A Spectrophotometric Evaluation of Lunar Catharina Crater Using Support Vector Regression Analysis for FeO and TiO₂ Estimations

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Abstract

Support Vector Regression (SVR) is an extended version of the Support Vector Machine (SVM) algorithm. It is an effective machine learning tool for handling huge complex data sets. SVR algorithm is introduced to the existing lunar FeO and TiO_2 concentrate estimation techniques. This machine learning algorithm is capable of transforming complex nonlinear problems into a higher dimensional feature space and solving it linearly. The SVR analysis of Moon Mineralogy Mapper (M3) data for lunar mineral concentrate estimation shows an upgraded result over the existing estimation methods. Outlier points are less sensitive to SVR and, hence it provides the best fit line or curve.

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1. Introduction

A major selenological process caused for the transformation of the lunar surface is space weathering. As the selenological process like impact cratering and surface exposure comes under the space weathering, it can affect the physical and chemical properties and selenomorphological features of the regolith. The thickness of the debris made up outermost layer varies from 4-5 meters in mare regions and 10-15 meters in highlands and has been maturing constantly. Scientific quantification of this maturation is termed maturity and is expressed in terms of maturity indices (Lucey et al., 2000). To perceive the transformations of the moon surface, we have to recognize the selenological processes behind the transformation and it provides information about the Chemical composition of the regolith. Remote sensing techniques, which utilize optical wavelengths of the electromagnetic spectrum, are considered as one of the most effective approaches to extract the chemical and mineral compositions of the regolith. Spectral information of the regolith extracted through remote sensing techniques is coupled with the spectral libraries generated from the lunar samples, for the effective understanding of the chemical composition of the regolith (Li 2007; Le Mouelic et al., 2000). Rock and soil samples, collected and analysed in various lunar missions, provide ground truth of the chemical composition of the lunar regolith. Lunar missions carried out by USA, Russia, China and India have provided crucial information about the mineral composition of the regolith. Lunar returned soil and rock samples provided the basic information about the chemical composition of the moon surface. Modern era lunar rovers performed in situ Seleno-chemical calibrations of the lunar soil. Based on these information standardised lunar spectral libraries are created upgraded.

Ferrous Iron ($Fe2^+$) and Titanium $^{3+}$ are the major mineral ions present in the lunar soil as metal oxides. As these are transition metal ions, chemical compounds bearing these metal ions have its characteristic properties. Hence several attempts were begun in the scientific community to estimate the chemical contents of Iron and Titanium in early periods of 1970. One of the major milestones in lunar regolith’s mineral concentrate estimation is Lucey et al. (2000) approach. They have estimated Iron and Titanium oxides of the regolith quantitatively. Kumar and Kumar (2014, 2024) recalibrated this method with hyperspectral data having high spatial and spectral resolutions. Chandrayaan 1 mission’s Moon mineralogy Mapper (M3) data effectively coupled with standard chemical concentrates of lunar landing sites for the estimation. The Current study introduces Support Vector Regression (SVR) analysis to upgrade the above mentioned FeO and TiO_2 estimations.

2. Materials methods and Study area

Hyperspectral data of the Moon Mineralogy Mapper (M3) in Global mode is used for the present study along with the standard FeO and TiO_2 wt % of the Apollo and Luna Landing sites. Iron and Titanium spectral signature bearing bands of M3 data and standard metal oxide contents of Apollo landing sites according to the USGS spectral library are the data used for the estimation. Seleno referenced NASA level 2 (reflectance) data is used as the prime data for the estimation. The M3 Reflectance data corresponding to the Apollo and Luna landing sites are used for training and that of the lunar near side crater Catharina for testing. The M3 lunar imaging spectrometer scanned the lunar surface from two different orbits of height 200 km and 100km, during its nine month operational period. Operational period of M3 is dived in to two optical periods namely OP1 and OP2. Both optical periods are further divided in to sub optical periods. The global mode data strips, captured from 200 km orbit covers approximately 50km of lunar regolith in width. Such an M3 32-bit floating point data has 85 spectral bands and 304 samples. Band Interleaved by Line (BIL) is the M3 image file format. The M3 Global data possess multiple spatial and spectral resolutions. This global data has 140m/pixel spatial resolution in sub-optical periods OP1, and OP2 A. But the spatial resolution of sub optical period OP2B and OP2C is 153m/pixel. Three different spectral resolutions are seen in M3 global data. In general spectral resolution of the global mode is 20nm, but some of the bands have a spectral resolution of 30nm or 40nm (Boardman et al., 2011; Lundeen et al., 2011; Kumar and Kumar 2024).

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Catharina crater of the southern hemisphere and located in the near side of the moon is selected as the study area. This old impact basin possesses an approximate diameter of 100 kilometres and central coordinates of 18.00°S and 23.60°E. Concerned metal oxide estimation process is shown in Figure1.

The entire Chemical content estimation process is completed in three phases. In the initial phase, data pre-processing has to be completed. The second phase, known as the data processing phase comprises of training and testing of the model. Finally visual out puts are generated by means of mineral maps and statistical parameters which comes under data post processing.

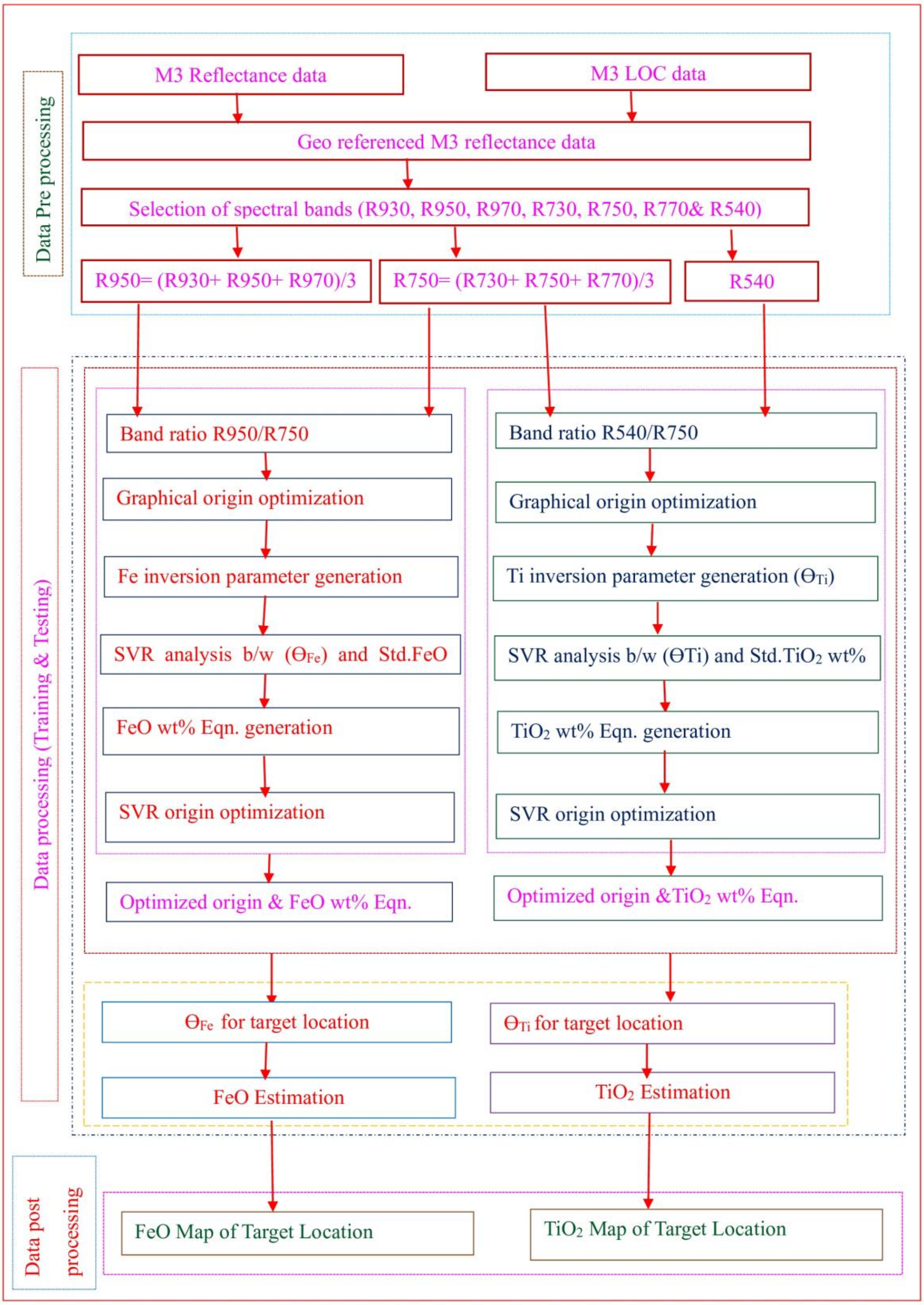

Figure 1: Flow diagram of Chemical content estimation

This Systematic approach is capable to estimate the lunar surface chemical contents quantitatively in terms of respective weight percentages. Based on a two-dimensional plot between the mineral inversion indices or Chemical ion sensitive parameters (Θ) and the available standard metal oxide weight percentages or chemical concentrates of the landing sites, an end member or origin for the transition metal oxides estimation is determined, followed by the weight percentage equations are generated. Using this end member target locations' data is processed. Chemical inversion indices for the Catharina crater is found out and then corresponding metal oxides are estimated.

Initially M3 Global reflectance data of the training sites are downloaded from the Act React quick map (https://quickmap.lroc.asu.edu). Then the relevant Spectral reflectances needed for the estimations are extracted from the downloaded data sets. Standard quantitative concentrates of the FeO and TiO_2 derived from USGS spectral library are collected.

The entire estimation process is based on an ideal hyper matured end member known as origin or source point. A point located in the top left portion of the two-dimensional albedo versus band strength plot with the most probable values is selected as the origin for FeO and optical maturity estimations. For TiO_2 estimation sufficient coordinate rotation is necessary and then the most probable point, plotted at the bottom left corner is taken as the source point (Lucey et al., 2000).

The origin optimization process consists of two processes, Provisional origin selection and SVR origin optimization. An initial estimate for origin is selected from the two-dimensional scatter plots and final origin is optimized by the SVR analysis. By making use of graphical (provisional) origins chemical inversion parameters are generated for the training sites data. Support vector regression analysis is performed between the metal sensitive parameters and standard chemical weight percentages of the training sites. The Spectral reflectance value at 750 nm and the band strength value with respect to the most probable regression coefficient is considered as the optimized origin or decisive origin for the lunar chemical concentrate estimations (Lucey et al., 2000; Kumar and Kumar, 2024).

The origin for FeO estimation is determined from the spectral bands of 750 nm and 950nm.The provisional origin is determined from the scatter plot between spectral reflectance of (R_{750}) nm and band strength or band ratio of (R_{950}/R_{750}). A point on the top left position of the scatter plot with lower spectral reflectance at 750nm and higher band ratio is selected as the provisional origin for FeO and optical maturity index estimations. (Kumar and Kumar, 2014; Lucey et al., 2000).

Spectral data of 540nm and 750nm bands are used for TiO_2 estimation. Provisional origin for TiO_2 estimation is fixed by plotting the spectral reflectances of 750nm against the UV-VIS ratio of (R_{540}/R_{750}). The point on the spectral plot which represents lower values of albedo and UV-VIS ratio can be considered as provisional origin for TO_2 estimation, placed at the bottom left corner (Kumar and Kumar, 2024).

In the SVR method, initially, chemical inversion parameters (Iron and Titanium inversion parameters) corresponding to the training sites are generated from the provisional origin and concerned spectral bands. Iron sensitive parameter is given in Eq. (1).

$$\Theta_{Fe} = -\tan^{-1}\left(\frac{\left(\frac{R_{950}}{R_{750}} - y_0\right)}{\left(R_{750} - x_0\right)}\right) \tag{1}$$

where,

R_{750} = Average spectral reflectance of 730nm, 750nm and 770nm (band average)

R_{950} = Spectral average of 930nm, 950nm and 970nm. (x_0 , y_0) represents the R_{750}, (R_{950}/R_{750}) values of the end member, origin or spectral constants of FeO and Optical maturity estimations. These spectral parameters remain constant for a specific configuration of sensor, chemical element, and standard spectral library used to analyze the reflectance spectra (Kramer et al., 2011; Kumar and Kumar, 2014; Lucey et al., 2000).

Eq. (2) represents the M3 Titanium sensitive index generated by the rotation of spectral coordinates.

$$\Theta_{Ti} = \tan^{-1}[(\frac{R_{540}}{R_{750}} - y_0)/(R_{750} - x_0)] \tag{2}$$

R_{540} and R_{750} represent the spectral reflectance values of 540nm and 750nm respectively. The (x_0, y_0) is the origin or spectral constants of TiO_2 estimation.

The M3 Mineral inversion indices are generated for the training sites with respect to the relevant equations. The SVR analysis is performed between the respective chemical inversion indices and the standard chemical concentrates. Regression coefficients are computed in each of the cases. The SVR source point is optimized from the M3 mineral inversion indices and the weighted chemical concentrates of the training sites. The spectral reflectance and band ratio value with respect to the most probable regression coefficient is selected as the decisive origin for chemical content estimations. Equation of the regression line or curve stands for the quantitative chemical concentrate estimation equation of the respective chemical content.

Finally, M3 mineral inversion indices of the test location or target crater are created using the decisive origins. Mineral indices of the regression equations are replaced with that of the test location to compute the chemical contents of the Catharina crater. It should be extended to the whole test data to map the entire crater. Simple low-pass filtering techniques are applied in TiO_2 estimation to remove noises and thus enhance the M3 data quality.

Heavy sizes of the M3 hyperspectral data strips create problems in extracting the reliable information. Moreover, the M3 data processing consumes very much time. Lunar Chemical content estimation has to deal with hundreds to thousands of M3 data strips and thus computational complexity becomes very high. So, Machine learning techniques can be used as an effective tool for information extraction from M3 data. The SVR analysis is utilized for the chemical content estimation of the lunar regolith. The lunar chemical inversion parameters have some nonlinear relationship with the actual chemical contents of the regolith and so linear regression methods are insufficient. To handle such a scenario of huge data having nonlinear properties, Machine learning techniques are effectively used. In such type of regression analysis SVR has an upper hand. The SVR is an upgrade of the well-known Support vector Machine (SVM) algorithm. In SVR the best fit line represents the hyperplane, and SVR minimizes the error between the predicted and actual values by maximizing the margin around the best fit line. Specialised windows or Kernel functions are used in the SVR analysis to handle non linear datasets. Kernel functions transform the data into the higher dimensional feature space with effective dimensionality reduction. Linear, polynomial, Radial Basis Function and sigmoid are the usually used kernel functions for regression analysis. Support vectors are the closest data points of the hyper plane or best fit line, which formulates the SVR model (Soman et al., 2011). The SVR formulation is successfully implemented by Python programming techniques.

Kumar and Kumar (2024) chemical concentrate estimation is different from the current study in data processing phase only. The former uses normal regression techniques for data fitting, while the later utilizes the SVR analysis.

3. Results

The M3 Mineral inversion indices are generated for the training sites using support vector regression analysis and quantitatively estimated and mapped the chemical contents of the Catharina crater. The decisive M3 origin for Ferrous oxide estimation is (0.08, 1.18) and that of Titanium dioxide is (0.07, 0.71). The quantitative chemical content estimation equations for FeO and TiO_2 with linear and nonlinear SVR analysis are given below.

$$FeOwt\,\% = 12.936 \times \Theta_{Fe} - 2.165 \tag{3}$$

$$FeOwt\,\% = 0.566 \times \Theta_{Fe}^{2} + 11.732 \times \Theta_{Fe} - 1.592 \tag{4}$$

$$TiO_2wt\,\% = 9.609 \times \Theta_{Ti} - 10.367 \tag{5}$$

$$TiO_2wt\,\% = 16.171 \times \Theta_{Ti}^{2} - 31.936 \times \Theta_{Ti} + 16.061 \tag{6}$$

Here Eqn. 3, Eqn. 5 represents linear support vector regression and Eqn.4, Eqn.6 represents nonlinear support vector regression respectively. The best fit lines and curves for these SVR analyses are given Figure2.

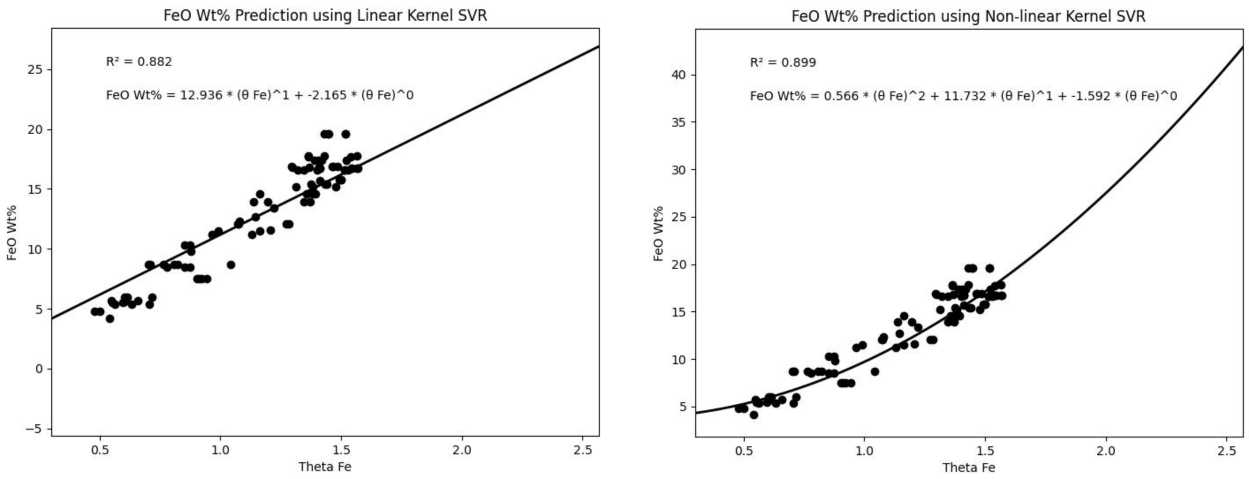

Fig. 2a: FeOwt% equation linear SVR

Fig 2b: FeOwt% equation nonlinear SVR

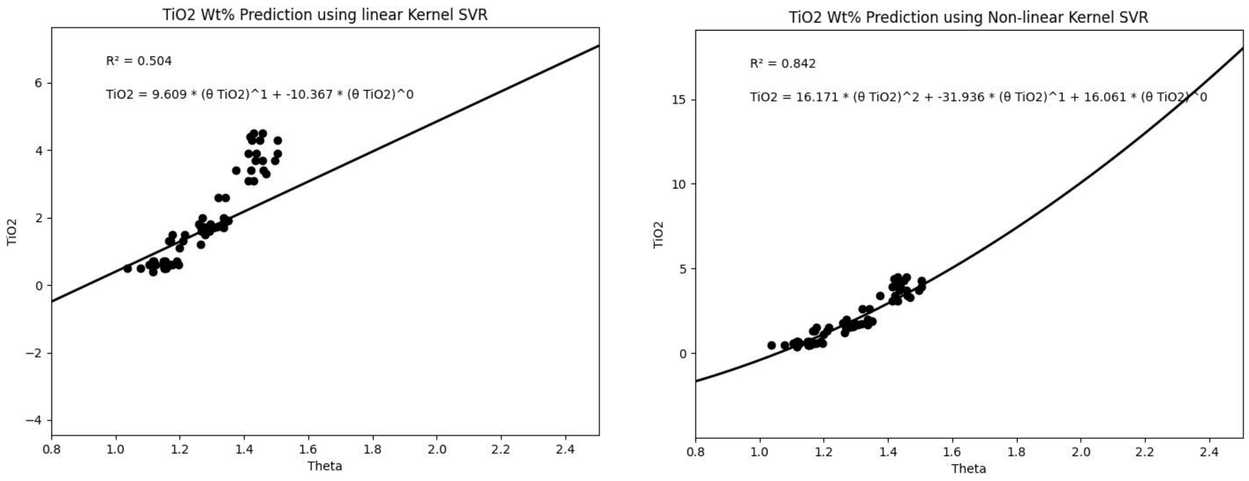

Fig .2c: TiO2 wt% equation linear SVR

Fig. 2d: TiO2 wt% equation Non Linear SVR

Figure 2: SVR plots

FeO and TiO_2 maps generated with linear and nonlinear SVR analyses are given in Figure. 3.

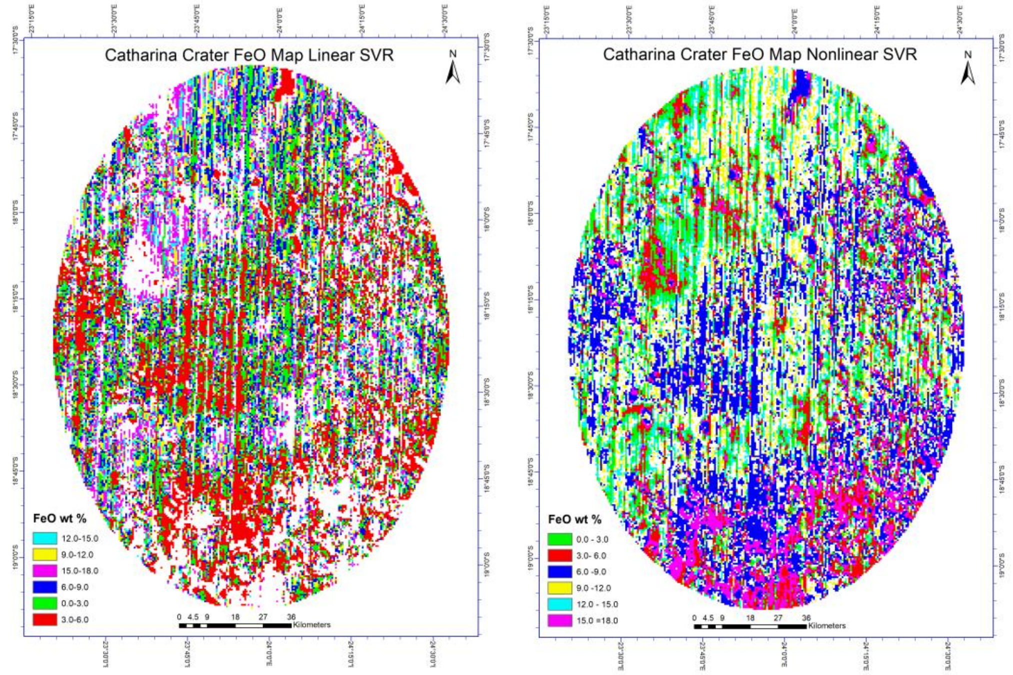
Catharina Crater FeO Map Linear SVR
Catharina Crater FeO Map Nonlinear SVR

Fig. 3a: FeO map linear SVR

Fig.3b: FeO map nonlinear SVR

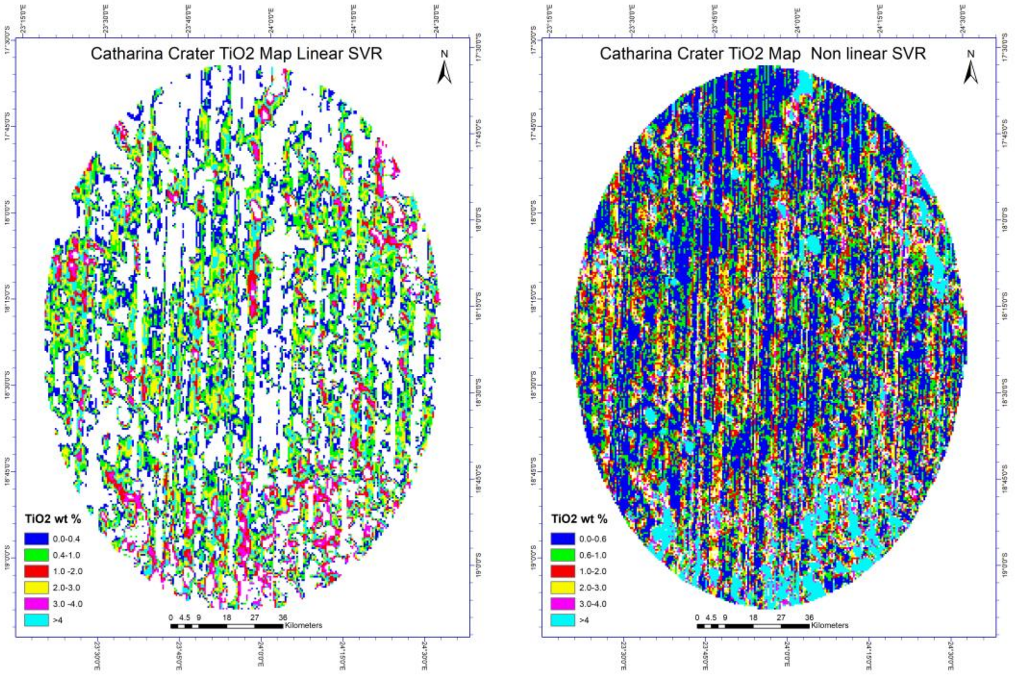
Catharina Crater TiO2 Map Linear SVR
Catharina Crater TiO2 Map Non linear SVR

Fig. 3c: TiO2 map linear SVR

Fig. 3d: TiO2 Map nonlinear SVR

Figure 1: FeO and TiO_2 Maps of Catharina Crater

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The weighted Ferrous oxide concentrate of the Catharina crater quantitatively varies from 0.15-18.15 and 0.02-18.23 in linear and nonlinear SVR estimations respectively. Mean value of weighted FeO content is 9.52 and 9.34 in former and later estimations respectively. Weighted Titanium dioxide concentrate varies from 0.11-4.73 in linear SVR estimation. Mean TiO_2 content in this method is 1.62. In the nonlinear method, it varies from 0.29 -13.99 with a mean value of 2.56.

4. Discussion and Conclusion

High resolution M3 hyperspectral data provides the opportunity to analyze the microscopic features of the lunar regolith. Considering the entire lunar soil characterization works, it can be seen that it improved progressively according to the techniques. Even though M3 data has some limitations, it provides good results in Chemical content estimation. On introducing SVR the results are improved. SVR is capable of handling nonlinear relationships and maximizes the accuracy of prediction by maximizing the margin around the best fit line. On handling the big datasets, the SVR reduces computational complexities when compared to the normal regression models. The SVM is capable of classifying the images, while the SVR is capable of predicting the data points and both can be effectively used for planetary mapping purposes. SVR and SVM are able to handle a large number of data, and so it would be the feature tools in planetary data analysis

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