RARE PHASE DETECTIONS IN CRISM DATA AT PIXEL-SCALE BY MACHINE LEARNING GENERATE NEW DISCOVERIES ABOUT GEOLOGY AT MARS ROVER LANDING AREAS: JEZERO AND NE SYRTIS.

M. Dundar[1], B. L. Ehlmann[2,3], Ellen Leask[2] [1]Computer & Information Science Dept., Indiana University-Purdue University, Indianapolis, IN, USA [2]Div. of Geological & Planetary Sciences, [3]Jet Propulsion Laboratory, California Institute of Technology, Pasadena, California (mdundar@iupui.edu)

Introduction: Discovery of aqueous minerals on the surface of Mars has revolutionized our understanding of the planet. Yet more remains to be discovered in existing data sets, utilizing improved techniques. One such example is the isolation and discovery of accessory mineral phases or phases in small scale exposures. Identifying these missing phases is critical for having a more complete understanding of the underlying geological formations on Mars toward resolving the question of origin. Small, rare phases on Mars that occur infrequently or at low abundances are important for two reasons. First, specific minerals such as alunite, jarosite, serpentine, and illite, among others, serve as direct environmental indicators of the geochemistry of waters on the Mars surface. Second, the identification of rare phases, even in just a few pixels, enables characterizing the mineral assemblages within a geologic unit, which are critical for identifying the thermodynamic conditions and fluid composition during interactions of rocks with liquid water. However, the detection of these spatially restricted mineral phases is difficult using existing typical CRISM (Compact Reconnaissance Imaging Spectrometer for Mars) processing techniques.

As part of our ongoing efforts to implement machine learning methods to fully automate mineral discovery in CRISM data, we have previously reported dozens of new jarosite and alunite detections across Mars [1]. Herein, we report new rare discoveries in significant locations for landed exploration with rovers.

Methods: Our methods have been developed in two phases. In the first phase around fifty images from the Nili Fossae and Mawrth Vallis regions were processed by a nonparametric Bayesian clustering technique [2]. This method generates a few hundred spectra per image processed, which are visually inspected and classified to create a spectral training library. This clustering approach is not only very computational but also requires a tedious task of manually assigning extracted spectra to classes. Toward fully automating mineral discovery, in the second phase, the training library collected in the first phase was used to implement two

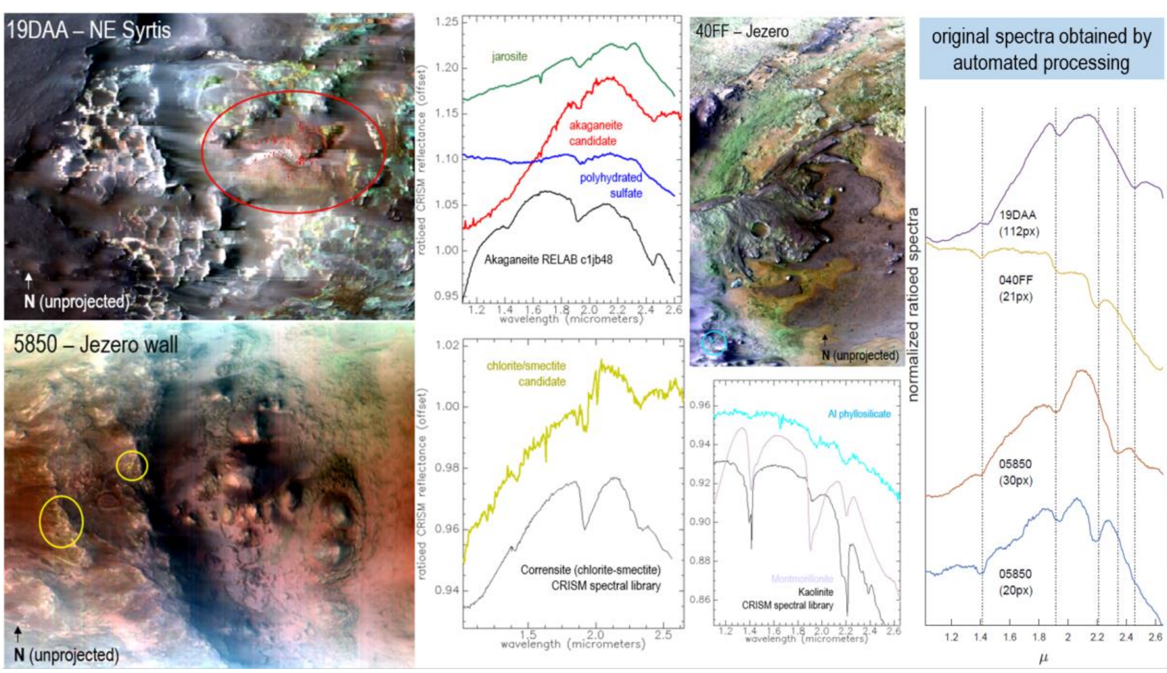

Figure 1. Small exposures of important accessory minerals at the Mars-2020 landing sites, discovered via automated processing with the Bayesian classification technique. CRISM false color infrared images are unprojected but oriented with north up. The single pixel detections are shown, with regions of interest circled. Original spectra extracted by the automated approach is shown in the far right panel. Pixels taken from automated detections are ratioed against several different denominators from "bland regions" to manually verify the detection. Reference library spectra are shown in black for comparison. Additional rare phase detections have been made in these images and their verification is the subject of our ongoing work.

models: a likelihood model for bland pixel identification for columnwise ratioing and a classifier model that operates on the ratioed data to render mineral classification. Both the likelihood model and the classifier uses our two-layer ensemble Bayesian Gaussian mixture model. The two layer Gaussian mixture model uses one mixture model for each spectral pattern in the lower layer. The number of components in a mixture model for a given pattern is determined by the number of images in which that pattern occurs as the model introduces one Gaussian component for every image the pattern is detected. Mixture models of spectral patterns in the lower layer are regulated by a global prior at the upper layer. This two-layer hierarchical model offers extreme flexibility and robustness for modeling pattern distributions. The lower layer models spectral variations of the same pattern across images whereas the upper layer models spectral variations across patterns. The model has several hyperparameters, which are tuned on the training library to encode information about existing pattern variations into the model.

Our models use 350 channels in the 1.0 - 3.5 µm range. As the discriminating features of each pattern fall in different subranges of channels, we adopt an ensemble learning approach to more effectively handle noisy spectral features. In this technique a single submodel is trained for each subrange and outputs of individual models are weighted differently for each pattern to produce an aggregate score for each pixel being classified. We have used initial models trained with around fifty images to classify new images in an active learning setting. The training data set is augmented with classified spectra from each image processed prospectively over time, which in turn is used to retrain models and classify new images. To date our models have been trained and tested with about five hundred CRISM images across Mars. The mineral classifier is designed to perform fine-grained classification with over one hundred sixty patterns composed of spectral classes of mineral phases, bland pixel categories, known artifacts, and unidentified patterns of potential interest.

Results: *Jezero Crater*: Olivine, $MgCO_3$, pyroxene, and iron smectite were previously detected in the sediments and floor of Jezero Crater using CRISM. Here, we report an aluminum phyllosilicate like kaolinite and montmorillonite in the walls of Jezero crater in an area accessible to the rover as well as Fe/Mg smectite in portions of the crater rim (Figure 1). The largest detections by area are reported here. We are in the process of vetting single pixel detections from the machine learning technique. These wallrock clay mineral detections likely indicate that blocks of crust from the surrounding NE Syrtis region with a characteristic Al phyllosilicate over Fe/Mg smectite stratigraphy [3,4] may be preserved in the Jezero wallrock – albeit disrupted by the Jezero impact – for exploration by the rover.

NE Syrtis: The NE Syrtis candidate landing site extended mission area includes Hesperian hydrated sulfates and jarosite along with late Hesperian/Amazonian fluviodeltaic sediments [5]. In one late Hesperian/Amazonian fluvial system, a new mineral phase is found associated with a local topographic low. The spectral characteristics are distinct from jarosite and other polyhydrated sulfates also present in the region. Locally, there is material with distinctive minimum at 2.45 µm and steep spectral slope at VNIR wavelengths (Figure 1). Elsewhere on Mars, this has been attributed to akaganeite [6], $Fe^{3+}O(OH,Cl)$. This is consistent with a geologic setting where salty, possibly acidic, late Martian waters flowed over the Syrtis lavas and sulfates forming a set of local lake basins, perhaps dammed by ice, which then evaporated [5,7]. Akaganeite and select iron sulfate materials are excellent candidates to explain the observed spectral properties of this new phase discovered by the Bayesian classification technique.

Conclusions and Future Work: Vetting of smaller mineral detections and those of other minerals (e.g., Al clays, hydrated silica, illite, analcime, chlorite, carbonate) recovered by our machine learning approach at Jezero, NE Syrtis, and Gale are the subject of our ongoing work. Importantly, these small detections of rare phases are crucial for guiding the rover and for contextualizing its discoveries. Although we reported results only from select locales owing to their significance, similar outcrops of rare phases have been detected across Mars along with several interesting patterns currently being considered as candidates for new phases. Our study demonstrates that machine learning can be highly effective in exposing tiny outcrops of rare phases in CRISM. Some of these detections may offer new cues toward a more accurate and complete geologic mapping of Mars paving the way for future discoveries.

References: [1] BL Ehlmann and M Dundar. "Are Noachian/Hesperian Acidic Waters Key to Generating Mars' Regional-Scale Aluminum Phyllosilicates? The Importance of Jarosite Co-Occurrences with Al-Phyllosilicate Units". In: *Lunar and Planetary Science Conference*. Vol. 46. 2015, p. 1635. [2] HZ Yerebakan, B Rajwa, and M Dundar. "The Infinite Mixture of Infinite Gaussian Mixtures". In: *Advances in Neural Information Processing Systems (NIPS)*. 2014, pp. 28–36. [3] Ehlmann et al., 2009, *JGR* [4] Goudge et al., 2015, *JGR* [5] Quinn et al., 2019, *JGR* [6] Carter et al., *Icarus*, 2015 [7] Skok et al., 4th Mars-2020 workshop