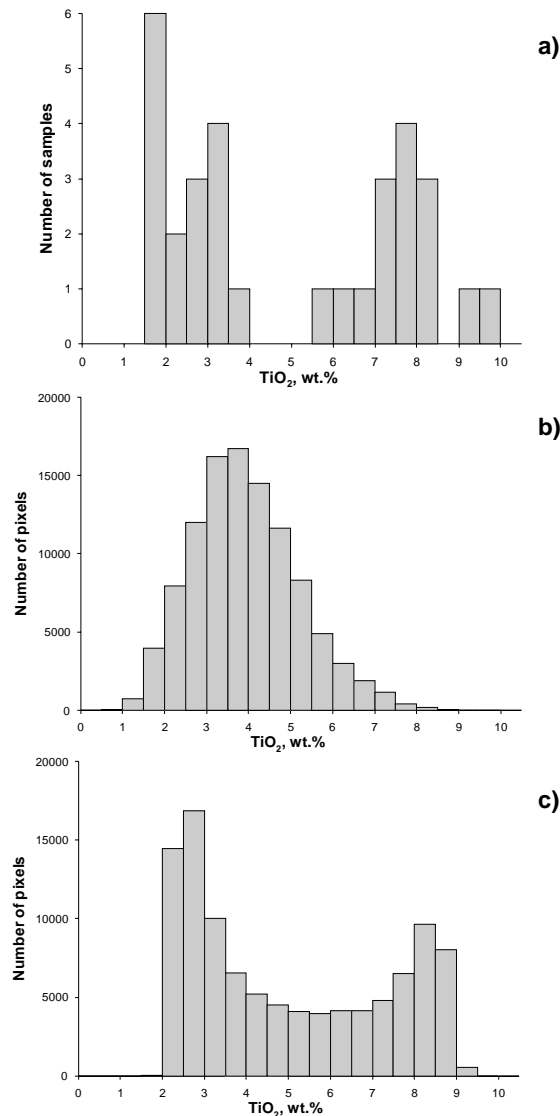


Fig. 1. Histogram of TiO₂ concentrations determined for mare soils: a) LSCC data; b) Clementine data, MLR prognosis; c) Clementine data, ANN prognosis.

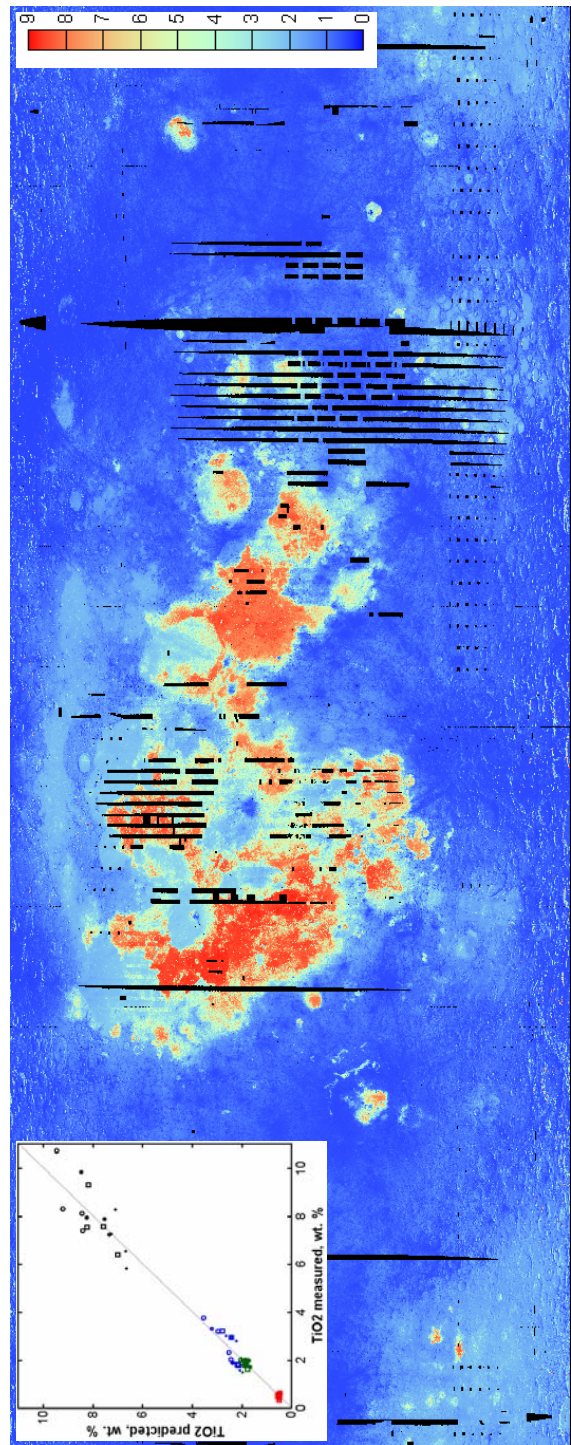


Fig. 2. ANN prognosis of TiO₂ abundance.

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