USING FUZZY LOGIC TO CLASSIFY PLANETARY LAVA FLOWS SEEN IN CROSS-SECTION

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Introduction: It is important to properly identify the character of a lava flow to understand its emplacement and geologic implications. For example, the models for the emplacement of simple ʻaʻā flows are fundamentally different from models for the emplacement of inflated pāhoehoe flows which both are very different from models for tube-fed lava flows [e.g., 1]. The misidentification of the lava flow type can lead to errors in the estimated lava flux of multiple orders of magnitude [e.g., 2]. Errors in lava flux result in comparable errors in estimates of eruption duration with concomitant issues with modeling of the magma plumbing system and source.

In introductory geology classes, lava flow classification relies on surface texture with the primary distinction being between smooth pāhoehoe and rough ʻaʻā breccia. Planetary volcanologists have largely relied on inferring surface texture from orbital remote sensing to classify lavas. However, the surface of a lava flow can be easily eroded or covered. Thus, only the uppermost and relatively pristine extraterrestrial lavas can be reliably classified. On Earth, older lava flows are primarily identified based on exposures in natural or artificial cross-sections. Key observables are the size, shape, and distribution of clasts, vesicles, and joints, as well as petrographic texture [e.g., 3]. Lava layers are seen in vertical exposures from orbit on Mars and the Moon [e.g., 4,5], but even high-resolution orbital data cannot resolve details of clasts, vesicles, and joints, making the interpretation of these layers difficult [6].

New (and near-future) data provide detailed views of lava flows on Mars and the Moon in cross-section. The Mars 2020 Perseverance rover has made systematic field observations of igneous rocks on the floor of Jezero crater [7]. These rocks could be from one or more lava flows, and the observations are being placed into a stratigraphy that can be related to an (imperfectly exposed) cross-section [8,9]. Furthermore, there are proposed missions to examine the lavas exposed in cross-section in the walls of the lunar pits [10]. These new and proposed observations of lava cross-sections are well-suited to lava classification built upon terrestrial methods.

Challenges: We see two significant issues when it comes to using terrestrial cross-sectional lava flow classification methods in a planetary context: (1) there is no widely accepted standard methodology for lava flow classification, and (2) real lavas and outcrops are messy.

No standards. A key issue for lava flow classification is that it is highly subjective; it is often possible to identify which institution one trained at by the way intermediate lava types are classified. Given that there is no widely recognized standard for classifying lavas, this problem cannot be entirely eliminated. However, it is possible to use an algorithm-like methodology to make the classification transparent, systematic and repeatable [3].

A messy world. Another major complication is that it is essential to capture the uncertainty in the classification of a lava. There are two main sources of uncertainty. First, many lavas are intermediate in type, exhibiting a mix of characteristics of end-member lava types. Second, real outcrops often do not allow all characteristics to be confidently observed. In other words, the quality of the exposure affects one's confidence in classifying lavas.

Solutions: We see the potential to address the issues with applying terrestrial lava classification methods in planetary science in the near future.

There is a method to build from. While not widely adopted, there is a systematic method for classifying lava flows that was developed for interpretation of terrestrial lavas seen in drill core [3]. This method does not eliminate the subjective nature of where one draws boundaries between different lava types, but it does force the systematic collection of observations for all lavas and enforces consistency in the interpretations. We suggest that this method can be modestly improved for the planetary context. In particular, [3] does not take stratigraphic relations into consideration. Figure 1 illustrates the basic cross-section of three major lava types. Note how a basal breccia is characteristic of only ʻaʻā flows while an upper breccia is characteristic of both ʻaʻā and rubbly pāhoehoe. In other words, identifying where an auto-breccia falls within a lava flow's internal stratigraphy is essential for properly classifying that flow.

Fuzzy-logic is for messy classifications. There are mathematical ways to work with "messy" problems with 'fuzzy logic' being specifically designed to deal with situations where classes have gradational boundaries [11]. In the case of lava flows, fuzzy logic can provide a quantitative measure of a given flow's affinity to each of the end-member types [3]. The key is to provide a list of key observables and a measure of how common or diagnostic a given observable is for each lava type. For example, a basal breccia is a very strong indicator for an ‘a‘ā flow. In contrast, spheroidal vesicles in the core of a flow are rare in all lavas but are significantly more common in pāhoehoe flows.

Calibrating against terrestrial analog data is the key to selecting appropriate weights for the diagnostic strength of an observable for a given lava type. We have extensive field observations from many dozens of lava flows across the Earth, including classic examples in Hawaii and Iceland as well as more intermediate lavas from across the western US and flood basalts around the world. While there are copious amounts of data in hand, this is still far from a case where “big data” methods can be applied. Instead, reasonable estimates for the values of the weights can be made by a team of experts as a starting point. These weights can then be iteratively adjusted to provide good results to the analog data.

It is appropriate to ask if lavas on Mars or the Moon could be different from any lava on Earth. The physics of lava flowing on the Moon, Mars and Earth should not be the cause of such differences. The effect of lower gravity is quite well replicated by the effect of lower slope. The cooling of lavas will differ, but in all cases molten lava is massively hotter than the ambient environment; this means the differences will be modest, unlikely to lead to fundamentally different types of lava. The major element compositional range of lavas on Earth generally exceeds that of the Moon and Mars, but a focus on more mafic terrestrial basalts would be appropriate. Effusion rate is the one parameter that may be significantly larger for some planetary flows than for the terrestrial analogs for which we have good field observations.

A final significant point is that the method from [3] includes consideration of the quality of observations. This is captured using “confidence values” for each observation. These are subjective but are expressed as numeric values ranging from 100% for perfect exposure to 0% if a characteristic is unobservable.

The application of this method to an unclassified lava flow has two basic steps. First, a value for confidence in the presence or absence of each key observable is collected. Then this value is multiplied by the weight of that observable for a given lava type. These products are summed and the result is divided by value for an ideal example of that lava type. This result can be reported as a percent to describe the degree to which the unknown lava is consistent with that lava type. These computations can be easily built into even a basic spreadsheet and are illustrated in Fig. 2. Completing this process for each lava type provides a picture of the relative affinity of the unknown lava to the various classes of lavas (e.g., pāhoehoe, ‘a‘ā, rubbly pāhoehoe) as well as the confidence in those classifications.

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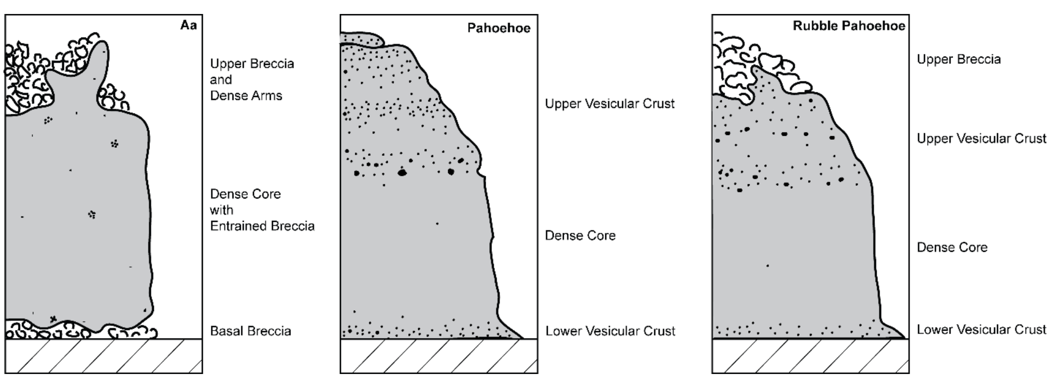

Fig. 1. Simplified diagram of some features used to classify three major types of lava flows.

	Ideal				Real		Unit A Results	
Observables	Lava	Intrusion		Observables	Unit A	Unit B	Lava	Intrusion
Feature 1	Weight L1	Weight I1		Feature 1	Weight A1	Weight B1	L1*A1	I1*B1
Feature 2	Weight L2	Weight I2		Feature 2	Weight A2	Weight B2	L2*A2	I2*A2
Feature 3	Weight L3	Weight I3		Feature 3	Weight A3	Weight B3	L3*A3	I3*A3
Feature 4	Weight L4	Weight I4		Feature 4	Weight A4	Weight B4	L4*A4	I4*A4
Feature 5	Weight L5	Weight I5		Feature 5	Weight A5	Weight B5	L5*A5	I5*A5
							%Lava = sum(L*A)/Sum(L)	
							%Intrusion = sum(I*B)/Sum(I)	

Fig. 2. Schematic of fuzzy logic lava flow classification method.