DATA-DRIVEN FUZZY WEIGHTS-OF-EVIDENCE MODEL FOR IDENTIFICATION OF POTENTIAL ZEOLITE BEARING ENVIRONMENTS ON MARS. G. R. L. Kodikara, and L. J. McHenry, Dept. of Geosciences, University of Wisconsin- Milwaukee, Milwaukee, WI 53211, gayantha@uwm.edu, lmchenry@uwm.edu.

Introduction: Zeolites are among the most common and widespread authigenic silicate minerals found in sedimentary deposits on Earth [1]. Zeolite occurrences in sedimentary environments on Earth can be categorized into six groups based on their geologic and hydrologic settings: 1) saline-alkaline lakes, 2) soils and land surfaces, 3) deep sea sediments, 4) open hydrologic systems, 5) hydrothermal alteration, and 6) burial diagenesis [2]. The highest concentrations of zeolites are found in glass-rich volcaniclastic deposits, since the volcanic glass is the major precursor of zeolites [2]. The formation and stability of zeolites are strongly dependent on the thermodynamic equilibrium of fluid-mineral reactions caused by water chemistry, and kinetically controlled non-equilibrium growth and dissolution reactions [1,2]. Therefore, the presence and nature of zeolites is a good probe to reconstruct the geological and hydrological history of zeolite-bearing environments on Earth (e.g. [3,4]).

Zeolites have also been identified on Mars using orbital remote sensing data [5,6]. Previous studies emphasized the difficulty of identifying and distinguishing non-analcime zeolites from polyhydrated sulfates from the visible to near-infrared spectral data. The only zeolite specifically classified was analcime, with others classified to the zeolite/sulfate class. It is also important to note that the zeolites have not yet been reported in Martian meteorites or in-situ data from Mars.

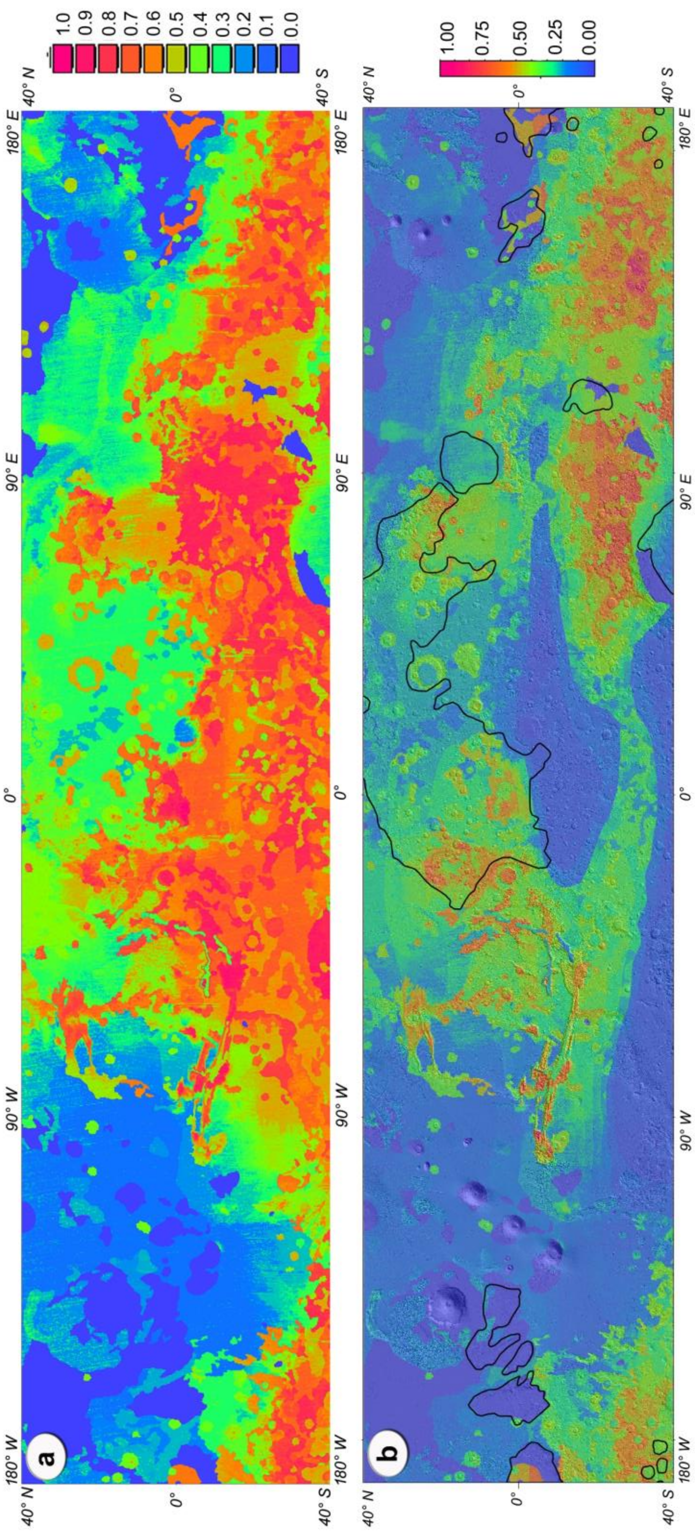
Therefore, the identification and delineation of prospective areas for zeolites on the surface of Mars could serve as a guide for further searches for zeolites using detailed orbital spectral image analysis and future in-situ observations. The predictive modeling for mineral exploration, one of the widely used statistical and probabilistic reasoning methods in geosciences, can be used in this case. In this study we applied the data-driven fuzzy weight-of-evidence method to model and map the prospective areas for zeolites on the surface of Mars.

Methods: The conceptual model developed here first models the suitable geologic and hydrologic environments for the formation of hydrous minerals, which are commonly formed under lacustrine, hydrothermal, diagenesis/metamorphic, or pedogenic processes, using the locations of already detected hydrous minerals using orbital data [6]. Then the presence of volcanic ash deposits (confirmed and modeled [7,8]) is used to confine the favorable areas for formation/presence of zeolites. The model used global mineralogical, geological, geomorphological, hydrological, physical, and elemental abundance maps derived from orbital data as evidential maps with the locations of the detected hydrous minerals using orbital data for the known mineral occurrences. The factor maps include NIR albedo and mineral maps from TES [9] and OMEGA [10], dust cover index maps from TES [9,11], TES day and night thermal inertia maps [12], GRS elemental abundance maps [13], Viking Global Mosaic (USGS), MOLA DEM (USGS), Geology map [14], Valley network map [15], Open-closed-basin map [16], pyroclastic ash distribution model [7], and potential pyroclastic deposits [8].

All the factor maps discussed above were imported to ILWIS (Integrated Land and Water Information System: https://www.itc.nl/ilwis/) via GDAL (Geospatial Data Abstraction Library: https://gdal.org/) and ISIS3 (Integrated Software for Imagers and Spectrometers - version 3: https://isis.astrogeology.usgs.gov/). The entire analysis was done using ILWIS, followed by re-projecting to a common coordinate system and resampling into 200 m/pixel resolution using the nearest neighbor method.

Fuzzy membership values for each evidential class in each map were determined by using the membership function curve derived from weights-of-evidence method, and manually based on the expert knowledge of the system concern [17]. The three-stage fuzzy inference engine used here consists of three parallel networks that sequentially combine collateral fuzzy evidential maps transmitted by the fuzzifier through the fuzzy OR and fuzzy AND operators to yield three/four intermediate fuzzy evidential maps in the first stage. These intermediate fuzzy evidential maps were combined using fuzzy gamma operator to create the synthesized fuzzy favorability map in the second stage. 25 models (inference networks) were generated changing the map combinations, fuzzy operators, and gamma values. The best hydrous mineral favorability model (Figure a) was selected using a validation (test and train) dataset. The third stage involved the generation of a favorability map of zeolites by combining hydrous mineral favorability fuzzy membership map with ash thickness and pyroclastic deposits maps (Figure b).

Results and discussion: The favorability maps for hydrous minerals and zeolites are shown in Figure a and b, respectively. This shows that the eastern and western



Arabia deposits, some sites of Medusae Fossae formation, some areas of Valles Marineris, Mawrth Vallis, highlands north of Hellas, Terra Cimmeria and Terra Sirenum regions show a high probability of finding zeolites based on this calculation.

Conclusion: The method applied here mapped the favorable areas for hydrous minerals and zeolites. This shows the capability of the model to cope with qualitative, quantitative, multi-source data/information on Mars, acquired from orbital data, which may be imprecise and incomplete due to the limitations of spatial resolution, spatial coverage, surface dust, instrumental biases, and other intrinsic biases.

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Figure 1. Favorability map of hydrous minerals (a), and favorability map of zeolite bearing terrains calculated using the data driven fuzzy weight-of-evidence method. Value range indicate the favorability (1 = high favorability, 0 = low favorability). Background in Fig (b) is a hillshade from MOLA DEM. Black outline in Fig (b): potential pyroclastic deposits.