

**OPTIMIZING EXOMARS PANCAM MULTISPECTRAL SCIENCE: INVESTIGATING THE LIMITS OF MATERIAL CLASSIFICATION.** R. B. Stabbins<sup>1</sup>, P. M. Grindrod<sup>1</sup>, S. Motaghian<sup>1</sup>, E. J. Allender<sup>2</sup>, and C. R. Cousins<sup>2</sup>, <sup>1</sup>Natural History Museum, London, UK ([r.stabbins@nhm.ac.uk](mailto:r.stabbins@nhm.ac.uk)), <sup>2</sup>University of St Andrews, UK.

**Introduction:** We present a tool for investigating the ability of PanCam, or any equivalent multispectral imaging system, to perceive material properties, such as mineral composition, in contrast to a background set of materials. This is performed by simulating the observation process, given the instrument spectral response and the material reflectance spectra, and exploring methods of multivariate analysis on the sample space.

**PanCam:** PanCam [1] is the mast-mounted multispectral stereo panoramic camera system for the ExoMars *Rosalind Franklin* rover [2], with a primary objective of visual geological characterisation, for the recognition of past habitability at the surface of Mars. PanCam will measure the VNIR (visible/near-infrared, 380nm-1100nm) spectral reflectance of surfaces across a multispectral suite of 12 narrowband filters, to infer the distribution and properties of materials across the environment [3]. Previously, the transmission profiles of the PanCam filter set were optimized by the PanCam Science Team for identifying a broad selection of minerals, expected to be encountered at the Mars surface [3]. The process considered the ability of a candidate set of filter profiles to reconstruct the mineral reflectance spectra of a large set by linear interpolation, and also to distinguish one group of minerals against another (e.g. phyllosilicates against iron oxides), via a set of 5 spectral parameters (algebraic operations between spectral bands) [3].

**Motivation:** Given data constraints during mission operations, there is a motivation to understand efficient modes of multispectral imaging, in particular using subsets of filters to measure spectral parameters (e.g. fig. 1). A significant understanding can be gained by study of the successful operations of the MSL Mastcam and MER Pancam multispectral instruments, and the CRISM hyperspectral orbital system [4,5,6]. However, there are differences in the spectral responses of these instruments, and thus an analytical and comparative study of PanCam is required at this preparatory stage, to select, and evaluate the efficacy of, certain spectral parameters for specific tasks, such as highlighting one particular material in contrast to an expected background.

**Pipeline Overview:** We have developed a general tool, as a Python software pipeline, for systematically investigating the spectral sampling space afforded by a particular spectral imaging system. The pipeline consists of the following components:

1. *Material Spectra:* First, the target and background materials are selected for a given study, and the reflectance spectra obtained. The *Western Washington University Vis-NIR Database* [7] has been used as an interface to a collection of spectral libraries, including the USGS speclib06 [8] and the Uni. Winnipeg *HOSERlab* databases [9]. The extraction pipeline involves choosing a species from a mineral group, importing all samples available, and interpolating and truncating the spectra to the range 380nm - 1100nm,  $\Delta\lambda=1\text{nm}$ .

2. *Instrument Model:* The reflectance spectra are sampled according to the spectral transmission of the filters of the given instrument, with noise applied, to give the expectation and uncertainty values of the observed multispectral reflectance.

3. *Spectral Parameters:* are calculated according to the methods developed for the *CRISM* orbital hyperspectral imager, presented by [10,11]. Where the central wavelengths of the PanCam filter suite do not match those available for CRISM, substitutes are explored.

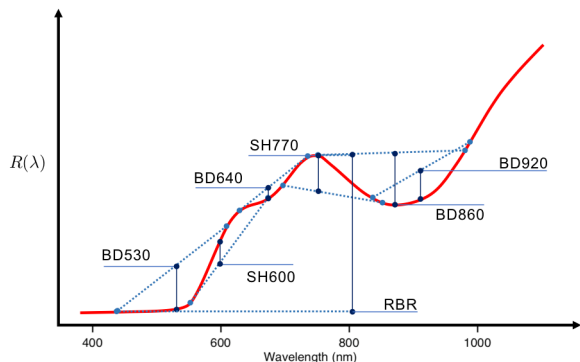
4. *Analysis:* The multivariate data is collected in a Pandas Dataframe and explored with the Seaborn visualization package. Scatterplots and histograms are produced to clearly illustrate how effective a spectral parameter (or combination) is at separating the spectral features of a target against a background. The separation is evaluated to provide rankings to spectral parameters, and broadly to the filters required to measure those spectral parameters.

**Example study of hematite against the background mineralogy of Oxia Planum:** Hematite, an iron oxide indicative of changes in oxidation conditions, has implications for water activity and past habitability, and has been a target of interest for the *Curiosity* rover at Vera Rubin Ridge [12]. Fig. 1 illustrates a set of spectral parameters, developed by [10,11], for the identification of hematite, that have been implemented here as an example. Minerals hosted in the *Western Washington Vis-NIR Database* [7] have been selected to represent the expected mineralogy of the Oxia Planum landing site for *Rosalind Franklin* [13], shown in fig. 2, with the sampling of PanCam indicated. A grid of paired scatterplots (fig. 3) then demonstrates which single parameters (diagonal histograms), and which combinations thereof, best separate the hematite target from the background.

**Future Work:** With the pipeline initiated, a number of expansions are planned. There is scope to improve the accuracy of the instrument model, by including component level details of the spectral sampling of the complete system (e.g. including the lens and detector response), and observation dependent uncertainty (e.g. illumination conditions and detector temperature). At present, spectral parameters are defined in advance; to generalize the pipeline, the complete combinatorial space of spectral parameters, for the standard operations of [10,11], will be explored. In addition to plotting the spectral parameters, the success of the spectral parameter as a qualitative tool can be investigated, in terms of the target-background contrast achieved in an image product. This is achieved by synthesizing spatial scenes of the target and background, via environment/imaging simulation software [14], and by processing the resultant images through the *ExoSpec* toolkit, a multispectral image analysis software package for ENVI, developed by the PanCam science team [15].

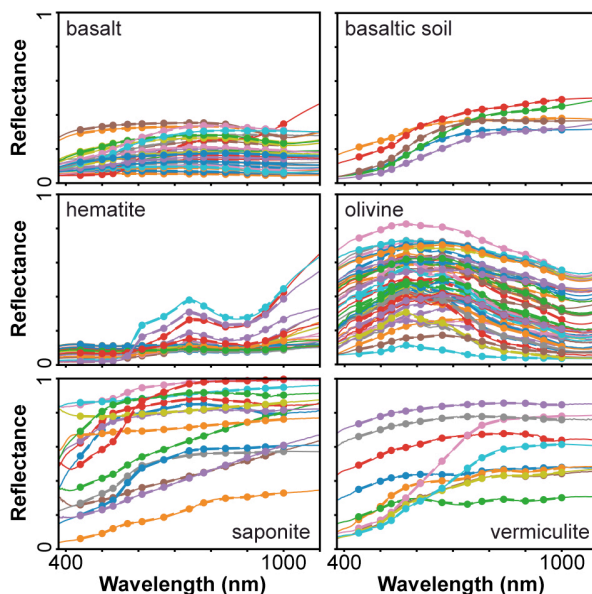
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**References:** [1] Coates A. J. et al. (2017), *Astrobiology*, 17, 511-541. [2] Vago J. L. et al. (2017), *Astrobiology*, 17, 471-510. [3] Cousins C. R. et al. (2012), *Plan. & Space. Sci.*, [4] Bell J. F. III et al. (2003) *JGR*, 108, E12. [5] Bell J. F. III et al. (2017) *Earth & Space Sci.*, 4, 7, 396-452. [6] Murchie S. et al. (2007) *JGR*, 112, E5. [7] Rice M. S. et al. (2016) <http://spectro.geol.wvu.edu/> [8] Clark R. N. et al. (2007) *USGS Digital Spectral Library*. [9] Cloutis E. et al. (2006) *LPSC-37*, #2121. [10] Pelkey S. M. et al. (2007) *JGR*, 112, E8. [11] Vivano-Beck C. E. et al. (2014) *JGR*, 119, E6. [12] Fraeman A. A. et al. (2020) *JGR*, 125, E5. [13] Quantin-Nataf C. et al. (2021) *Astrobiology*, In Press, DOI:10.1089/ast.2019.2191. [14] Stabbins R. B. et al. (2018) *LPSC-49*, #2099. [15] Allender E. J. et al. (2018) *SPIE Remote Sensing XXIV*, 107890I.

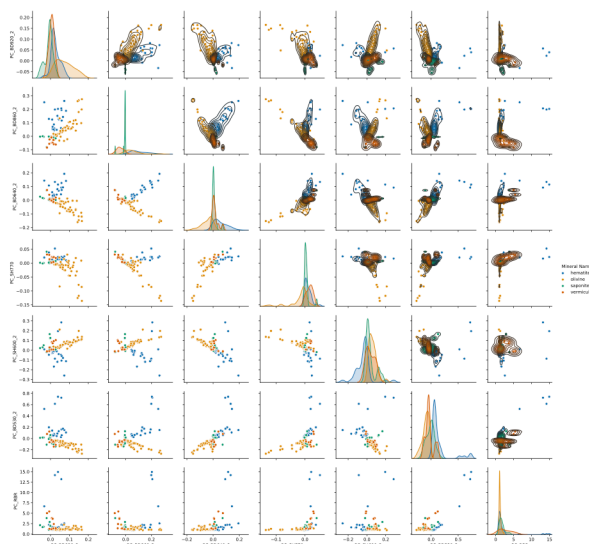


**Figure 1.** Illustration of the CRISM VNIR spectral parameters on an exemplary hematite spectra

(*RPN\_OOX\_04*). *BD*= Band Depth, *SH*= Shoulder Height, *R*= Ratio. [10,11].



**Figure 2.** Input mineral reflectance data for target (hematite) and background (basalts, vermiculite, saponite and olivine). Data sourced via the Western Washington Spectral Database[7].



**Figure 3.** Paired scatterplots of the spectral parameters computed with PanCam sampling, indicating data distribution of hematite (blue) against background minerals (orange, green, red) across the sampling space. Univariate plots (diagonal) indicate single spectral parameter discrimination, bivariate indicate advantage of combinations. Upper plots give density contours.