INVESTIGATING THE SIZE AND AGE OF PYROCLASTIC DEPOSITS ON MERCURY USING DEEP LEARNING. M. Leon-Dasi[1], S. Besse[2] and A. Doressoundiram[1], [1]LESIA Observatoire de Paris, Université PSL, CNRS, 5 place Jules Janssen, 92195 Meudon, France, [2]European Space Agency (ESA), European Space Astronomy Centre (ESAC), 28692 Villafranca del Castillo, Spain.

Introduction: The images and spectral data acquired by the MErcury Surface, Space ENvironment, GEochemistry, and Ranging (MESSENGER) mission have evidenced the existence of vents and pyroclastic deposits (denominated faculae), product of explosive volcanic eruptions that have occurred in the past [1,2]. An individual analysis of a selection of faculae has provided new insights into the characteristics of these features and has highlighted the variability in spectral properties across and within deposits [3,4]. However, the diversity of these features in terms of morphology, shape, location, and spectral properties complicates the global characterization and timing of the volcanic eruptions. The complexity increases when considering that pyroclastic deposits on Mercury are not always isolated, they sometimes overlap due to the proximity of the vents or to multiple eruptions happening in the same location which form compound vents [5].

The initial constraints on the timing of volcanic eruptions suggest that this activity has an age of 3.25 to 1 Ga [1]. Further studies relying on analysis of the degradation level of the craters that host a deposit propose that explosive volcanism started at 3.6 Ga and then continued to the present time as an episodic phenomenon or at a decreasing rate [6]. This timing methodology allows to define an upper limit for the age of the deposits located inside craters, but does not further constrain the timing of the eruptions. Regarding the determination of the deposit size, first estimates have been produced mainly based on a visual inspection of the enhanced color map of Mercury. However, the pyroclastic deposits are diffuse in nature and their properties are modified as the material mixes with the background terrain. This complicates the task of uniquely identifying and delimiting the extent of these deposits. Altogether, the wide diversity found in these features, coupled with the large amount of spatial and spectral data returned by the MESSENGER mission make this a suitable problem to be tackled with deep learning techniques.

Methodology: In this work we train an unsupervised three-dimensional convolutional autoencoder (3DCAE) to extract the relevant features that characterize the pyroclastic deposits and obtain cluster maps. To do so we process individual footprints of the Mercury Atmospheric and Surface Composition Spectrometer (MASCS) instrument to form hyperspectral images at the location of each vent. These images have two spatial dimensions (width and height) with a spatial resolution of 0.07 deg/px and a spectral dimension with 230 channels ranging from 300 to 1450 nm. The 3DCAE was originally applied by [7] to cluster the types of crops in Earth observation images, and proved to be effective in delimiting the extent of different fields. We make use of 380,000 reflectance footprints obtained from the Mercury Surface and Spectroscopy (MeSS) database [8] in the region surrounding each deposit. The hyperspectral images are divided into patches around each pixel. The hyperspectral image patches are the input to train the neural network and extract the relevant features, which are then used to cluster each pixel. These cluster maps provide a unified framework that highlights the differences between and inside the deposits, allowing to compare them and define their limits.

Spectral investigation of deposit size and age: Delimiting the size of the pyroclastic deposits is important to constrain the volume of volatiles that have driven such an eruption. Previous studies have defined the diameter of a selection of deposit by analyzing the variations in spectral properties and assuming a circular shape [3]. While the deposits formed by a single explosion are usually roughly circular, this is not always the case. In fact, the interaction with the terrain and the superposition of deposits due to multiple eruptions happening in the same or in neighboring vents affect the shape and properties of the deposit. The clustering maps consider the spectral and spatial information extracted by the 3DCAE and provide a single framework to compare and delimit the deposits. Figure 1 provides an example of the cluster maps around different deposits and the relation with the sizes that were previously defined by [3] through a spectral analysis assuming a circular deposits. For the deposit on the Mistral crater, we observe that the cluster layers match the initial size estimate while revealing irregularities in the deposit shape and highlighting two separated focus that can point to separate eruptions. The advantage of using cluster maps for defining the extent of the deposits is more evident in the study of the Orm facula, since it provides more information on the interaction of deposited material that overlaps.

The pyroclastic deposits and volcanic vents are expected to evolve over time, and as a result fade and become more diffuse [9]. The characterization of this

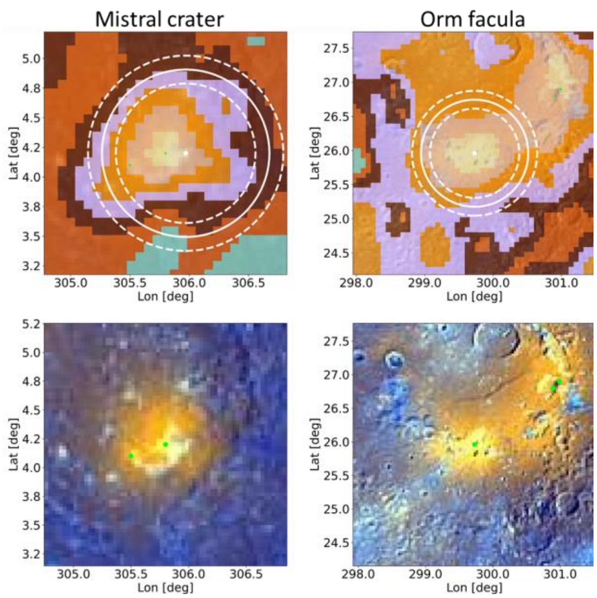

Figure 1. Top: cluster maps of the pyroclastic deposits on the SE of Mistral crater (left) and the Orm facula (right). The white circle indicates the previous size estimates assuming a circular deposit. The dashed circles correspond to one standard deviation of the deposit radius [3]. Bottom: MDIS enhanced color images of the deposits. The location of the vents is marked by green dots.

evolution will allow to time the eruption event and improve our understanding on the history of interior processes in the planet. Regarding the vent, this is evidenced by the level of degradation which affects the texture of the walls and the floor [10]. The spectral properties of the deposit are expected to change with time due to the effect of space weathering which results in a reduction of the spectral contrast relative to the background [1]. However, the intrinsic differences in the deposits and the effect of other phenomena such as the degree of mixing with the background material and the change in grain size have complicated this analysis. In this work, we propose to use the cluster maps to analyze the spectral properties of each facula in the context of its background terrain. To do so, we categorize each deposit in a spectral type that, rather than being defined by the absolute spectral value at one point in the deposit, is defined by the degree and sparsity of the variation in spectral properties between the center and the outside of the deposit, as evidenced by the cluster maps. These spectral types are then compared to the upper age limit provided by the degradation level of the host crater. The first analysis indicates a relation between the variation in spectral properties along a deposit and the maximum age limited by the host crater analysis.

Conclusion and perspectives: To obtain a more robust assessment of the results, we aim at comparing the insights on the age of the deposits derived from the spectral classification with an assessment of the morphological degradation of the vent. We plan to continue our research to understand the physical and chemical phenomena that determine the spectral variability of the vents by analyzing the features extracted by the deep learning network.

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