A DATA-DRIVEN MACHINE LEARNING APPROACH FOR DETECTING ALBEDO ANOMALIES ON THE LUNAR SURFACE. S. Strukova[1], S. Gleyzer[2], P. Peplowski[3], G. Pipilis[4], J. Terry[5], [1]University of Murcia, Murcia 30003 Spain, strukovas@um.es, [2]University of Alabama, Tuscaloosa AL 35401 USA, [3]Johns Hopkins University Applied Physics Laboratory, Laurel MD 20723 USA, [4]National Technical University of Athens, Athens 10682 Greece, [5]University of Georgia, Athens GA 30602 USA.

Introduction: Planetary surface observations are routinely made across a wide range of electromagnetic wavelengths (e.g., radar, infrared, optical, ultraviolet, x-ray, gamma-ray). Each wavelength provides unique information about the surface's chemistry, mineralogy, and history. This includes reflected solar light, the magnitude of which is known as surface albedo. Many different elements contribute to varying extent to the albedo and the albedo can be related to the underlying elemental distribution. These relationships are generally well-known for the Moon, making it an ideal location to test new approaches to linking measurements at different wavelengths in anticipation of applying these techniques to other planetary surfaces where the relationship is less understood.

We built a predictive model based on the compositional maps of the Moon derived from Lunar Prospector data to quantify the relationships between chemical element concentrations and the surface albedo. Our goals are to make predictions about albedo based on the elemental composition and uncover any possible anomalies that can have roots in the geologic history of a planet. This provides a way of studying the Moon with existing data, which is valuable given the infrequent opportunities for new measurements by planetary spacecraft. Moreover, the shape and the location of anomalies on the lunar surface can provide insights into processes that produced them and their subsequent evolution.

Datasets: The dataset consists of several maps of the Moon from the Lunar Prospector Gamma Ray and Neutron Spectrometer [1]. The element maps include gamma-ray derived concentrations for Fe (iron), K (potassium), Th (thorium), and Ti (titanium). The albedo map was derived from the Lunar Reconnaissance Orbiter LOLA instrument [2].

Methods: The spatial resolution of the albedo and element composition maps differ by many orders of magnitude. To address this challenge, we made use of an adaptive spatial gaussian blurring technique where each pixel of the image is blurred proportionally, based on the 2D projection of the Moon. In particular, pixels that fall in an X km radius around the target pixel are used for the blurring. This way, the resolution of the albedo map can be adjusted to match the resolution of the element composition maps.

To predict the albedo based on the relationships between chemical elements composing the surface of the Moon, we train a machine learning regression model on a subset of the surface. In particular, the inputs of the model are the chemical elements and the albedo is the target. The final best performing model was the extreme gradient boosting regression model (the corresponding learning objective is regression with squared loss, learning_rate = 0.1, n_estimators = 30, max_depth = 5). This model is used to predict the full albedo (Figure 1), leading to a representative error map. The error map shows where the relationship between albedo and surface composition breaks down, and by extension where albedo is not driven by geochemistry.

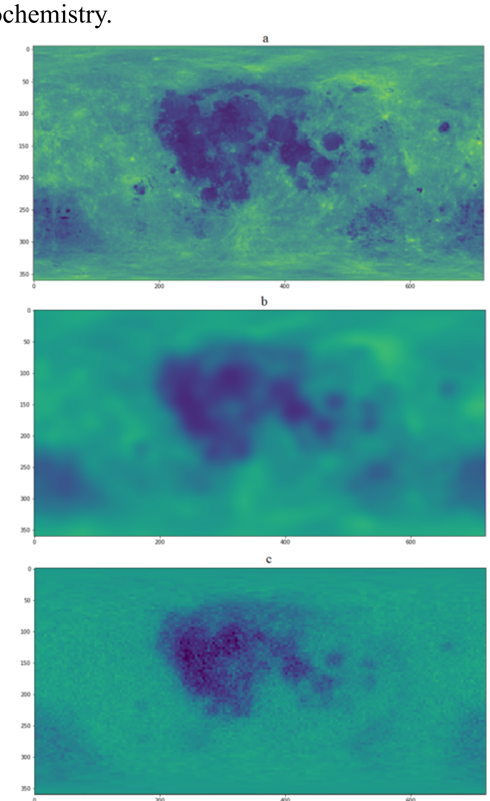

Figure 1 - Original (a) and bloored (b) versus predicted (c) albedo

Interactive analyzer: the interactive analyzer[1] (Figure 2) displays contours around regions of pixels whose predicted error value is higher than a given

[1] The open source code can be found at https://github.com/ML4SCI/MLMapper/tree/main/Lunar_Prospector/ML_for_Planetary_Albedo_Sofia_Strukova

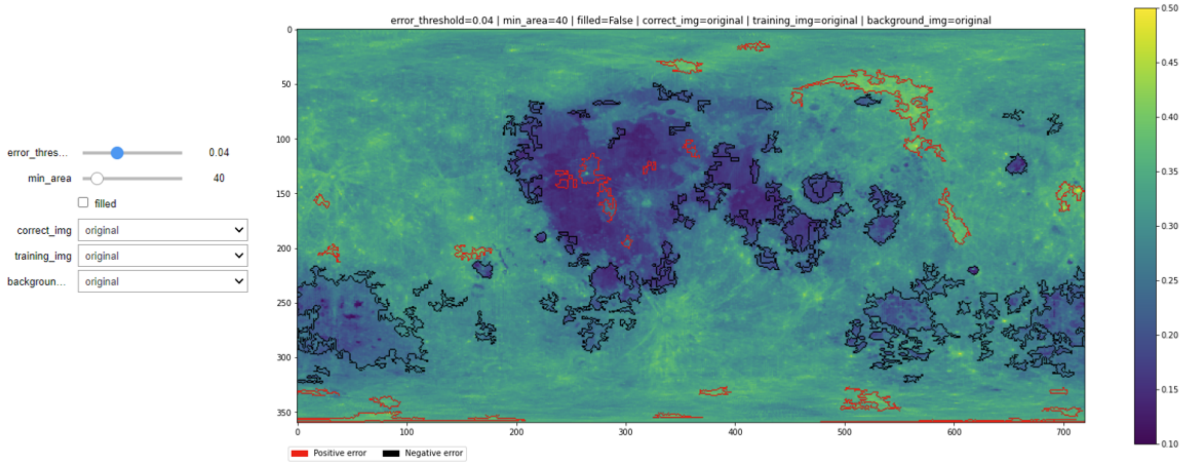

Figure 2 - An example of the interactive analyzer showing the difference between predicted and measured albedo (error threshold = 0.04, minimal area = 40)

threshold. The tool allows adjustment of the error threshold, a minimum area of the regions, as well as other parameters to configure how the image is displayed.

The reason behind some of the contours can already be explained based on some regions that are darker by default (e.g., crater Shackleton displayed anomalously high reflectance with regard to the surrounding south polar region [3]). Many error contours correspond to young craters and rays, suggesting a link between error and age (see next section). Finally, other errors may be linked to chemistry that is not represented in the Lunar Prospector dataset used for this study (Fe, Ti, K, and Th), as these elements make up 20% or less of the total chemical inventory present at all locations.

Optical Maturity: Optical maturity measures how long material has been on the lunar surface, exposed to the harsh space environment. Space exposure can, among other things, darken a material. Thus, two chemically-equivalent rocks with a different exposure age can have different albedo, meaning that bright material may simply be young. This offers the possibility of using the error map to identify younger optically immature materials independently from previously established techniques, as well as identifying young surface regions at a spatial scale at which existing techniques (e.g. crater counting) may not be reliable.

Discussion: This work can be further used as a base for predicting relationships between albedo and chemical composition on other airless bodies in order to obtain precise results and support ongoing and future missions. Mercury is a logical location at which to extend this work. The albedo of the Moon is generally much lower than that of Mercury, but the albedo of the lunar maria is similar to that of Mercury, despite Mercury's low surface iron centrations [4]. This suggests a more significant role for space weathering on Mercury, which can be quantified via application of the machine learning techniques described here.

Conclusions and ongoing work: We analyzed the chemical composition and albedo of the Moon using machine learning methods with the goal of characterizing the relationship between albedo and surface chemistry. Because this relationship is well known on the Moon, this work served to verify the validity of our machine-learned-based approach. By making the albedo maps of comparable resolution to the element maps and removing the spatial resolution difference, we made the data more comparable for training and prediction. This was helpful to minimize potential artifacts that arise from the resolution effects. Our resulting predicted albedo map, and difference from the measured abledo, revealed locations where chemistry is not the dominant effect, for example in optically immature regions.

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