**PROGNOSIS OF $TiO_2$ ABUNDANCE IN LUNAR SOIL USING CLEMENTINE AND LSCC DATA: A NONLINEAR APPROACH.** V. V. Korokhin, Yu. G. Shkuratov, D. G. Stankevich, V.G. Kaydash, Astronomical Institute of Kharkov V.N. Karazin National University. 35 Sumskaya St., Kharkov, 61022, Ukraine, dslpp@astron.kharkov.ua.

**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 spectophotometric 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: $\log P = w_0 + \sum_{q=1}^{6} w_q a_q$, where $w_0$ and $w_i$ 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 a higher correlation with composition parameters in comparison with 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 composition components, e.g., pyroxene and maturity degree [4,5]. This is not the case for titanium. Although MLR map demonstrates more or less realistic distribution of $TiO_2$ 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 give up to 10%); the abundance for highlands is overestimated; data for mare regions indicate an unimodal continuum of $TiO_2$ concentrations (see Fig. 1b), whereas sample data show a strongly bimodal distribution of $TiO_2$ concentrations (see Fig. 1a).

This discrepancy suggests several possibilities: the bimodal distribution of $TiO_2$ in the sample collections is an artifact of sampling as it was noted by Gillis et al. [6]; or most likely 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 [7], Fig. 1: plots for low-$TiO_2$, high-$TiO_2$ maria, Apollo-14 and 16 highland samples do not lay on the same line and form separated groups.

There is another method for $TiO_2$ prognosis, developed by Lucey et al. [8]. However it also gives unimodal distribution. Gillis et al. [6] have revised this method suggesting to consider two lunar surface classes. 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 $TiO_2$ concentrations distribution became bimodal. Unfortunately, the classification proposed by Gillis et al. [6] is too difficult for using and is applicable for mare regions only.

We suggest an alternative nonlinear method for the titanium prognosis.

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

To take into account the different behavior of $TiO_2$ 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 the point of 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 morphological 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 statistics similar to LSCC one. Both the ANNs are trained by LSCC dataset.

In Fig. 2 results of this prognosis are shown. Noise in the ANN map became significantly lower in comparison with MLR. Correlation diagram for LSCC data (see inset in Fig. 2) shows that points corresponding to different morphological classes (plotted by different colors) lay on the same diagonal line, correlation coefficient between predicted and measured values is very high (0.99). Histogram of $TiO_2$ distribution (Fig. 1c) is now very similar to Fig. 1a. Such results given by the system of two weakly nonlinear ANNs allow a conclusion that correlation between optical parameters and abundance of $TiO_2$ inside of morphological classes is nearly linear, but the character of these relations is different from class to class.

**Conclusions:** The ANN technique allows us to study empirical links between optical characteristics of lunar soil and composition parameters without restrictions on the character of these relations. New nonlinear method for prognosis of $TiO_2$ abundance based on the

ANN approach is proposed and a new map of $TiO_2$ distribution over the lunar disk has been built. The results of our work could be useful for the strategy in analysis of lunar data obtained with spacecrafts especially for the Chandrayaan mission.

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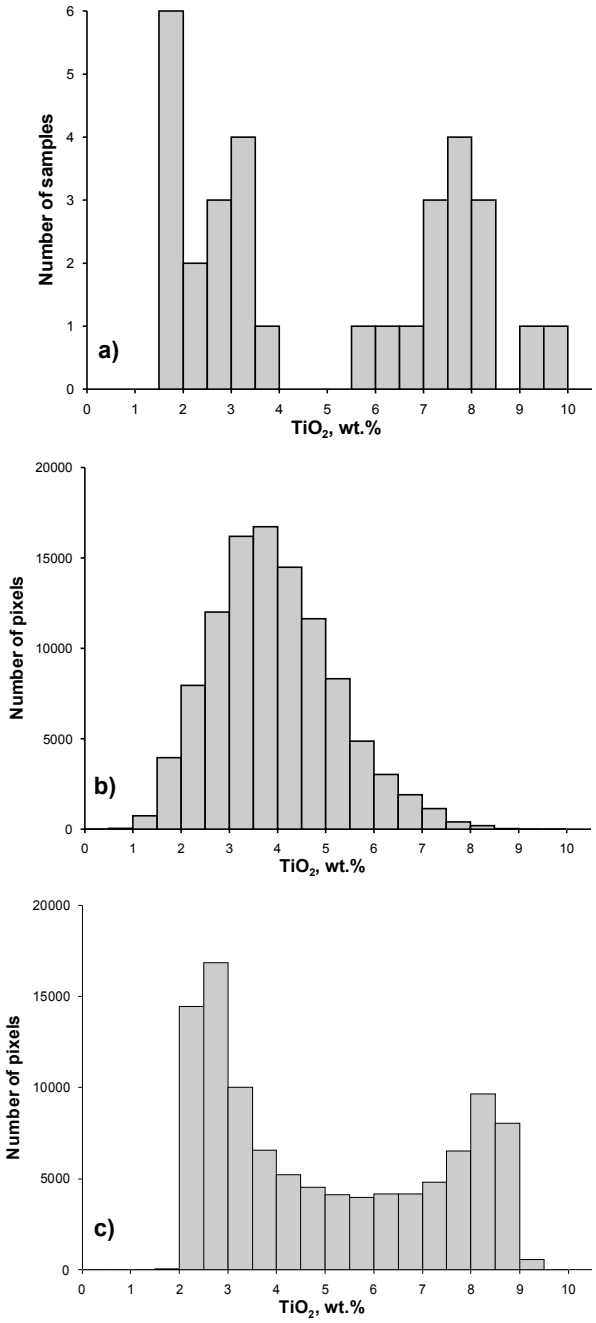


Fig. 1. Histogram of $TiO_2$ concentrations determined for mare soils: a) LSCC data; b) Clementine data, MLR prognosis; c) Clementine data, ANN prognosis.

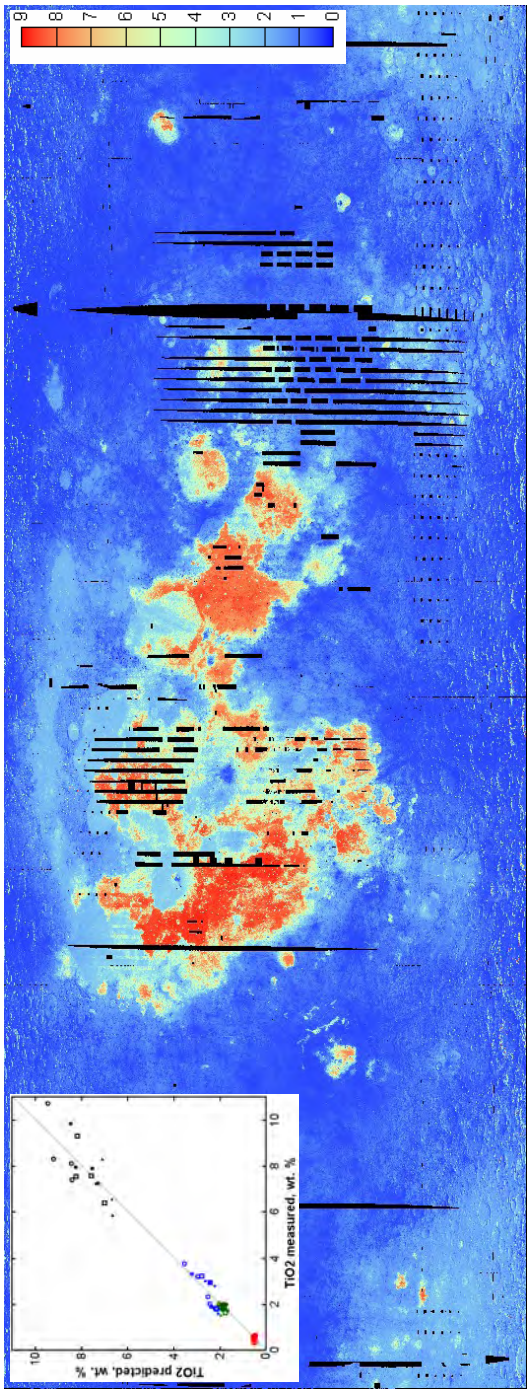


Fig. 2. ANN prognosis of $TiO_2$ abundance.

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