

Composition and Impact-Generated Structure of Planetary Crusts
Revealed by Dimensionality Reduction: Moon & Mars

by

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"Something emotive abides in the land... To hear the unembodied call of a place, that numinous voice, one has to wait for it to speak through the harmony of its features... One must wait for the moment when the thing... ceases to be a thing and becomes something that knows we are there."
- Barry Lopez, *Home Ground*

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INTRODUCTION

Humanity has long translated the numinous mysteries of the sky into the prose and poetry of ordinary life: calendars, compass points, genealogies, moral codes, and omnific gods. From Galileo's first sketches of the Moon to modern gravimeters and spectrometers, each generation has looked deeper into the cosmos to ask who we are and why we exist.

Today, this translation takes the form of measurement. Modern planetary science now stands at a threshold where the scale and complexity of our observations have exceeded the reach of traditional analytical tools. NASA's Gravity Recovery and Interior Laboratory (GRAIL) mission has mapped the lunar gravity field at four-kilometer resolution, revealing kilometer-scale variations in crustal density and porosity. Meanwhile, instruments such as the Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) have returned hyperspectral imagery capable of resolving subtle mineralogical variations in the Martian crust. These datasets offer the opportunity to interrogate the composition and structure of planetary bodies, but they also pose a significant analytical challenge: relevant signals are embedded in correlated, high-dimensional measurements where conventional averaging techniques can obscure structures of interest.

Dimensionality Reduction (DR) techniques are a subset of unsupervised machine learning algorithms that distill complex datasets into a smaller set of meaningful dimensions. These techniques have transformed the interpretation of spectroscopic data. Principal Components Analysis (PCA), Factor Analysis (FA), and related approaches isolate coherent spectral variations, enabling weak mineral signatures to be identified amongst significant interference from atmospheric, dust, instrument, or other mineral signatures.

However, similar techniques have seldom been applied to gravitational or geophysical data, even though these also contain correlated structures arising from underlying physical processes. This thesis explores how dimensionality reduction can bridge the methodological divide of big data and big insight, revealing composition and structure in the planetary crusts of the Moon and Mars.

In planetary science, one domain where such hidden structure is especially consequential is impact cratering. Impact cratering is a fundamental geologic process that continues to shape the subsurface architecture of the Moon and once dominated the evolution of the ancient crusts of Earth, Venus, and Mars. The stresses and temperatures of impact events fracture, bulk, melt, and compact crustal materials, generating and destroying pervasive porosity that in turn governs crustal thermal conductivity, magmatic ascent, and volatile storage. Of any planetary body, the Moon preserves this impact record most clearly: devoid of plate tectonics and significant atmospheric or hydrologic processes, it retains an integrated history of bombardment that has also affected Earth, Venus, Mars, and beyond.

This dissertation, *Composition and Impact-Generated Structure of Planetary Crusts Revealed by Dimensionality Reduction: Moon & Mars*, applies and extends dimensionality-reduction methods to planetary datasets through four linked studies.

Spectroscopic Foundations (Chapter 1) - Factor Analysis is applied to Mars hyperspectral data to isolate weakly expressed mafic mineral signatures within the Circum-Isidis Capping Unit, suggesting a shared origin for stratigraphically correlated rock units within and outside of Jezero Crater. This work demonstrates how statistical decomposition can reveal weak compositional signals and motivates analogous approaches for other planetary datasets.

Planetary DR Methodological Validation (Chapter 2) - Building on those insights, a new framework called Guided Endmember Extraction (GEEX) is developed for correlated and repeatable planetary data structures. Validated on GRAIL gravitational profiles of lunar impact craters, GEEX significantly improves the precision of our estimate for the lunar depth of pore closure, as well as the dependence of crater gravity signatures on regional porosity and crater diameter.

Crustal-Thickness Trends (Chapter 3) - GEEX is used to identify theorized, but previously undetected, relationships between crustal thickness and crater gravity anomalies, providing new constraints on how local crustal structure modulates impact-induced porosity.

Basin-Scale Porosity Evolution (Chapter 4) - Finally, GEEX-derived crater metrics are applied to analyze the spatial distribution of deep porosity around major lunar basins. These results resolve porosity at depths of ~5–20 km and at basin-scale lateral resolution, illuminating how impact-generated porosity decays through time and varies across the lunar crust.

These chapters trace a conceptual arc from composition to structure, from Mars to the Moon, and from established to novel analytical methods. They show that dimensionality reduction can serve as a powerful codebreaker for planetary data, working across hyperspectral, gravitational, and many more (topographic, seismic, magnetic...) domains. The framework developed here provides not only new quantitative insights into martian compositional and lunar crustal evolution but also a generalizable toolset for analyzing correlated, high-dimensional datasets across the Solar System. In doing so, it bridges the early intuition of planetary observers, that life on Earth could be guided by the sky, with the modern capacity to translate the cosmos' unfathomable mysteries into a language of quantitative understanding.

CHAPTER 1: The Circum-Isidis Capping Unit: An Extensive Ashfall Deposit Exposed in Jezero Crater

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Abstract

Several mineralogically diverse regions across Mars are capped by dark-toned rock formations emplaced during the Noachian-Hesperian transition, an era encompassing a shift in volcanism from dominantly explosive to effusive. However, these caprocks' origins are uncertain, limiting insight into the nature of this shift. We explore the potential volcanic ash origin of a widespread (~50,000 km²) mafic caprock in the Circum-Isidis region via an integrated photogeologic and remote-compositional analysis. We also investigate whether this unit is genetically equivalent to a mafic rock formation exposed in the floor of Jezero Crater. We find: (a) the Jezero Floor and Capping Units are morphologically, stratigraphically, and compositionally similar, suggesting a shared formation mechanism, and (b) the tonal layering and draping characteristics of the Capping Unit are most consistent with a volcanic ash origin atop the ultramafic Olivine-Rich Unit, also an ash. Our hypotheses can be tested by the Perseverance rover and studies of returned samples.

Plain Language Summary

In its early history, Mars volcanism transitioned from explosive to lava style eruptions. We test hypotheses for the origins of a rock formation overlying the region surrounding Perseverance rover, finding this unit is most likely a volcanic ash. We also test whether this rock unit is exposed specifically in Jezero Crater, the current location of the Perseverance rover. We find that this unit not only is equivalent to the rock formation that Perseverance landed on but also may aid in understanding the causes behind Mars' volcanic transformation ~3 billion years ago.

1 Introduction

Dark-toned mafic caprocks are globally distributed across Mars, such as in Nili Fossae (Mustard et al., 2009), Mawrth Vallis, Sinus Meridiani (McLennan et al., 2019), Gale crater

(“Cratered Surface” in Anderson et al. (2015)), and Oxia Planum, the proposed landing site for the ExoMars lander (Quantin-Nataf et al., 2021). These geologic units superpose mineralogically diverse rock formations and were emplaced during the Noachian-Hesperian transition. This period encompasses shifts in aqueous surface environments and the putative dominant style of volcanism on Mars, from explosive to effusive volcanism (Bandfield et al., 2013; Michalski & Bleacher, 2013; Robbins et al., 2011) as well as from broadly low-calcium to high-calcium pyroxene volcanic products (Baratoux et al., 2013; Mustard et al., 2005; Poulet et al., 2009). Hypotheses for the origins of these caprocks are diverse, including deposition as volcanic lava flows (Bishop et al., 2013; Bramble et al., 2017; Tornabene et al., 2008), impact melts (e.g., Mustard et al., 2009), or impact or volcanic-related air-falls (Bramble et al., 2017; Cannon et al., 2017; Edwards & Ehlmann, 2015). Resolving the formation mechanisms of these geologic units, though they may differ, would contribute to efforts to constrain the causes and nature of the Noachian-Hesperian transition, including shifts in surface environments and volcanism.

This study examines one of the most geographically widespread ($\sim 50,000 \text{ km}^2$) and well-exposed examples of these mafic caprocks, the Capping Unit of the Circum-Isidis region (Figure 1a). It is also a potential target for sample caching by the Perseverance rover for return to Earth-based laboratories (Farley et al., 2020). The Capping Unit immediately overlies and is geographically coextensive with the Olivine-Rich Unit, which has been shown likely to be a volcanic ash deposit (Kremer et al., 2019; Mandon et al., 2020). Based on its strong coextensive relationship with the Olivine-Rich Unit as well as its apparent draping of bowl-shaped topography (Mustard et al., 2009), we explore the hypothesis that the Capping Unit may also be a volcanoclastic airfall deposit.

We also investigate whether this rock formation is equivalent to the mafic, crater-retaining Jezero Floor Unit, currently under investigation by Perseverance rover (Farley et al., 2020). Stratigraphic and morphologic commonalities between these two units have been noted (Sun & Stack, 2020). Advanced statistical and noise-reduction techniques now allow for a more rigorous comparative compositional analysis between the Jezero Floor and Capping Units. Demonstrating equivalency between these two rock formations would allow insights from the rover to be applied to the more extensive regional Capping Unit.

2 Background and Geologic Context

The Capping Unit overlies the Olivine-Rich Unit and Noachian basement (see Figure 1e)—both ancient, mineralogically diverse geologic units, with detections of Fe-Mg phyllosilicates (Bramble et al., 2017), serpentine, and carbonates (Ehlmann & Mustard, 2012). The Capping Unit is generally characterized by a dark-toned, crater-preserving surface that tops mesas with steep bounding scarps (see Figure 2a). Please note that the Capping Unit of this study is geographically and geomorphically distinct from the Pitted Capping Unit of Goudge et al. (2015) (see Supporting Information S1). Spectra of the unit show weak mafic (1 and 2 μm) signatures with a mixture of olivine (Bishop et al., 2013; Bramble et al., 2017). The age of the unit is likely between 3.6 and 3.96 Ga, forming after the Isidis impact dated by Werner (2008), but before Syrtis Major lavas that are stratigraphically above it (Mustard et al., 2009).

The floor of Jezero Crater contains an olivine-carbonate geologic unit (“light-toned floor unit” in Goudge et al. (2015)) superposed by a mafic, crater-retaining floor (the “Jezero Floor Unit” of this study; “Volcanic Floor Unit” in Goudge et al. (2015)). An “Undifferentiated Smooth (Us)” unit mantles the Jezero Floor Unit (Stack et al., 2020), and recent work has determined that it likely formed after the Floor Unit (Kah et al., 2020; Stack et al., 2020; Warner et al., 2020).

Recent work shows they have similar spectral signatures, indicating that the Us may be derived from the crater-retaining floor (Horgan et al., 2020; Warner et al., 2020). Thus, we follow previous studies (e.g., Goudge et al., 2015; Horgan et al., 2020; Salvatore et al., 2018; Schon et al., 2012; Shahrzad et al., 2019) and treat them as a single unit. Age estimates derived from crater-counting for the Jezero Floor Unit have ranged widely from 1.4 Ga (Schon et al., 2012) to 3.45 Ga (Goudge et al., 2015). Hypotheses for the origin of the crater-retaining Jezero Floor Unit are similar to that of the Capping Unit, including deposition as a lava flow (Goudge et al., 2015; Schon et al., 2012), cemented aeolian/fluvial sediments (Kah et al., 2020; Stack et al., 2020), or as an airfall deposit (Stack et al., 2020).

We rule out a few formation hypotheses for the Capping Unit based on previous work. An origin as an Isidis-related product/impact melt is not possible given the Capping Unit's stratigraphic position above post-Isidis features such as the Olivine-Rich Unit and Jezero Crater's rim (Kremer et al., 2019; Sun & Stack, 2020). Additionally, the Capping Unit is a coherent layer of rock that exclusively superposes and thinly drapes (with thicknesses not exceeding 10 of meters) the Noachian Basement and Olivine-Rich Units (Kremer et al., 2019; Mustard et al., 2009), precluding an origin as an igneous intrusion. Although the Capping Unit is darktoned, mafic, and crater-retaining, these characteristics in a rock formation do not exclude a clastic origin as discussed in Edgett and Sarkar (2021). Work thus far has been ambiguous regarding whether the Capping Unit is a lava derived from Syrtis Major or vents (Bishop et al., 2013; Bramble et al., 2017; Tornabene et al., 2008), a product of impact condensates (Cannon et al., 2017), an aeolian erg deposit, or a volcanic ashfall (Bramble et al., 2017; Cannon et al., 2017; Edwards & Ehlmann, 2015). This study explores the merits of these hypotheses.

We map the extent of the Capping Unit and characterize its stratigraphic position, internal layering, draping characteristics (including relief-to-thickness ratios), and regional uniformity (morphologic, compositional). We compare our results with previous observations and the expected characteristics of ancient rocks deposited as lava flows, impact products, aeolian ergs, and ashes. We additionally compared the morphologic, stratigraphic, and compositional characteristics of the Capping and Jezero Floor Units. These analyses use data from the High-Resolution Imaging Science Experiment (HiRISE), the Context Camera (CTX), and the Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) aboard the Mars Reconnaissance Orbiter. Detailed spectral analyses are facilitated by endmember extraction using the statistical method Factor Analysis.

3 Methods

3.1 Mapping

To examine the regional uniformity of the Capping Unit, we conducted mapping in our study areas (14°–24°N, 76°–80°E) on the northwestern margin of Isidis and (2.5°–4°N, 82.5°–86°E) in Libya Montes at a 1:50,000 scale, using HiRISE and CTX images as well as the Murray Lab CTX mosaic (Dickson et al., 2018; Malin et al., 2007) (see Figure 1; see Supporting Information S1 for a list of images used in the study).

Mapping was guided by the Capping Unit's unique geomorphic characteristics: a dark-toned, crater preserving surface, steep bounding scarps, mesas typically 1–5 km in diameter (see Figure 2a), and its stratigraphic superposition of the Olivine-Rich Unit mapped by Kremer et al. (2019) (see morphological characteristics therein). Just as the Olivine-Rich Unit exhibits locally alternating, internal tonal layers, the Capping Unit has also been observed to exhibit layering at its base with alternating tonality (Bramble et al., 2017). Layering in the Capping Unit was

distinguished from layering in the Olivine-Rich Unit by the presence of boulders (see Figures 2b and 2d).

3.2 Draping Characteristics

We explore the Capping Unit's draping characteristics: how it is oriented (i.e., dipping) with respect to underlying topography and how thinly it drapes kilometer-scale, bowl-shaped outcrops. This examination helps to differentiate between (a) deposition as an airfall (volcanic/impact) and (b) origins as a lava flow or aeolian erg. The former mechanisms would tend to drape topography thinly and with a high degree of parallelism. Although aeolian ergs and lava flows may pile against or flow over topography, thin draping (e.g., a relief-to-thickness ratio of $\sim 10:1$) across kilometer-scale, bowl-shaped topography would suggest against these mechanisms as they tend to fill, not drape low-lying depressions (Livingstone et al., 1996).

To investigate these draping characteristics, we used high-resolution Digital Elevation Models (DEMs) derived from HiRISE stereo pairs created either by the HiRISE team at the University of Arizona or in-house using the Ames Stereo Pipeline (see Table S2 of the Supporting Information S1 for Observation IDs).

Outcrop orientation was measured along four stratigraphic layers: the top surface of the Capping Unit, its contact with the Olivine Rich Unit (ORU), layering within the ORU (if apparent), and the ORU's contact with the Noachian basement. It should be noted that the top surface of the Capping Unit is eroded as evidenced by impacts/pits and yardangs. Orientations of the Capping Unit outcrop surfaces (calculated from baselines on the order of 100 m) are within $\sim 5^\circ$ of horizontal (see Figure 3). The depositional mechanisms considered here (lava flow, aeolian erg, impact condensate, and ash fall) deposit materials horizontally. If the surface of the landform has

remained near-horizontal, then it likely has retained its original depositional orientation. For detailed methodologies, see Text S1 in Supporting Information S1.

We additionally made topographic profiles of the Capping Unit outcrops in bowl-shaped depressions (i.e., sloping downward in all directions at the margins) to assess whether draping occurred in all directions or just from one side (e.g., downslope from a source). These measurements helped to differentiate between formation scenarios involving effusive lava and various clastic origins, the former being less likely to drape such landforms equally on all sides or with a high relief-to-thickness ratio. We also examined data from the Mars Orbiter Laser Altimeter (MOLA) aboard Mars Global Surveyor (Smith et al., 2001) to find the topographic range for the unit as a whole.

3.3 Spectral Signal Extraction

We assess and compare the diagnostic spectral signatures of the Capping, Olivine-Rich, and Jezero Floor Units using reflectance spectra measured by the CRISM instrument (Murchie et al., 2007) on the Mars Reconnaissance Orbiter. Similar spectral signatures between these would imply common mineralogy and lend evidence to the hypothesis of a shared origin. We use three techniques to highlight weak spectral components in the geologic units of this study: (a) endmember extraction using the HySime algorithm introduced by Bioucas-Dias and Nascimento (2008), (b) Dot-Product Mapping, and (c) Dot-Product Noise Removal.

Endmember extraction uses Factor Analysis, a statistical method that calculates eigenvectors (or “endmembers”) representative of independent variance in a data set. The first eigenvector accounts for the greatest spectral variance, while each successive eigenvector describes less. Low-order eigenvectors—those describing the most variance—tend to have spectral shapes that can be interpreted as surface/sample spectral signals and varying degrees of

structured noise (e.g., Tarnas et al., 2021). While eigenvectors are useful for identifying the presence of spectral features, they should not be interpreted as exact 1:1 surface/sample signals (e.g., Tarnas et al., 2021). Endmember extraction has been applied to Mars spectral data to identify mineral components with both narrow (e.g., Amador et al., 2018; Das et al., 2022; Tarnas et al., 2019; Thomas & Bandfield, 2017) and broad absorption features (Glotch et al., 2006). Here, we use the HySime algorithm instead of the R-mode algorithm because laboratory studies have shown it to be more reliable due to HySime's separation and exclusion of noise subspaces, though non-Gaussian noise can still be present in resultant eigenvectors (Tarnas et al., 2021).

Following endmember extraction, we implemented a method called Dot Product Mapping to identify areas where each endmember is most strongly represented in the data (Das et al., 2022). This involves calculating the dot-product of an eigenvector of interest with each pixel in an Region of Interest (ROI), creating a full dot-product map. Areas that have a spectral shape corresponding to that eigenvector will have higher positive values, and those that have the inverse shape will have more negative values. This technique aids the interpretation of what may be causing variation in the data, such as mineral components (e.g., spatially correlated deposits), structured noise (e.g., noisy columns), etc. Further details on these methods are given in the Text S2 in Supporting Information S1.

4 Results

4.1 Mapping and Geomorphic Measurements

We mapped 415 outcrops covering an area of approximately 5,500 km², distributed across a region spanning ~50,000 km² and over 3 km of elevation (see Figure 1). With minor exceptions, the Capping Unit is always observed overlying the Olivine-Rich Unit. In addition to characteristic 1–5 km mesas in the Nili Planum and Libya Montes regions, we observe a more widespread

(~4,200 km²), contiguous exposure of the Capping Unit in Northern Nili Fossae (see Figure 2c). We find the Pitted Capping Unit of Goudge et al. (2015) is morpho- logically and geographically distinct from the Capping Unit of the present study (see Text S3 in Supporting Information S1).

Tonal layering in the base of the Capping Unit has been previously noted in Nili Planum by Bramble et al. (2017). We confirm the presence of bouldery, tonal layering across the regional extent of the unit. When apparent, this layering is parallel to sub-parallel to layering in the Olivine-Rich Unit. Figures 2c and 2d show examples of layering in the Capping Unit separated by over 20° of latitude (1,000 km) and 3,000 m of elevation. These two examples also show the layering in both the Capping and Olivine-Rich Units have similar expressions in thickness (meter-scale) and tonal variation (i.e., although the uppermost Capping Unit surface is relatively darker than the Olivine-Rich Unit, the tonality of layering in both tends to be similar; see Figure S6 in Supporting Information S1).

Topographic profiles were extracted from four Capping Unit outcrops with bowl-shaped depressions: two in Nili Fossae (Figure 3), one in Nili Planum, and one in Libya Montes (Figure S5 in Supporting Information S1). The surfaces of outcrops of the Capping Unit strongly conform to bowl-shaped concavities defined by the underlying Olivine-Rich Unit (ORU) and Basement Unit, with a relief-to-thickness ratios of roughly 10:1 (Figure 3). The Cap-ORU contact and any apparent layering in the ORU are subparallel in each case.

Dip measurements of several stratigraphic surfaces and internal bands were completed at seven outcrops (summarized in Figure 3). In each case, the one standard deviation variation of the dips was below 1.5°.

4.2 Morphological and Stratigraphic Comparisons to the Jezero Floor

The Capping and the Jezero Floor Units share several geomorphic characteristics. Circular pits and craters with raised rims are present on both units with sizes ranging from less than 10 m up to ~100 m in diameter. Preservation in both varies from sharp-rimmed to rounded, less well-preserved rims. Cavities tend to be variably filled with aeolian sediments.

At the outcrop-scale, both units show sharp, scarp margins. Outcrops erode into lobate, sometimes sub-circular shapes with angular recesses. With further erosion, margins become scalloped and light-toned (e.g., Figures 2g and 2j).

Finally, each unit stratigraphically overlies light-toned olivine-bearing rocks with layering. Figure 2j additionally shows possible layering in the Jezero Floor Unit that is subparallel to the layering in the olivine-bearing unit beneath it. Yardangs are present in some outcrops of the Capping Unit but not the Jezero Floor Unit.

4.3 Spectroscopy

We analyzed five CRISM images acquired across the extent of the Capping Unit and one over the Jezero Floor Unit (locations are in Figure 1). We find that the third or fourth eigenvectors of the Capping and Jezero Floor Unit outcrops exhibit a pair of broad absorptions at 1 and 2 μm that in laboratory spectra are due to Fe^{2+} crystal field absorptions. These spectral properties are strongly consistent with laboratory spectra of pyroxenes. The eigenvectors from the different sites show a high degree of correspondence to each other and to laboratory spectra of high-calcium pyroxene (HCP), low-calcium pyroxene (LCP), and a Shergotty meteorite (RELAB IDs in Table S4 of the Supporting Information S1).

We also examined HySime endmember eigenvectors from Olivine-Rich Unit exposures proximal to our Capping Unit outcrops (Figure 4b). The shapes of the Capping Unit and ORU

eigenvectors are similar within individual CRISM images. We discuss possible reasons for these similarities in Section 5.2.2 of the Discussion.

5 Discussion

Here we synthesize our Results and previous findings, leading us to the interpretation that (a) the Capping Unit and Jezero Floor represent a single, genetically linked unit (Section 5.1), (b) that this geographically vast rock formation exhibits characteristics most consistent with an origin as a volcanic ash (Section 5.2), and finally, (c) that this unit, combined with the Olivine-Rich Unit, may represent the products of related eruptions (Section 5.2.3).

5.1 Equivalency to the Jezero Floor

In the Results section, we note morphological (Section 4.2), stratigraphic (Section 4.2), and compositional (Section 4.3) similarities between the Capping and Jezero Floor Units. We conclude that the Jezero Floor and Capping Units are genetically equivalent, and that they represent one vast geologic unit.

5.2 Origin

Here we compare observations of the Capping Unit with the expected characteristics of impact condensates, lava flows, aeolian ergs, and volcanic ash-falls.

5.2.1 Layering, Draping, and Regional Uniformity

Layering of alternating tonality in the base of the cap—which is subparallel to layering in the Olivine-Rich Unit and apparent in each far-flung region of exposure—is difficult to explain as a spherule deposit. Spherule exposures on Earth and Mars have not been observed to exhibit such tonal bands (Edwards & Christensen, 2011; Simonson & Glass, 2004), which casts doubt on an impact-product origin.

Both lava flows and aeolian ergs can create deposits which appear to drape topography. For example, an aeolian erg may pile against sloped terrain and a low-viscosity lava flow may inundate a bowl-shaped depression from all sides (particularly if originating from vents across a wide area). However, the Capping Unit thinly conforms to bowl-shaped depressions, with relief-to-thickness ratios of approximately 10:1 over kilometer-scale outcrops (see Figure 3). Thin draping to this degree suggests against deposition as an aeolian erg or lava flow, as either mechanism would tend to fill, not thinly drape such depressions (Livingstone et al., 1996). The Capping Unit does not appear to flow along topographic lows, as would be expected from a lava flow. Furthermore, the remarkably uniform morphology and layering of Capping Unit outcrops separated by 1000s of kilometers and 1000s of meters of elevation (see Figures 2c and 2d) casts doubt on an aeolian erg hypothesis.

An ash-fall origin is consistent with the Capping Unit's exceptionally thin draping of bowl-shaped topography, regional uniformity, as well as its meter-scale bands of alternating tonality (e.g., Houghton & Carey, 2015).

5.2.2 Association with Olivine-Rich Unit

An ash-fall hypothesis is further supported by the Capping Unit's strong stratigraphic and geomorphic similarities with the Olivine-Rich Unit, shown by Kremer et al. (2019) and Mandon et al. (2020) to most likely be a volcanic ash deposit. Across 50,000 km², the Capping Unit is virtually always observed overlying the Olivine-Rich Unit (Figures 1b and 1c). Their contact and internal layers are parallel (Figure 3b). Tonal layering within both units are similar in both vertical scale and tonality (Figure 2e). The Capping Unit thinly and conformably drapes topography (Section 3.2), very similar to the behavior of the Olivine-Rich Unit (Kremer et al., 2019). Within

Jezero Crater, Kah et al. (2020) note tonal and textural similarities between the Jezero Floor Unit and the Olivine-Rich Unit beneath it.

Beyond these stratigraphic and geomorphic associations, we can also compare the composition of these two units. Figure 4b shows the similarities in crystal-field absorptions between the Olivine-Rich and Capping Units. We interpret that this is a pyroxene signal tied to bedrock composition, not the composition of weathered sediments, because the eigenvector Dot-Product Map of the pyroxene signal is distributed uniformly across both units instead of being concentrated in topographic lows (e.g., craters, pits) or at the edges of scarps.

The conformable contact between both rock formations across such a wide region is notable given the Olivine Rich Unit's high friability (Kremer et al., 2019). This, in tandem with observations of strikingly similar layering structures, draping behavior, and compositional associations all point to a shared formation mechanism as an air-fall deposit from a volcanic source.

5.2.3 The Olivine-Rich and Capping Units: A Shared Source?

The many similarities between the Olivine-Rich and Capping Units further prompts consideration of the following possibility: that these two geologic units may represent the products of related eruptions. Possible causes for the ultramafic to mafic geochemistry observed include a pre-depositional geochemical shift in magmatic source(s) or post-depositional alteration by aqueous processes (Kaufman et al., 2022). If the former, analyses of melt inclusions in sample olivine crystals would potentially lend insight into a chemically evolving magmatic system on Mars. If the latter, in-situ and lab analyses would help determine the timing and nature of aqueous activity at Jezero Crater (Kaufman et al., 2022).

The precise location of a source for this extensive amount of volcanoclastic material remains unclear. Source vents could have been overlain by Syrtis Major lavas or eroded away in the significant time since emplacement. As yet unidentified, highly eroded sources may exist as have been found in other regions of Mars (Michalski & Bleacher, 2013).

5.3 Validation

Our remote-sensing investigation prompts hypotheses that in-situ analysis by Perseverance rover can test. Origin (e.g., deposition as volcanoclastic or lacustrine epiclastic) may be assessed by examining the unit's grain morphology and whether the unit exhibits planar versus cross-bedded features. For example, Ruff et al. (2014) demonstrated an air-fall origin for the olivine-rich rocks in Columbia Hills by examining the unit's highly angular grain morphology. Equivalency of the Capping Unit and Jezero Floor may be tested through bulk chemical analyses and a more detailed inspection of morphology. The hypothesis that the Olivine-Rich and Capping Units are products of related eruptions may be similarly substantiated by further in-depth morphological and compositional analyses.

5.4 Implications

5.4.1 Timing of Aqueous Activity at Jezero

A volcanic ash-fall origin for the Jezero Floor, as opposed to a cemented lacustrine/erg origin, would allow future Earth-based laboratory analysis to determine the timing of the unit's deposition. This would provide a critical upper bound on the age of Jezero's aqueous activity.

Should the Jezero Floor and olivine-bearing unit beneath it prove to be a sequence of ashes, this would support the hypothesis that the Delta Unit lies at least mostly above instead of between the Olivine-Rich and Jezero Floor Units.

5.4.2 Mars' Volcanic Transition 3 Ga

Given the Capping Unit's age of 3.6–3.96 Ga (Mustard et al., 2009; Werner et al., 2008) it was likely emplaced during a global shift in Mars volcanism in the late Noachian/early Hesperian: from explosive to effusive volcanism (Bandfield et al., 2013; Robbins et al., 2011) as well as from broadly low-calcium to high-calcium pyroxene volcanic products (Baratoux et al., 2013; Mustard et al., 2005; Poulet et al., 2009). The timing and underlying causes of this volcanic transition are uncertain. However, analysis of melt inclusions within returned samples from the Capping and Jezero Floor Units could help resolve competing causal hypotheses in the literature for this shift, such as volatile depletion (Bandfield et al., 2013) versus cooling of the mantle (Baratoux et al., 2013).

6 Conclusions

We mapped and analyzed the Circum-Isidis Capping Unit's stratigraphic position, internal layering, draping characteristics, and regional uniformity. Comparing to the expected characteristics of several proposed formation mechanisms, we find its expression is most consistent with deposition as a volcanic ash. Geomorphic and compositional similarities with the Jezero Floor Unit imply that the two units are related, either in terms of a formation mechanism, or even the same formation event/sequence.

We note many similarities between the Capping Unit and Olivine-Rich Unit, including their stratigraphic correlation, similar internal layering morphologies (tonality alternations, vertical scale), parallel contacts and internal layers, and a conformable contact across 50,000 km², despite the notably friable nature of the Olivine-Rich Unit (Kremer et al., 2019). This prompts consideration of the possibility that these two rock formations represent the products of related eruptions. The ultramafic to mafic chemistry of this possible “sequence” could have been caused by either pre- or post-depositional processes (e.g., a chemically evolving magmatic source or

differences in exposure to aqueous alteration as suggested by Kaufman et al., 2022). Future detailed morphologic and compositional analyses by Perseverance rover may be able to provide further insight into these possibilities.

This sequence of ash layers, which would likely include fluid and melt inclusions within the olivine grains, would have tremendous petrologic value for understanding the magmatic processes that occurred during the unit's formation concurrent with the Noachian/Hesperian

transition. This makes it an important target for in-situ exploration and sampling by the Perseverance rover.

The origins and petrogenetic relationships of dark-toned caprocks in several other mineralogically diverse regions on Mars are uncertain and remain as an area of future work. Regional analyses of integrated photogeologic and compositional datasets are required to ascertain the origins of those rocks, and comparative studies are required to understand their relationships to each other. Though their origins likely differ, understanding their formation histories would contribute to efforts to constrain the causes and nature of the Noachian-Hesperian transition, including transformations in surface environments and volcanism.

Data Availability Statement

Laboratory spectra included here may be acquired from the NASA/Keck Reflectance Experiment Laboratory (RELAB) at Brown University (<https://pds-speclib.rsl.wustl.edu/search.aspx>). HiRISE images may be downloaded from the mission's website (<https://hirise-pds.lpl.arizona.edu/PDS/>). The CTX image mosaics can be found at the Murray Lab at Caltech (<http://murray-lab.caltech.edu/CTX/tiles/beta01/>). CRISM images and the MOLA map are available from the Planetary Data System Geosciences Node (<https://pds-geosciences.wustl.edu/missions/mro/crism.html> and <https://pds-geosciences.wustl.edu/missions/mgs/mola.html>, respectively). Some of the research was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration (80NM0018D0004). The data used in this paper are available at <https://zenodo.org/record/6354669#.YjHoLHrMKUI>.

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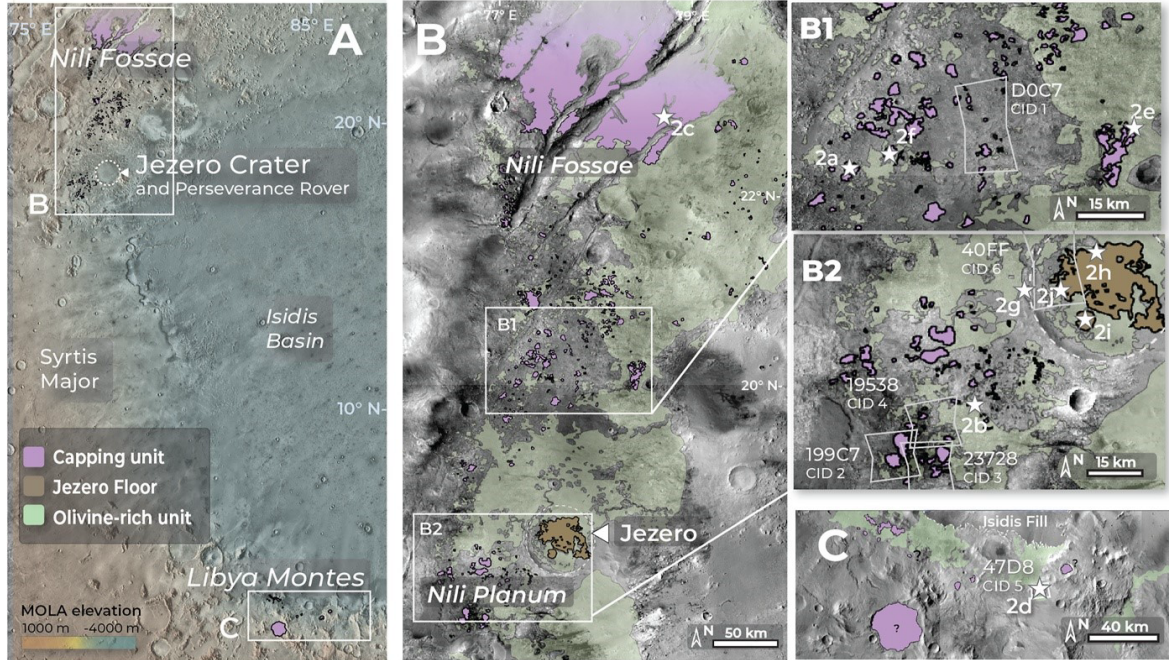
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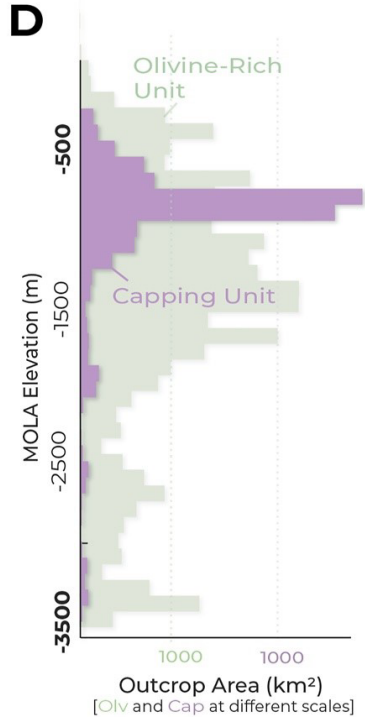
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Capping Unit - Geographic Extent



Topographic Extent



Stratigraphic Comparison to Jezero

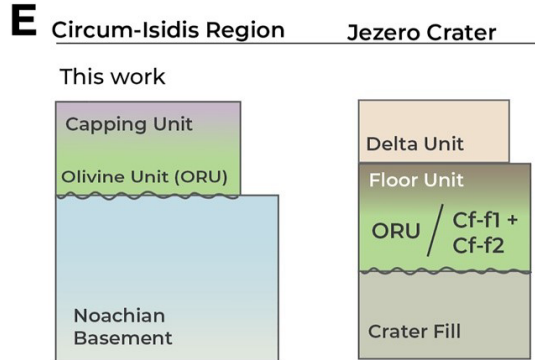
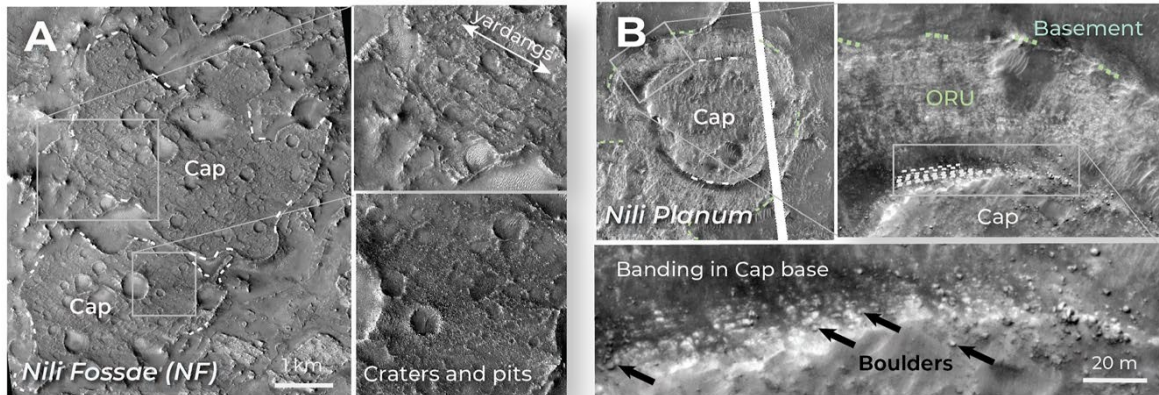
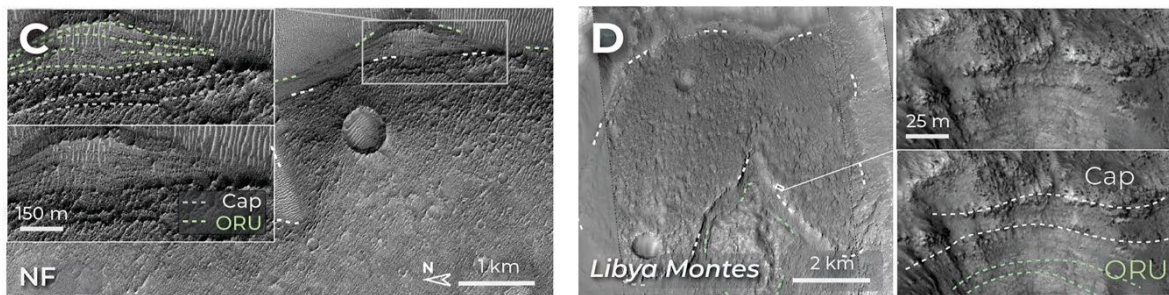


Figure 1-1. (a) A map of the Circum-Isidis Capping Unit (purple) on a Thermal Emission Imaging System (THEMIS) daytime basemap overlaid by a semi-transparent MOLA elevation map. Smaller outcrops of the Capping Unit appear black. (b) The Capping Unit, Olivine Rich Unit (ORU; mapped as green (Kremer et al., 2019)), and the Jezero Floor Unit (brown) in the Nili Fossae/Nili Planum region. Locations of the outcrops shown in Figure 2 (stars) and the CRISM footprints used to produce eigenvectors in Figure 4 are indicated. (c) Outcrops in Libya Montes. Question marks note outcrops with no apparent ORU beneath them. (d) The topographic extent of the Capping Unit compared to the topographic extent of the Olivine-Rich Unit. (e) Our proposed stratigraphic hypothesis for Circum-Isidis Region and Jezero Crater.

Capping Unit distinguishing characteristics



Capping Unit examples [separated by 1000 km distance and 3000 m elevation]



Comparison to Jezero Floor Unit

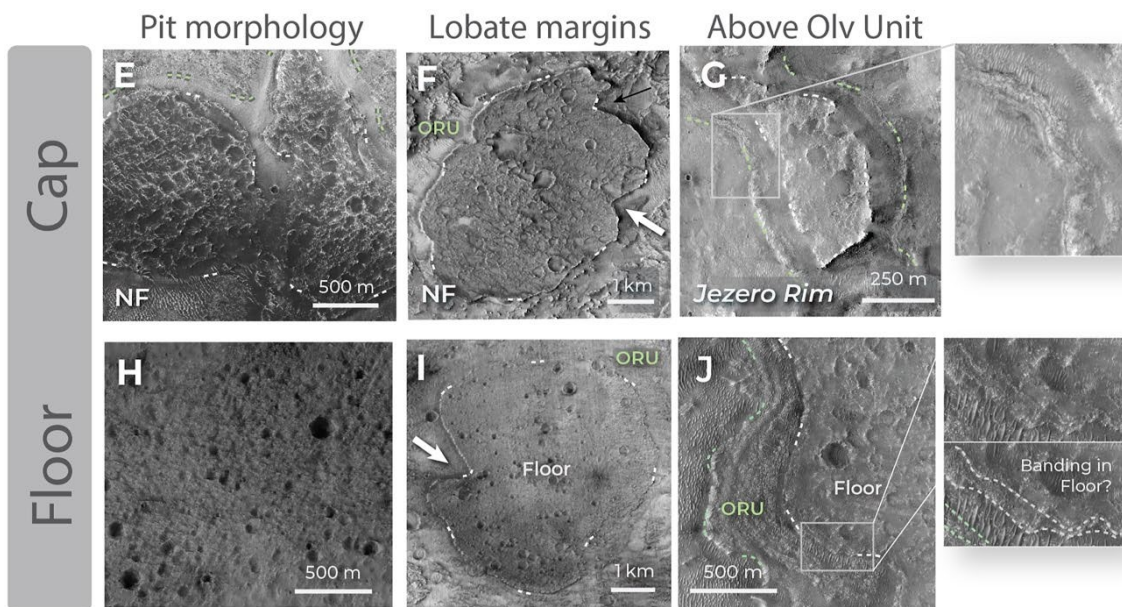
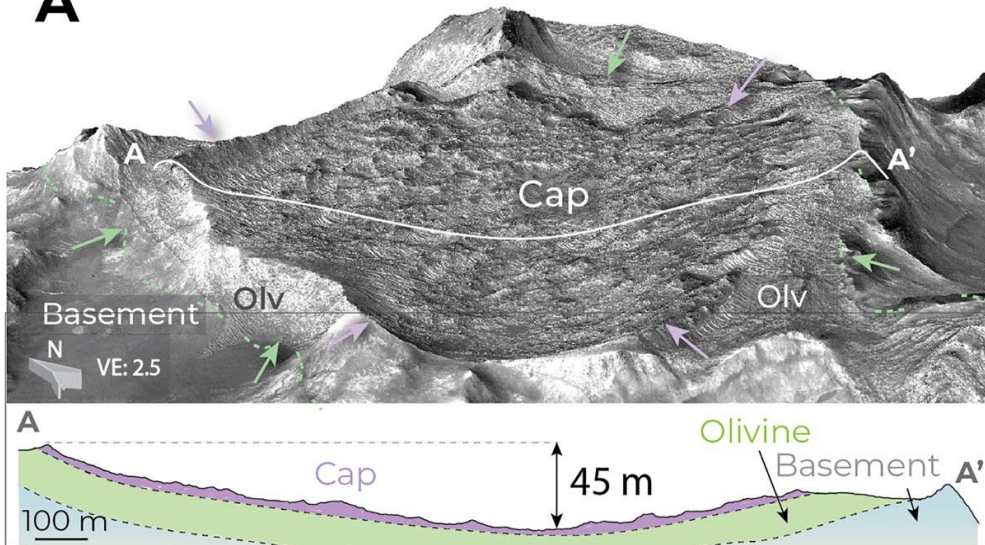


Figure 1-2. (a) Distinguishing morphological characteristics of the Capping Unit including a pitted, crater-retaining surface with steep, lobate bounding scarps and occasionally yardangs. Widely spaced dashed lines indicate outcrop edges (white, Capping Unit; green, Olivine-Rich Unit (ORU)). (b) Stratigraphic position over the Olivine-Rich Unit (ORU). Insets in (b) show the light tone, fracturing, and tonal layering emblematic of the ORU and layering at the base of the Capping Unit. Black arrows indicate boulders in these bands. (c and d) Capping Unit banded outcrops in Northern Nili Fossae and Hashir crater in Libya Montes. Note boulders in Cap bands versus none in ORU bands in (d). (e–j) Comparisons between the Capping and Jezero Floor Units: crater/pit morphology (e and h), lobate margins with white arrows indicating angular recesses (f and i), and stratigraphic relationship with banded, olivine-bearing exposures (g and j). The inset in (j) shows possible layering in the Jezero floor subparallel to layering in the olivine-bearing unit beneath it. All image IDs are noted in Table S1 of the Supporting information S1.

Capping Unit in bowl-shaped topography

A



Comparison of stratigraphic dips

B

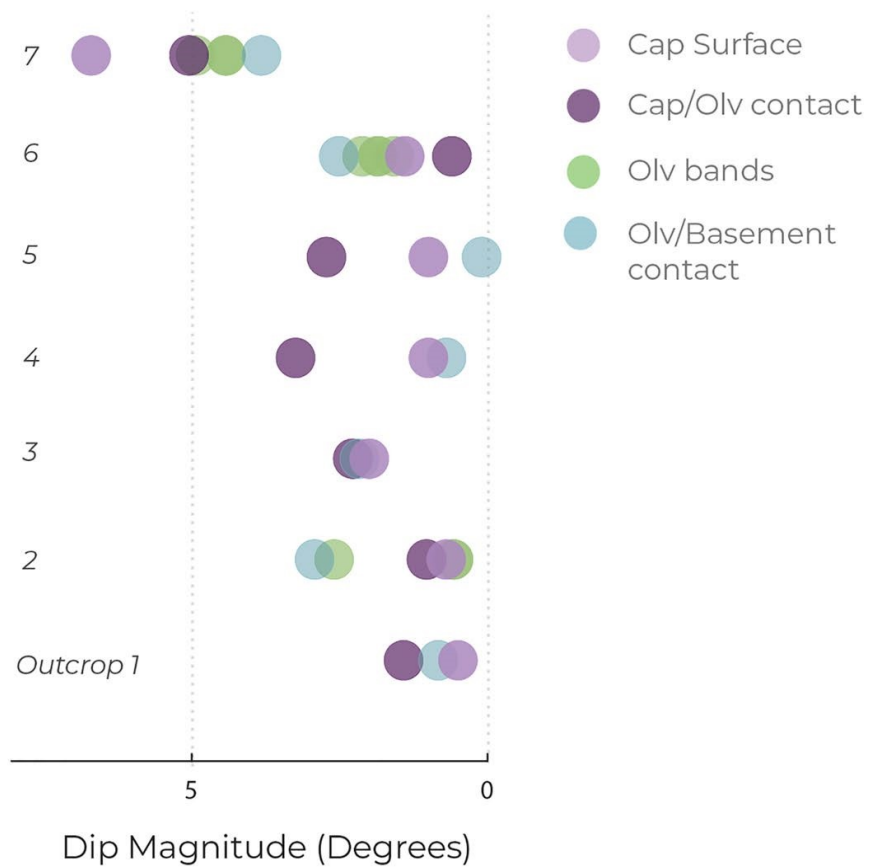


Figure 1-3. (a) Perspective view and interpreted cross-section of the Capping Unit draping the Olivine-Rich Unit and basement rock (DTEEC_002756_1830_002822_1830). Vertical exaggeration indicated in figure. Cross-section location indicated by the white line. The Olivine-Rich Unit and Capping Unit are indicated by green and purple arrows respectively. (b) Dip angles calculated for several Capping Unit outcrops and associated stratigraphic layers, where each line is a separate outcrop, numbered 1–7. Olv = Olivine Rich Unit. Outcrop locations are noted in Table S3 of the Supporting Information S1.

Compositional comparisons

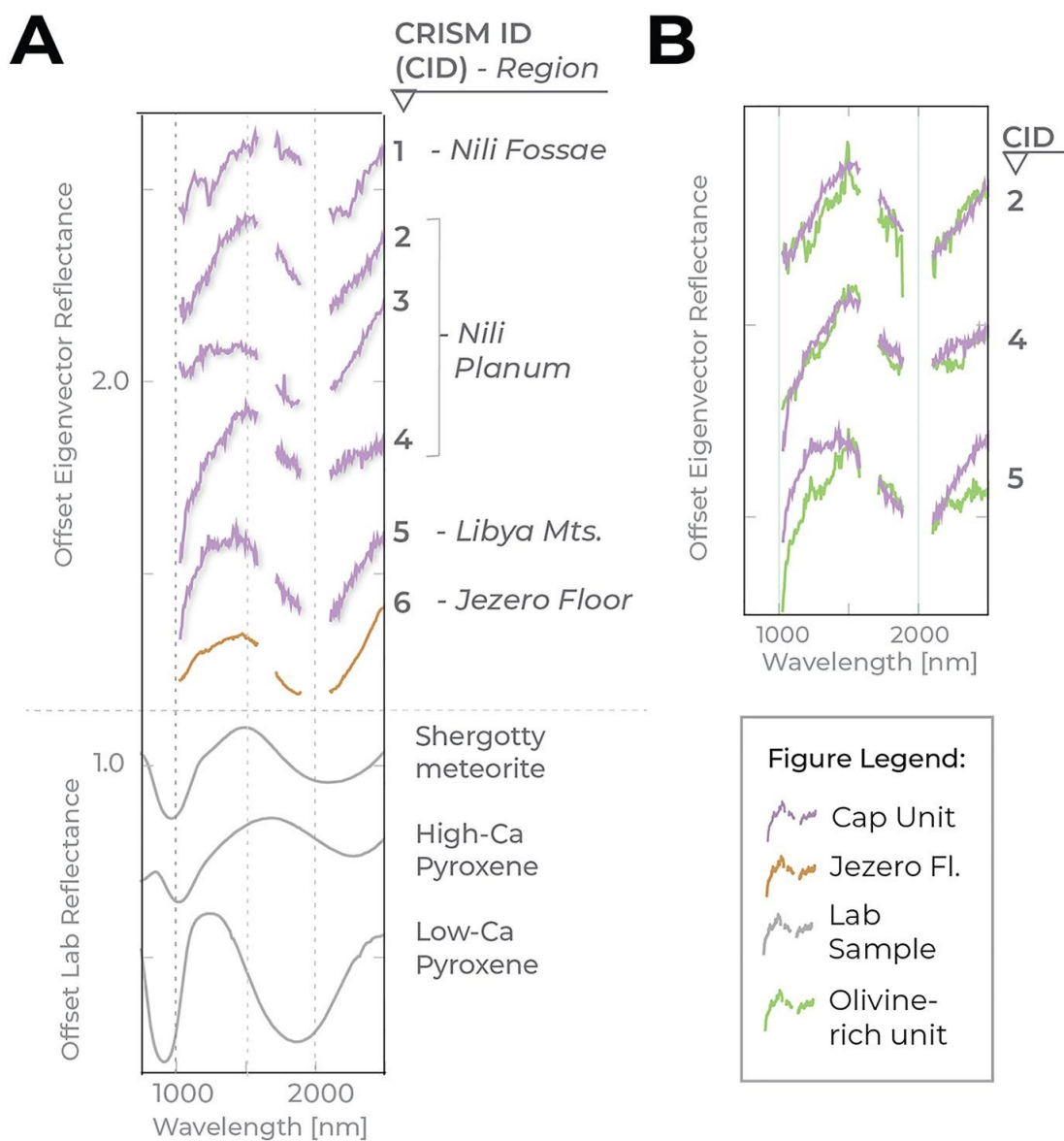


Figure 1-4. (a) Eigenvectors from the Capping Unit, Jezero Floor Unit, and RELAB laboratory spectra for comparison purposes. (b) Eigenvectors from Capping Unit and Olivine Rich Unit (ORU) outcrops within single CRISM images. Gaps in spectra are for regions of atmospheric and instrument noise. CRISM ID numbers and footprints correspond to those in Figure 1b. See Tables S4 and S5 in Supporting Information S1 for full RELAB/CRISM IDs.

CHAPTER 2: A Dimensionality Reduction Framework for Planetary Science: Case Study of Gravitational Signatures of Lunar Impact Craters

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In Review

Abstract

The increasing size and resolution of planetary datasets has necessitated the development of analytical techniques that isolate geophysically meaningful structures while preserving analytical precision. Motivated by recent applications in infrared spectroscopy, we present a new framework for statistical analysis of planetary datasets called Guided Endmember EXtraction (GEEX). This framework enhances the well-known dimensionality reduction technique Principal Components Analysis (PCA) by emphasizing treatment of correlated data points and strategic data subsetting. We validate our approach on a case study of impact-induced signatures in lunar gravity data produced by the Gravity Recovery and Interior Laboratory (GRAIL) mission.

While previous work using area-averaging techniques has yielded several first-order insights into the structure and porosity of the lunar crust, much of the observed variation in crater-related gravity anomalies remains underexplained. We show that GEEX reproduces several key findings from these studies with an order of magnitude greater precision, including a transition associated with the lunar depth of pore closure, a feature previously detectable only via additional Bayesian analysis. Notably, our results reveal previously unidentified, distinct eigenvector "shapes" for positive and negative gravity anomalies and a critical porosity of 16.5% at which craters are equally likely to produce positive or negative anomalies, implying that the porosity of the shallow lunar crust is not at equilibrium.

Collectively, our results not only deepen our understanding of lunar crustal structure and the impact cratering process, but also demonstrate GEEX's broader potential to enhance the interpretation of large planetary datasets.

1 Introduction

Impact cratering is a fundamental geologic process, having shaped planetary surfaces and subsurfaces since the formation of the Solar System. The Moon is an ideal environment for studying the generation and evolution of porosity via impacts because of its ease of access, abundant and high-quality datasets, and lack of geologically significant hydrosphere or atmosphere. Understanding how impacts have modified planets is central to unraveling the long-term geochemical and geophysical evolution of planetary crusts and interiors, including critical effects on heat flow, volatile storage, tectonic activity, and the development of habitable environments.

Datasets produced by modern planetary missions, such as NASA's GRAIL (Gravity Recovery and Interior Laboratory) and MRO (Mars Reconnaissance Orbiter) missions, provide information about planetary crusts and interiors at an unprecedented scale and resolution. The size and complexity of modern datasets, however, present both significant opportunities and challenges. In particular, the ability to extract meaningful and precise signals from datasets of gravity, topography, spectra, and seismic properties can often be limited by methodological approaches. Infrared spectroscopy has seen significant advancements in applied statistical methodologies, where dimensionality reduction techniques have greatly enhanced remote detection and interpretation of mineralogical composition (Thomas & Bandfield, 2017; Amador et al., 2018; Tarnas et al., 2019, 2021; Das et al., 2022; Hundal et al., 2022). Here we assess how such approaches may enable novel insights into lunar structure and impact processes using gravitational data.

Although dimensionality reduction techniques have proven effective in interpreting complex spectral datasets, they have yet to be widely applied in the analysis of planetary gravity data. This gap is particularly notable given the availability of exceptionally high-resolution gravity

measurements from NASA's GRAIL mission, which extends up to spherical harmonic degree and order 1500 and offers the most detailed static gravity field of any planetary body, including Earth (Zuber et al., 2013; Park et al., 2015; Goossens et al., 2020). With a spatial scale of ~ 4 km, these data reveal both global-scale structure and fine-scale crustal heterogeneity, exposing a variety of subsurface features such as buried dike swarms (e.g., Deutsch et al., 2019) and basin ring faults (e.g., Andrews-Hanna et al., 2014). GRAIL's dataset is not only highly spatially resolved but also characterized by low noise and high internal consistency, making it a rich dataset for investigating the structure and evolution of the lunar interior.

Despite the availability and exceptional resolution of the GRAIL dataset, the precise gravitational effects of impact craters remain underexplored, with existing models only able to explain a fraction of the variation observed in gravitational anomalies associated with lunar craters (Bierson et al., 2016; Izquierdo et al., 2021; Soderblom et al., 2015). These studies incorporating area-averaging techniques have provided a variety of geophysical insights, including the detection of the depth of pore closure and a notional structure for the Moon's upper crust (Soderblom et al. 2015, Izquierdo et al. 2021). However, these techniques come with significant limitations. For example, the estimated diameter breakpoint at 93 km associated with the depth of pore closure has an uncertainty of 62 km, about 65% of the nominal value. Furthermore, although crustal thickness has been suggested to affect impact signatures in models, this effect remains unobserved in area-averaging analyses (Bierson et al. 2016). These challenges in signal isolation and loss of precision extend beyond studies of impact gravity anomalies, impeding advancements across diverse areas of planetary science. Gravitational study of the Moon is one of many areas of planetary data analysis that would benefit significantly from dimensionality reduction techniques.

We outline a statistical dimensionality reduction methodology for planetary gravity data called Guided Endmember Extraction (GEEX), pronounced "geeks". GEEX offers a quantitative framework for characterizing structural variability in geophysical data and assessing how such variations systematically change with underlying physical parameters. This approach emphasizes the treatment of correlated data and strategic data subsetting to enhance signal clarity and minimize contributions of artifacts or extraneous structures. We derive radial gravitational profiles from the same lunar highland impact craters ($D = 27\text{-}201$ km) analyzed in Soderblom et al. (2015), a study that employed conventional area-averaging techniques. Our implementation of GEEX uses Principal Components Analysis (PCA), a simple and robust dimensionality reduction technique.

In Section 2 we review successes and limitations of previous studies on impact-induced gravity on the Moon, followed by a background on dimensionality reduction techniques. In Section 3 we describe our GEEX framework and how we apply it to our crater gravity profile dataset. In Section 4 we use GEEX to derive a set of "eigenvectors", profile shapes that capture statistically significant variations in Bouguer gravity across the impact crater dataset. We interpret the geologic significance of these eigenvectors and compare our results to those of conventional area averaging methods to assess the improved precision enabled by GEEX. We further use GEEX to examine the effects of diameter and target porosity. In Section 5, we summarize our conclusions, discuss the implications of the case study, and finally explore the potential utility of this framework in future analyses.

2 Background

2.1 Lunar Gravity Studies of Impact Craters

Here we apply GEEX to radial gravitational profiles of impact craters in Gravity Recovery and Interior Laboratory (GRAIL) data, one of a variety of potential applications of GEEX to gravity and other planetary datasets.

2.1.1 Background: Impacts and Porosity Generation

Impact cratering is a fundamental geologic process that governs planetary evolution across a vast range of spatial and temporal scales (Melosh, 1989). Impact craters inject heat, drive material redistribution through ballistic ejection and internal mixing, modify rotational inertia, and variably generate or destroy porosity (Melosh 1989). Much recent work has focused on the role of impact craters on the evolution of planetary porosity at a variety of spatial scales, ranging from micron-scale modification in the regolith to large-scale structural modifications that penetrate into the mantle (Huang et al., 2022; Wahl et al., 2020; Wiggins et al., 2019, 2022). The Moon provides an ideal environment for studies of impact cratering because of its negligible atmosphere or hydrologic cycle, abundant global and high-resolution datasets, and proximity to Earth.

Impacts variably create and destroy porosity, with the sign, magnitude, and location of these changes being dependent on the target and impact properties. Porosity is created during impacts by extensional fracturing, faulting, redistribution of material, as well as dilatant bulking in response to shear stress (Alejano & Alonso, 2005; Collins, 2014; Melosh, 1989; Pilkington & Grieve, 1992; Rajšić et al., 2024; Wiggins et al., 2019, 2022). Meanwhile, porosity may be destroyed by the initial compressive shockwave of an impact, thermal annealing, melt-production, convergent flow paths, and changes to overburden pressure (Melosh 1989).

The depth at which a crater structurally disturbs the crust can be approximated by the depth of the transient crater, defined as the bowl-shaped structure formed when the expanding crater reaches its deepest extent. This depth corresponds to between one-third and one-fourth of the

transient crater diameter (Melosh & Ivanov, 1999). Due to gravitational instability, the transient cavity collapses, forming a final crater that is shallower and wider than the original cavity. The final crater radius R is related to the transient crater radius (R_T) by $\frac{R}{R_T} = 1.02 \left(\frac{R}{R_*}\right)^{0.079}$, where R_* is the radius of the simple-complex transition on the Moon (Holsapple, 1993). Craters in our diameter range ($D = 27\text{-}201$ km) produce transient crater depths corresponding to depths between approximately 5 and 50 km, with exponentially more craters represented at smaller sizes.

To analyze trends between impact-induced gravity and regional porosity (a proxy for pre-impact porosity), we use shallow porosity data derived by Besserer et al. (2014). As noted above, a significant percentage of the craters in our dataset (~90%) excavate depths of 25 km or less within the lunar crust, making the application of shallow porosity, rather than bulk porosity, a reasonable approximation.

2.1.2 Background: Gravity

We use the Bouguer gravity of craters to interpret changes in subsurface porosity under an assumption of constant density. Bouguer gravity removes the effect of topographic variations with an assumed constant density. Ideally, Bouguer gravity coincides with subsurface gravitational anomalies. The interpretation of Bouguer gravity data is affected by several factors such as deviations from the gravity field's assumed density, including subsurface changes in porosity, and the distance/depth of the gravity signal source from the spacecraft. Porosity changes can be inferred from gravity data assuming the grain density of a terrane is relatively constant using the formula $\phi = 1 - \frac{\rho_b}{\rho_g}$, where ϕ is porosity, ρ_b is bulk density, and ρ_g is grain density.

Gravity data may typically be expressed in terms of spherical harmonics, and we will later use this to our advantage when applying GEEX. Spherical harmonics are a set of orthogonal basis functions defined on a sphere. Similar to Fourier series, sets of spherical harmonics, when multiplied by appropriate coefficients, can be summed to define any square integrable function on a sphere $f(\Omega)$:

$$f(\Omega) = \sum_{l=0}^{\infty} \sum_{m=-l}^l f_{lm} Y_{lm}(\Omega)$$

where Y_{lm} is a spherical harmonic function of degree l and order m , f_{lm} is the corresponding weight assigned to that particular function, and $\Omega = (\theta, \varphi)$ is the position on the sphere, where θ is colatitude and φ is longitude. Longer-wavelength features, such as crustal bulges, are represented by lower degree and order spherical harmonic functions, whereas shorter-wavelength features, such as complex craters, are described by higher-degree and order terms. The equivalent cartesian wavelength λ_c of a spherical harmonic of degree l is given by $\lambda_c \approx 2\pi R_p / \sqrt{l(l+1)}$, where R_p is the radius of the sphere or planetary body on which the function is defined. Craters may be minimally described by the half-wavelength resolution of a degree, $\lambda_c/2$. The maximum degree $l_{\max}$ of a spherical harmonic function is often used to define the smallest/shallowest resolvable features. More mathematical preliminaries necessary for understanding spherical harmonic applications to geophysics can be found in Wieczorek et al. (2015).

We use the highest resolution Bouguer gravity field currently available for the Moon, GRGM1200B RM1 model with $\lambda = 1$, calculated to degree and order 1200 by Goossens et al. (2020). This gravity field assumes a density of 2550 kg/m³ for the lunar crust. For this study, we follow the example of Izquierdo et al. (2021) and use only spherical harmonic degrees 7–650. This corresponds to a maximum half-wavelength resolution of ~ 8 km. Degrees 1–6 were filtered out to

remove the effects of the crustal asymmetry, and degrees greater than 650 were removed to reduce noise. A cosine taper was applied to degrees $l = 600-650$ to reduce ringing. Gravitational data was analyzed using pyshtools, an open-source archive of spherical harmonic data analysis routines (Wieczorek & Meschede, 2018).

Previous workers have isolated impact craters from overlapping gravitational features using Residual Bouguer Anomaly (RBA) to gain important first order insights (Bierson et al., 2016; Izquierdo et al., 2021; Milbury et al., 2015; Soderblom et al., 2015). This technique produces a single number for each crater that describes the impact's net gravitational anomaly change. This net change is calculated by subtracting the area-weighted mean of an exterior region, between the rim-flank and 2 radii (R) from the crater center, from an interior region, the area weighted mean of data interior to the rim. Soderblom et al. (2015) used RBA to (a) constrain the depth of pore closure on the Moon and (b) find that crater diameter and regional porosity are important factors correlated with post-impact anomaly. However, Bayesian statistical models were required to find this transition at craters $D \sim 90$ km, producing large error bars ~ 70 km wide. Milbury et al. (2015) modeled lunar impacts and supported the findings of Soderblom et al. (2015). Furthermore, Bierson et al. (2016) expanded on these studies, testing a variety of terrane properties using a linear model. This study was again unable to show the effects of parameters beyond diameter and regional porosity, and their linear model explained only 10% of the observed variation in RBA. More recently, Izquierdo et al. (2021) highlighted breaks in slope of en masse RBA data to detect a structural transition 3-5 km deep in the lunar megaregolith, again requiring Bayesian analysis due to high scatter in the data.

2.2 Dimensionality Reduction and Guided Endmember Extraction (GEEX)

GEEX is a generalized framework for applying dimensionality reduction techniques to planetary data. Dimensionality reduction and clustering algorithms together comprise the broader class of analytical tools referred to as Unsupervised Machine Learning. Dimensionality reduction techniques are a set of algorithms that identify and extract meaningful patterns and structure by representing data along lower-dimensional axes of variation. Examples of dimensionality reduction techniques include Principal Component Analysis (PCA; Johnson & Wichern, 2007), Independent Component Analysis (ICA; Stone, 2004), Factor Analysis (FA; Gorsuch, 1983; Bioucas-Dias & Nascimento, 2005), Non-negative Matrix Factorization (NMF; Gillis, 2020), and manifold learning (e.g., t-SNE; Maaten & Hinton, 2008). Each of these dimensionality reduction techniques may produce either orthogonal or non-orthogonal components and constitute either a linear or non-linear approach.

Application of the GEEX framework can hypothetically utilize any dimensionality reduction technique, including those outlined above. However, our case study focuses on the use of PCA within the GEEX framework, as PCA is not only robust, but also the simplest form of dimensionality reduction. PCA identifies a set of orthogonal components, called eigenvectors. The first eigenvector aligns with the “shape” of greatest variation in the dataset. Each following orthogonal eigenvector captures progressively less variance. Each eigenvector has an associated eigenvalue, characterizing the amount of variance encompassed by that eigenvector. Linear combinations of these eigenvectors, when weighted by appropriate coefficients, can be summed together to reproduce the original dataset. Because variations captured by each PCA eigenvector are mutually independent, there is no redundancy in the representation of the data. This property enhances interpretability, as each eigenvector isolates a distinct mode of variation, making PCA an attractive technique for a wide range of data analysis scenarios.

PCA may be successfully applied to planetary datasets using a minimum of two steps: (1) data standardization and (2) data matrix decomposition, resulting in eigenvectors and eigenvalues. However, this bare-bones approach to PCA may fail to target structures of interest within a dataset, either missing such features entirely or incorporating substantial interference from structured noise or extraneous components. Therefore, PCA and related techniques can benefit greatly from additional preparation and analysis steps, such as those offered by GEEX.

3 Methods

We describe the steps of the GEEX methodology and present our tailored application to gravitational profiles of lunar craters. To illustrate this approach, we first apply GEEX to a simplified and schematic example of 11 crater profiles, each sampled at five points, before extending the analysis to our full dataset of 1,184 profiles, each sampled at seven points.

GEEX encompasses the following key steps: (1) strategic selection of input data in physical space, (2) strategic selection and cleaning of data in signal space, (3) employment of standardization methods that preserve data correlations, (4) Dimensionality Reduction. The resulting output components or “endmembers” can then be used in analysis of geological or geophysical processes. To further enhance the isolation and interpretability of GEEX derived trends, we additionally employ (5) Dot Product Value analyses and (6) further iterative subsetting.

In our analysis, "dimension" refers to an axis along which measurements are recorded. Data sample, feature, or instance refers to an n -dimensional observation of a geophysical structure. Data profile refers to a one-dimensional set of measurements. Data measurements refer to zero-dimensional scalar quantities representing the magnitude of an element at a defined coordinate, such as a position, wavelength, or timestep. For a complete set of definitions for terms used in this

study, please refer to Table 1 of the Supplementary Materials. Despite this study's focus on one-dimensional profile datasets, GEEX may be applied to data of any number of dimensions.

Step 1. Strategic Input Data Selection in Physical Space

Effective application of GEEX requires a dataset that contains repeatable, correlated signals, such as mineral spectra or gravity anomalies associated with impact craters. Assessing the suitability of the dataset is therefore a critical first step. Data must be able to be manipulated such that corresponding measurements capture the same part of the signal of interest. The sample resolution and number of samples in a dataset may also affect whether GEEX can be properly applied. For instance, to perform PCA, the dimensionality of the dataset imposes a constraint: the number of independent samples (e.g., data profiles) must be at least equal to the number of measurements per sample (e.g., points per profile) to avoid rank deficiency in the covariance matrix (see below).

Careful selection of input data is essential to highlight relevant trends within related datasets and minimize unwanted variations. The shapes of PCA eigenvectors and the magnitudes of their corresponding eigenvalues depend strongly on the variance of the input data. Therefore, input data can be strategically selected to emphasize more nuanced or weakly expressed structures and trends.

For our application of GEEX to lunar gravitational profiles, we exclude craters expected to show variations beyond the scope of the study. This includes the following: 1) structural differences in crater shape, such as simple vs. complex, 2) geochemical variation, such as the contrast between the lunar highlands, maria, and South Pole Aitken basin, and 3) craters with outlier residual Bouguer anomalies among craters in their geographic region.

Our study therefore uses a set of complex lunar highland craters ($N = 1184$) with diameters $D = 27\text{-}201$ km, the same set as studied in Soderblom et al. (2015), which were in turn selected from a compilation in Head et al., (2010). Highland craters are defined as those whose mean surrounding terrane elevation, defined as between the crater's rim flank (Pike 1977) and $2R$, exceeds 0.5 km. This diameter range was selected to exceed the simple-complex transition and to exclude craters sizes at which mantle mantle uplift is measurable in the crater center ($< 0.2 R$). Craters in the dataset used by Soderblom et al. (2015) were selected from the Head et al. (2010) compilation based on the uniformity of their residual Bouguer anomaly, and likewise exhibit few dominant variations outside of the two parameters of interest in our case study (porosity and crater size), making them appropriate for GEEX analysis. Variations outside of the scope of this study, including those due to crustal thickness and age, have not been previously shown to have measurable effects on the RBA signatures of craters (Bierson et al. 2016). Using the same dataset as Soderblom et al. (2015) allows us to compare the results of GEEX with those of conventional statistical methods currently being used in gravity analyses. Locations of analyzed craters are shown in Figure 1.

While basin-scale porosity production has been characterized by many previous modeling studies, showing it to be the most important crater size range for porosity production (e.g., Huang et al., 2022; Wahl et al., 2020; Wiggins et al., 2019), observational constraints of these models are limited. Porosity production in basin-scale impacts is difficult to study via analysis of gravity measurements because they are large enough to uplift the mantle, obscuring the effects of impact-induced porosity production and compaction. Meanwhile, we do not have robust observational constraints on how impact craters of any size range (basin scale and smaller) produce and destroy

porosity, requiring studies of craters smaller than those that uplift the mantle in seismic and gravity datasets.

Complex craters are numerous on the lunar surface (1184 in this study's inventory). However, their influence on lunar porosity evolution remains incompletely explored. Gravitational profile data, for instance, has not previously been studied for this diameter range. Given these are the largest craters that can be studied via gravity analyses before mantle uplift obscures porosity relationships, we are providing important insights into how craters generally create and destroy porosity as a function of distance from the crater center. Insights from this work can be further explored via modeling and potentially extrapolated to larger basin impacts. As mentioned earlier, complex craters in our diameter range ($D = 27\text{-}201$ km) structurally disturb the crust between 5 and 50 km of depth. Thus, this size range probes the range of crustal thicknesses expected in the lunar highlands, which is between 20 and 60 km deep.

While the overwhelming majority of the original 1185 complex craters examined in Soderblom et al. 2015 have been previously and unambiguously demonstrated using photogeologic evidence (Head et al., 2010) as being complex craters, Crater 1176 (Figure S2, see also supplementary table of Crater IDs T2) is the sole crater in the Soderblom et al. (2015) inventory to have photogeologic and gravitational characteristics that preclude unambiguous identification as a complex crater. Therefore, except where mentioned below, this crater is excluded from our analyses. Throughout our presentation of our case study, we refer to the dataset comprising all $N = 1184$ craters as the “full dataset”.

Step 2. Strategic Input Data Selection in Signal Space

Along the coordinate dimension of sample profiles (e.g., wavelength, distance from crater center), the range of measurements should also be reduced and cleaned to isolate desired trends and structures while also reducing structured variations outside the scope of the analysis.

For this study, isolating our desired signal along the coordinate dimension involves two steps: 1) determining the best length of the radial gravity profile from each crater center and 2) selecting a subset of the gravity data's spherical harmonics to isolate radial variations about the center of the crater (Figure 6). We use gravity profiles extending from the crater center to $2R$ from the crater center, including both the crater and a proximal background region for context. While it is true that this region may be affected by ejecta, regions further afield also give less information about the pre-impact target (e.g., pre-impact porosity) at the crater location. Soderblom et al. (2015) performed analyses on several background annulus sizes, finding that a maximum distance of $2R$ from a crater's center provides a reasonable reference for defining background regions in gravity analyses.

Impact craters are generally radially symmetric, suggesting that isolating azimuthally invariant components of the gravity field may enhance the identification of crater-induced anomalies. To achieve this, we transform the Bouguer gravity field into zonal harmonics within a rotated reference frame, where the north pole is designated as the crater center. Zonal harmonics, a subset of spherical harmonics with order = 0, exhibit radial homogeneity, propagating outward from the pole like a ripple.

In Figure 2 we compare the Bouguer gravity field before and after the application of zonal harmonic decomposition for an example crater. While the original Bouguer gravity map highlights a pronounced anomaly associated with the crater, additional regional features complicate the surrounding signal. By restricting the analysis to zonal harmonics in the rotated reference frame,

we retain only the radially symmetric components, excluding radially asymmetric features. Since zonal harmonic fields are inherently radially symmetric, radial averaging is unnecessary. Additionally, crater RBA measurements of our dataset reproduce the results of Soderblom et al., 2015 after our application of zonal harmonics (see Figure S2).

Step 3. Data Standardization for Correlated Structures

For dimensionality reduction techniques to effectively compare variations across features of varying sizes and magnitudes, the data must be standardized across both horizontal (coordinate) and vertical (magnitude) dimensions. In the coordinate dimension, it is critical that measurements sample the same or analogous parts of the relevant structure in each data instance. For example, in our application below we resample gravity profiles to provide measurements at consistent radius-normalized distances from crater centers, ensuring that key features, such as the rim, are represented uniformly across each profile (see also Figure 1).

A key distinction between standard PCA applications and its use for correlated profile data lies in the standardization of the vertical/magnitude component of profile measurements. Standard PCA applications often involve centering and normalizing data along individual dimensions among all data profiles (e.g., across all values of x_k^1 , see Step 4). In contrast, our approach preserves correlations within individual profiles by standardizing each profile independently across all dimensions (see Figure 1D for a schematic example). This can be achieved by scaling each profile to a unit norm (so that the length of the profile equals one) or by normalizing by its own standard deviation, depending on the objectives of the analysis.

To apply standardization to our crater gravitational profiles, distances along each profile are first normalized by the crater radius and then interpolated onto a fixed set of equally spaced, radius-normalized distances extending from the crater center out to two crater radii (see Figures 3

and 4). These seven points are selected to prevent oversampling of the smallest gravitational profiles while ensuring consistent comparison across crater sizes. The smallest craters in our dataset are $D = 27$ km, and our maximum spherical harmonic degree corresponds to a half-wavelength resolution of 8 km. Sampling at twice the half-wavelength resolution, consistent with Nyquist sampling, results in 6 points per profile. An additional interpolated point at the crater center yields a total of seven points. Because dimensionality reduction requires inputs of uniform dimension, the resolution of the entire analysis is determined by the lowest-resolution observation. Please refer to Table 1 and Figure 4 to compare the seven selected radius-normalized distances to key morphologic features in impact craters for the size range of our study.

The mean of each profile is subtracted, centering it at 0 mgal. The profile is then normalized to a unit norm of 1 by dividing by its length, the square root of the sum of its squared values. This normalization ensures all profiles have the same length, facilitating comparisons across craters of different sizes. However, this method may also amplify noise, as profiles with minimal variation are scaled to the same length as those with significant dynamic range.

Step 4. Dimensionality Reduction Calculation: PCA Eigendecomposition

The next step involves dimensionality reduction resulting in endmembers. Endmembers represent dataset patterns that arise due to a combination of geologic and/or other structured factors (e.g., instrument artifacts, atmospheric interference).

We provide a brief background here on Principal Component Analysis (PCA), as it forms the basis of the dimensionality reduction applied in our study of lunar crater gravity anomalies. Given its computational efficiency and interpretability, we also suggest that PCA serves as a suitable entry point for broader applications of GEEX.

PCA eigenvectors are derived from a dataset's covariance matrix. A covariance matrix is a symmetric, positive semi-definite matrix that describes how data is spread along its original coordinate axes. Consider a dataset D consisting of N profiles, where each profile X_k is represented by p points corresponding to a consistent set of radius-normalized distances (Figure 5).

$$D = \{X_k\}_{k=1}^N \text{ and } X_k = [x_k^1, x_k^2, x_k^3, \dots, x_k^{(p)}]$$

To understand the relationships between these variables, we need to calculate a covariance matrix Σ for our dataset:

$$\Sigma = \begin{bmatrix} \text{Cov}(x^{(1)}, x^{(1)}) & \text{Cov}(x^{(1)}, x^{(2)}) & \dots & \text{Cov}(x^{(1)}, x^{(p)}) \\ \text{Cov}(x^{(2)}, x^{(1)}) & \text{Cov}(x^{(2)}, x^{(2)}) & \dots & \text{Cov}(x^{(2)}, x^{(p)}) \\ \vdots & \vdots & \ddots & \vdots \\ \text{Cov}(x^{(p)}, x^{(1)}) & \text{Cov}(x^{(p)}, x^{(2)}) & \dots & \text{Cov}(x^{(p)}, x^{(p)}) \end{bmatrix},$$

where $\text{Cov}(x^{(i)}, x^{(j)})$ is the covariance between two points in the profile. This can be calculated in the following manner:

$$\text{Cov}(x^{(i)}, x^{(j)}) = \frac{1}{N} \sum_{k=1}^N \left(x_k^{(i)} - \mu \right) \left(x_k^{(j)} - \mu \right),$$

where k represents is the k^{th} profile in the dataset. The eigenvectors and eigenvalues of this covariance matrix can be calculated using a linear algebra package in a coding software.

Each eigenvector represents a distinct orthogonal direction or ‘shape’ of variation. Eigenvectors may be represented in a graphically analogous manner to a typical geological profile, where the vertical dimension has the same units as the vertical component of the input data.

Eigenvectors are sign agnostic, meaning they represent a range of variation captured by both their positive and negative modes. In a profile graphical representation, a negative mode corresponds to a reflection about the horizontal axis, equivalent to multiplying all magnitude values by -1.

The first eigenvector captures the most variation, while each subsequent eigenvector captures progressively decreasing amounts of variation. The first few eigenvectors often capture a substantial portion of the dataset's total variance, revealing the primary structural patterns inherent in the data. The number of eigenvectors corresponds to the dimensionality of the data. In the study of crater gravity anomalies in Section 4, the dataset's dimensionality will correspond to the number p of points sampled along each crater's gravitational profile.

An eigenvector's "variance explained" captures the percentage of total variation represented. Variance is calculated by dividing an eigenvector's eigenvalue by the sum of the entire set of eigenvalues.

Step 5. Dot Product Value (DPV) Analyses

GEEX further distinguishes itself from standard dimensionality reduction workflows through the additional step of Dot Product Value (DPV) analysis (Figure 6). A DPV is a single, dimensionless number that summarizes the shape of a feature by measuring the dot product between a profile and an eigenvector, $DPV = X \cdot v$, where X is a profile and v is an eigenvector. In our study below, both profiles and eigenvectors are normalized to have unit length equal to 1. Therefore, a DPV close to 1 indicates strong alignment between a profile and an eigenvector, while a DPV near -1 reflects a similar shape but inverted orientation—the “negative mode” of the eigenvector (Fig. 3). A DPV close to zero indicates little correspondence between the two. In our schematic example (Figure 6), 11 crater profiles yield 11 DPVs, with the sign and magnitude of each DPV reflecting the similarity between a given profile and the eigenvector.

DPVs provide an effective metric for comparing profile shapes across a dataset. They can be plotted against varying parameters, such as diameter, to reveal trends, or mapped spatially through Dot Product Mapping, where each pixel is assigned a DPV value from -1 to 1 . This highlights areas that closely match an eigenvector or its negative mode, improving the interpretation of spatial patterns. Applying this step to our lunar crater gravitational profiles, we are able to use DPVs to analyze systematic trends across large crater populations.

Conceptually, DPVs are similar to Residual Bouguer Anomalies (RBAs), which quantify the net gravitational effect of an impact crater relative to a regional baseline. However, whereas RBAs are computed by finding the difference between single representative values for the crater interior and exterior, DPVs capture radial variations within both regions, using first-order variations from the first eigenvector as a comparative baseline. In Section 4, we establish DPV thresholds for predictable positive and negative impact-induced anomalies and examine how high-DPV profiles vary with diameter and regional porosity.

Step 6. Dimensionality reduction using iterative DPV or geophysical variable subsets

Additional insights into dataset variability can be gained by subsetting data based on a geological or geophysical variable, such as elevation, regional porosity, or the size of a geomorphological feature. In the case of a dataset that, for instance, has data instances taken at several distinct elevations, the dataset may be divided into discrete elevation ranges, each containing a sufficient number of data instances to perform an independent dimensionality reduction calculation (see Figure 7). In the same example, by plotting eigenvalue 1 as a function of elevation, trends in first-order data variability can be examined. A decrease in eigenvalue 1 across elevations may indicate either (a) a decrease in how well the subset's eigenvector 1 characterizes data instances with elevation or (b) a systematic shift in data instances toward either

the positive or negative mode of the first eigenvector, reducing the overall variance captured. In cases where eigenvector 1 changes shape significantly from one subset to another, it may be challenging to interpret changes in the magnitude of eigenvalue 1.

Alternatively, comparing DPVs calculated with respect to a reference vector, such as the full dataset's eigenvector 1, may yield more interpretable trends than comparing changing eigenvalues. However, this approach would target changes to data profile shape instead of dataset variability. A break in slope in either eigenvalue magnitude or DPV as a function of a geophysical variable, potentially reveals changes in geologic variability or shape. Without subsetting, the dominant variations captured by the first few eigenvectors and eigenvalues may not reflect more nuanced changes of interest.

To explore impact-induced gravitational trends further, we apply Step 6 of GEEX to subsets of finely spaced diameter and porosity ranges to see how eigenvectors, eigenvalues, and profile shapes change across these geophysical variables. We also compare our results to previous work to directly evaluate improvements in precision offered by the GEEX framework. Subsetted diameter ranges may reveal subtle changes in profile shape with (a) depth, providing insights into the structure of the crust, or (b) size, revealing how impact cratering processes like central uplift evolve with diameter. Subsetting by porosity may reveal the radial scales at which different processes influence porosity. Processes that enhance porosity are expected to be more pronounced in low-porosity regions, whereas those that reduce porosity should have a stronger expression in high-porosity terrains (Soderblom et al. 2015, Milbury et al. 2015, Bierson et al. 2016).

While dimensionality reduction can be applied to datasets with as few observations as coordinate dimensions, we adopt a more conservative approach, calculating endmembers only for

geophysical subsets with at least 21 craters—three times the minimum required for a seven-dimensional input dataset.

4 Case Study Results

Below, we present the results of our GEEX methodology and compare with previous conventional studies that employed area-averaging techniques. Our results section follows the structure of GEEX steps 4-6: dimensionality reduction, DPV analyses, and further subsetting. We first show the eigenvectors calculated for this study that describe the most important independent shapes of variation in our crater gravity profile dataset (Sections 4.1 and 4.2). Then we use DPV analyses to analyze profiles that are well-characterized by Eigenvector 1, leading us to better understand important gravity profile shapes for complex craters (Sections 4.3 and 4.4). Last, we discuss the results of further subsetting by iteratively running eigendecomposition on finely spaced diameter and regional porosity crater subsets to further explore important changes in variability with these geologic variables (Section 4.5).

4.1 Eigenvector Results

Our results section on eigenvectors comprises a comprehensive examination of all eigenvectors derived from the full dataset of $N = 1184$ highland craters (Figure 1). Throughout the presentation of our case study, we distinguish between eigenvectors calculated using the entirety of our dataset (full dataset) as, e.g., "Eigenvector 1 of the full dataset" ($V1_{FD}$) and eigenvectors and eigenvalues calculated for subsets of our dataset as, e.g., "Eigenvector 1 of a given subset" ($V1_{Subset}$) and "Eigenvalue 1 of a given subset" ($\lambda1_{Subset}$).

PCA of our full dataset produced a total of seven eigenvectors, shown in Figure 8. Seven eigenvectors are produced because each input profile was resampled to seven points due to resolution constraints (see Section 3). Each eigenvector has the same dimensions as a standardized

gravitational profile: radial distance from crater center and relative gravity. However, unlike a profile, eigenvectors are sign-agnostic, meaning they represent a range of variation captured by both their positive and negative modes. For each eigenvector, we explain the percent of total variance in the dataset captured by that eigenvector, its eigenvalue, shape, and interpreted geophysical significance. While the full dataset can be effectively approximated using contributions from the four dominant eigenvectors, below we discuss one-by-one all seven eigenvectors to illustrate the full range of shapes required to satisfy dimensionality constraints and achieve 100% reconstruction of the dataset.

The variation of gravitational profiles is highly concentrated in Eigenvectors 1-4 (V_{1FD} - V_{4FD}), which account for 97.6% of the total variation seen in the data. This means the gravitational profiles can be effectively reconstructed with 97.6% accuracy by using linear combinations of just these four eigenvectors, each weighted by appropriate coefficients.

Eigenvector 1 (V_{1FD}) (Figure 8a) is the most important shape of variation within our full dataset, capturing 64% of the total variance. Broadly, this eigenvector captures the primary interior-exterior contrast of crater anomalies. The eigenvector profile tapers linearly from the crater center to the rim, beyond which the profile remains flat.

The utility of V_{1FD} for interpretation of gravity data is apparent when compared with the Residual Bouguer Anomaly (RBA). RBA provides a single number that characterizes a crater's influence on regional gravity: first by computing area-average values for a crater's interior and exterior gravity and then subsequently taking the difference of these values. This lowers the dimensionality of GRAIL data of a crater from up to 1,442,401 dimensions (for $l_{max}=1200$) to one dimension: a single RBA value per crater. However, the interior tapering of V_{1FD} , from center to rim, indicates that RBA averages an interior gravity signal that is not nominally flat. In Section 4.5

we demonstrate that this ostensibly minor simplification leads to a substantial loss of precision. We further explore an alternative, more precision-efficient approach for characterizing each crater with a single value through DPVs (Section 4.2.-4.4).

Eigenvector 2 of the full dataset (V_{2FD}) captures 20.3% of the dataset's variation. This eigenvector is flat between 0.667 and 1.0R, with relatively even slopes on either side, indicating anticorrelated behavior between (a) the rim and rim flank regions and (b) the crater center and exterior regions. This eigenvector may highlight variations in gravitational profiles due to central uplift.

Eigenvector 3 of the full dataset (V_{3FD}) captures 9.7% of the variation in the dataset. This eigenvector exhibits an 'S'-shape, with alternating gravitational highs and lows. The central peak and rim/rim flank regions are anticorrelated with the crater floor and exterior region beyond the rim flank.

Eigenvector 4 of the full dataset (V_{4FD}) captures 3.6% of the variation and exhibits an 'M'-shape. In this case, signals at the crater center, crater rim, and 2.0R are correlated while those at 0.667, 1.333, 1.667R are anticorrelated. The region between 1.33 and 1.667R is relatively flat. Eigenvectors 5-7 of the full dataset (V_{5FD} - V_{7FD}) comprise only 2.3% of this dataset's signal. Each successive eigenvector describes finer-scale variations, while Eigenvector 7 of the full dataset exhibits negligible amplitude and eigenvalue within the margin of error.

In brief, Eigenvector 1 captures the broadest, most statistically significant shape within our dataset, while each subsequent eigenvector introduces an additional oscillatory mode of finer-scale variation. The remaining 36% of the variation captured by the remaining eigenvectors (V_{2FD} - V_{7FD}) appear to describe variations other than a simple contrast between a crater's interior and exterior. Eigenvectors 2-4 (V_{2FD} - V_{4FD}), for instance, show an increase or a decrease in the crater

interior within $0.6R$, possibly encompassing variation due to mantle uplift or central peak formation.

4.2 Dot Product Values Analyses: Gravity Anomalies

Dot Product Values (DPVs) were calculated for the full dataset of craters by taking the dot product between each relative gravity profile and Eigenvector 1 for the full dataset ($V1_{FD}$), yielding one DPV per crater (Figure 9). $V1_{FD}$ captures the most statistically significant 'shape' of variation in our relative gravitational profiles, accounting for 64% of the dataset's total variation. Therefore, DPVs with respect to $V1_{FD}$ offer a single number per crater, quantifying the extent to which its profile aligns with the optimal low-dimensional representation of this dataset as derived from our dimensionality reduction analysis.

Because relative gravity profiles and eigenvectors in our study each have a length of 1, DPVs range between 1 and -1. DPVs of 1 result when the relative gravity profile and $V1_{FD}$ closely resemble each other, whereas DPVs of -1 result when the relative gravity profile is the negative mode (inverse) of $V1_{FD}$ (see Figure 6). DPVs of intermediate values result when relative gravity profiles do not resemble either the positive or negative modes of $V1_{FD}$, for instance, when a profile resembles a different eigenvector, such as $V2_{FD}$ - $V7_{FD}$. The majority of crater DPVs cluster near ± 1 , with 79% falling within 0.5 of these extrema (Figure 9). This indicates that $V1_{FD}$ well characterizes a significant fraction of the crater gravity profiles in our dataset.

We next use DPVs of craters to explore how craters' relative gravity profiles vary with physical measurements such as net gravity anomaly, diameter and porosity. We begin by examining the averaged relative gravity profiles of craters with different ranges of DPVs.

A majority (95%) of craters with $DPV > 0.5$ exhibit negative RBA values, meaning the mean interior anomaly is less than the mean exterior anomaly (see Figure 10). Conversely, 71%

of craters with DPV values less than -0.5 exhibit positive RBA values, meaning the mean interior anomaly is greater than the mean exterior anomaly. Craters with DPVs between -0.5 and 0.5 are characterized by ambiguous net gravity anomalies, meaning they are not more likely to have positive or negative RBA values. These ambiguous-anomaly craters make up only 21% of the craters in our full dataset.

Profiles with high absolute DPVs ($|\text{DPV}| > 0.75$, Figure 11) possess distinct contrasting shapes. This indicates differences in the distribution of impact-induced signals produced by mechanisms that either increase or decrease local gravity. Profiles with DPVs greater than 0.75 exhibit smooth, rounded shapes, similar to a sigmoid curve, that taper to flat slopes at the crater center and $2R$. The negative anomaly in the crater center extends partially outside of the crater rim as far as $1.6R$, with an inflection point near the crater rim, at $0.83R$. From this we infer that, to first order, the combined effects of mechanisms that generally decrease gravity, such as fracturing, faulting, dilatant bulking, slumping, and ballistic redistribution, create diffuse features in gravity profiles that extend beyond the crater rim.

Profiles with DPVs less than -0.75 exhibit a distinctly more angular shape (Figure 11). These profiles produce a sharply concentrated central positive gravity anomaly that linearly tapers towards the baseline, terminating in a distinct discontinuity at the crater rim. From this we infer mechanisms that generally increase gravity—such as compressive shockwaves, central uplifts, and thermal annealing—generate sharp, confined gravity features that do not extend beyond the crater rim. Further strategic subsetting of data may enable future analyses to disentangle the contributions of distinct processes in observed gravity profiles, particularly with the help of impact modeling.

We hypothesize that the radial relative gravity profiles of the craters in our dataset with DPVs of > 0.75 and < -0.75 are representative of those for lunar craters with negative and positive

gravity anomalies, respectively. Our hypothesis is supported by the fact that 98% of craters in our dataset with $DPV > 0.75$ have negative RBAs and that 87% of craters with $DPV < -0.75$ have positive RBAs. Assuming this hypothesis is true, these DPV profiles can be used to constrain physical models that attempt to recreate the physical processes that may affect porosity in impact craters with positive or negative gravity anomalies.

4.3 Dot Product Value (DPV) Analyses: Diameter

Having established that DPVs can be a useful proxy for the sign of crater gravity anomalies, we now use DPVs to explore the relationships between negative and positive gravity anomalies and different physical properties of craters, namely diameter and regional porosity. All Dot Product Values (DPVs) in this subsection were calculated by taking the dot product between each relative gravity profile and Eigenvector 1 for the full dataset ($V1_{FD}$), yielding one DPV per crater (Figure 9).

First, we examine diameter trends. Impact craters of varying diameters are expected to exhibit different proportions of positive and negative gravity anomalies. This is because impacts of different sizes deliver varying amounts of kinetic energy and excavate material from varying depths within the lunar crust. We applied a moving window approach to subset by diameter: craters were grouped into overlapping diameter bins 20 km wide, with the window advancing in 10 km increments across the full dataset. Then within each diameter subset, we calculate based on DPV the percentage of crater gravity anomalies that are positive ($DPV < -0.5$), negative ($DPV > 0.5$), or ambiguous (DPVs -0.5 to 0.5 , Figure 12). All subsets have a bin size of 20 km, except for the smallest diameter bin with midrange value of 30, which ranges from 27-40 km. We exclude 18 craters with diameters between 140 and 201 km from further analysis, as the limited number of craters in each 20 km bin at these sizes precludes robust trend identification.

In Figure 12, we find that the smallest craters in our study ($D = 27\text{-}40$ km) are equally likely to exhibit either positive gravity anomalies (red) or negative gravity anomalies (blue). At these small diameters, craters are equally likely to increase or decrease the gravity of the target, consistent with findings by Soderblom et al. (2015). Previous work has interpreted this to suggest the lunar crust excavated by these impacts is in a state of equilibrium, consistent with a megaregolith thickness of ~ 8 km (Soderblom et al. 2015, Izquierdo et al. 2021).

Next, we examine trends for intermediate-sized complex craters ($D = 30\text{-}80 \pm 10$ km). We find that, with increasing diameter, the proportion of craters with negative anomalies increases steadily while the proportion with positive anomalies decreases steadily. This may mean that mechanisms that reduce gravity (e.g., fracturing, bulking) are more efficient at larger diameters and/or with increased depth (Wiggins et al. 2019, 2022). This hypothesis aligns with an expected negative porosity gradient depth (Besserer et al. 2014), where reduced porosity enhances the efficiency of energy transmission through rock, facilitating fracturing and bulk material displacement. Larger craters also are formed by impact events with higher kinetic energies, also likely leading to greater porosity generation (Collins 2014, Milbury et al. 2015, Wiggins et al. 2019, 2022).

For large complex craters ($D = 80\text{-}110 \pm 10$ km), the proportions of craters with positive and negative anomalies remain steady as a function of diameter. This plateau is potentially consistent with craters intersecting the lunar depth of pore closure, beyond which pore spaces are removed by overburden pressure and thermal annealing, consistent with seismic data and previous crater gravity studies (Soderblom et al., 2015; Toksöz et al., 1974).

For the largest craters in our dataset ($D = 110\text{-}130 \pm 10$ km) we observe a sharp increase in the proportion of craters with ambiguous gravity anomalies, with net decreases in the proportions

of craters with negative or positive anomalies. Other eigenvectors that expressed more nuanced gravitational variations may be more strongly expressed at this diameter range. It is unclear what may be causing this change in gravitational behavior.

4.4 Dot Product Value (DPV) Analyses: Regional Porosity

Now we explore trends with regional shallow porosity. Previous work using area-averaging techniques on the same dataset studied here has shown trends toward higher average RBAs with increasing regional porosity for impact craters (Soderblom et al., 2015, Figure 13A). In order to benchmark GEEX's performance relative to the state-of-the-art, we first grouped craters into subsets based on their regional porosity values (moving window size 1%) and then calculated the proportion of craters in each subset with positive, negative or ambiguous gravity anomalies (Figure 13B). We also examined the distribution of DPV values for craters within three ranges of regional porosity values (Figure 13C).

In Figure 13B, we observe that at very low porosities ($10-12 \pm 0.5\%$), negative gravity anomalies (blue) represent a majority ($>80\%$) of impact craters, while $<20\%$ have a positive anomaly (red), and nearly none have an ambiguous anomaly (black). Starting at porosities $>11 \pm 0.5\%$, we observe a significant decrease in the proportions of impact craters with negative anomalies and a significant increase in the proportions of positive anomalies as a function of porosity. Meanwhile, craters with ambiguous anomalies increase significantly in proportion from $12-13 \pm 0.5\%$ porosity but then exhibit only a subtle net increase in proportion up to 20% porosity.

Figure 13C shows the change in the distribution of DPVs for three porosity ranges, summarizing the data in Figure 13B. At low to mid porosities ($10-16 \pm 0.5\%$), a majority of anomalies are negative, while at high porosities (17-20%), a majority of anomalies are positive. Importantly, the fraction of positive and negative anomaly craters is roughly equal ($\sim 40\%$ each) at

a narrow porosity range of $16.5 \pm 0.5\%$ (Figure 13B, C). This cross-over occurs at porosities higher than our highland crater dataset's average shallow porosity of 15.6% or the average shallow porosity of the moon at 16.1%. This may indicate that the shallow porosity of the moon is not in equilibrium.

4.5 Eigenvector Analysis of Crater Diameter Subsets

We are interested in how the shape of gravitational profiles changes over distinct diameter ranges for a few reasons: (1) to compare GEEX's ability to detect the $D \sim 90$ km break-in-slope observed in Soderblom et al. (2015), hypothesized to indicate the lunar depth of pore closure, and (2) to gain novel insights into how the shape and variability of gravitational profiles changes with size/depth of excavation (as indicated by eigenvalue). To investigate very finely spaced changes in diameter, we first grouped craters from our full dataset into 111 overlapping subsets based on diameter, with each subset spanning 50 km and advancing by 1 km increments (Figure 14). We then performed eigendecomposition for each subset, resulting in 111 sets of eigenvectors and eigenvalues. We then assessed the relationship between eigenvalue 1 for each subset ($\lambda_{1\text{Subset}}$) and its midrange diameter.

In Figure 14B, we observe that $\lambda_{1\text{Subset}}$ is highest for the subset with the smallest craters (52 ± 25 km) in our dataset and that $\lambda_{1\text{Subset}}$ declines significantly towards larger crater sizes. High eigenvalues (~ 0.6) for small diameters indicate that the gravitational profiles of these craters are well characterized by both the positive and negative modes of subset Eigenvector 1's ($V_{1\text{Subset}}$), meaning that small craters are producing positive and negative anomalies in a predictable and repeatable manner. Steadily decreasing eigenvalues with increasing crater diameter indicates one or a combination of two possibilities: either (a) larger crater subsets are not as well characterized by their subset eigenvector 1's, suggesting that other profile shapes are more common, and/or (b)

crater profiles are shifting to either the positive or negative mode of the eigenvector, decreasing the magnitude of variation that that subset eigenvector captures.

We also observe a break in slope for this trend in $\lambda 1_{\text{Subset}}$ values at around 92 km (Figure 14B), which coincides with a break in slope observed previously in the relationship between RBA and diameter at 93^{+47}_{-19} km (Soderblom et al., 2015, Figure 14C). While Bayesian statistics were necessary to identify the break in slope in the Soderblom et al. study, the break in slope in our analyses of $\lambda 1_{\text{Subset}}$ is readily apparent upon visual inspection. However, the break in slope at ~92 km is most clearly displayed when the subset has a bin size of 50 km. Soderblom et al. (2015) attributes this break in slope to the lunar depth of pore closure, beyond which impact-induced pore space is closed due to viscoelastic annealing of pore-space driven by the Moon's thermal gradient and overburden pressure. A similar break in slope is observed in the gravitational signatures of terrestrial impact craters, though at smaller diameters ($D \sim 20\text{-}30$ km) due to the increased gravity of Earth (Pilkington & Grieve, 1992). This transition is consistent with seismic models that also predict a change in lunar crustal structure at depths of 20-30 km (Toksöz et al., 1974), corresponding to the depths probed by $D \sim 90$ km craters: 19-26 km using scaling laws by Holsapple (1993). Importantly, while both methods, RBA and GEEX, show similar breaks in slope, the GEEX eigenvalue subset plot exhibits a break in slope that is clearly visible by-eye, while the RBA break in slope requires Bayesian statistics to identify.

Additional breaks in slope appear in the plot of $\lambda 1_{\text{Subset}}$ in Figure 14B at diameters >92 km. For instance, a break in slope occurs at a diameter of ~110 km, which coincides with a marked increase in the number of craters with ambiguous anomalies as can be seen in Figure 12. This and additional breaks in slope in Figure 14B may potentially reflect the relatively small numbers of

craters that occur in our dataset at these larger diameters (Figure 14A) and are not discussed further.

Among the 111 previously discussed subsets, we selected seven subsets at ~ 20 km intervals (Figure 14A) for further gravity analysis (Figure 15). We grouped craters in each subset according to their DPVs, creating one group of craters with $DPV > 0.5$ (negative gravity anomalies) and another of craters with $DPV < -0.5$ (positive gravity anomalies), and calculated an average, normalized relative gravity profile for each group and subset (Figure 15A), as well as the 1σ range variability for profiles in each diameter range.

In Figure 15A, for craters with negative anomalies, shown on the left, we observe a break in slope at $0.667R$ in relative gravity profiles that becomes increasingly pronounced at larger diameters. This profile break at $\sim 0.667R$ is consistent with previous models of Bouguer profiles with negative interior anomalies (e.g., Collins et al. 2014). This break in slope may correspond to the migration of the crater wall toward the $0.667R$ position with increasing crater size (Pike 1977).

For craters with positive anomalies ($DPV < -0.5$), shown on the right of Figure 15A, we observe that profiles abruptly flatten outside of the crater rim at small diameters. This flat region migrates inward to $0.667R$ at larger crater diameters. Additionally, for craters with positive anomalies, a break in slope at $0.333R$ becomes more pronounced with larger crater diameters. These two trends may be due to an increased concentration of impact energy toward the crater center with increasing crater size. We interpret the sharpening of these anomalies with diameter to be a consequence of impact energy being rapidly dissipated through pore space compaction, thereby limiting the horizontal extent of compression. Indeed, Figure 13C indicates craters within high-porosity terrains (17-20%) exhibit predominantly positive anomaly craters, consistent with this interpretation.

Subsequently, in Figure 15B, we compare the $V1_{\text{Subset}}$ for all seven diameter subsets (colored lines; colors and diameter ranges shown in Figure 14A) and the eigenvector 1 for the full dataset $V1_{\text{FD}}$ (black line). We observe that $V1_{\text{Subset}}$ profiles are largely similar to each other and $V1_{\text{FD}}$ for midrange diameters of 52-124 km. This suggests that for craters with diameters less than 106 km, $V1_{\text{FD}}$ provides a robust representation of their axis of greatest variation. However, the eigenvector profiles for larger craters exhibit a pronounced elevation at 1R relative to neighboring eigenvector magnitudes at 0.667R and 1.333R. This indicates that $V1_{\text{FD}}$ does not provide a robust representation of variations for the largest craters in our dataset. It also implies that the largest craters in our dataset are more likely than smaller craters to exhibit ambiguous anomalies that are not clearly positive or negative.

5 Conclusions

Our study has outlined the procedures and potential benefits of a generalized framework for the application of dimensionality reduction techniques to planetary datasets called Guided Endmember EXtraction (GEEX). We provide a full recipe for the generalized use of GEEX that may be applied to a wide range of planetary sciences datasets.

In our case study, GEEX offers a refined methodology for analyzing gravitational data, surpassing earlier approaches in both detail and precision. It represents a natural progression in gravity analysis, from zero to one-dimensional investigations of crater gravity. We presented a case study on lunar highland complex craters, analyzing trends with crater diameter and comparing with previous results. Our comparison of GEEX with area-averaging techniques, particularly Residual Bouguer Anomaly (RBA), revealed that GEEX successfully reproduces key findings, such as (1) negative anomalies become increasingly prevalent with increasing diameter, until (2) a distinct change in slope at $D \sim 90$ km, potentially linked to the lunar depth of pore closure, as

suggested in Soderblom et al. (2015), and (3) anomalies are correlated with porosity, becoming more negative with increasing porosity.

However, GEEX goes well beyond previous area-averaging and zero-dimensional analyses, offering additional key insights:

1. GEEX identifies the break in slope associated with the lunar depth of pore closure without the need for additional Bayesian analyses.
2. Broad shapes for positive and negative anomalies are shown, potentially providing observational constraints for the gravitational effects of distinct impact-driven mechanisms that increase or decrease gravity.
3. Equal proportions of positive and negative anomalies are found at $16.5 \pm 0.5\%$ shallow porosity, a relatively high porosity that exceeds global and dataset averages, implying that shallow lunar porosity is not in equilibrium.

GEEX also offers new geologically significant insights into how impacts influence porosity evolution. For the first time, it enables the characterization of observed complex crater gravitational profiles, showing distinct differences in the shape of profiles for positive and negative Bouguer anomalies. These profiles provide a valuable tool for future studies aiming to better understand porosity creation and destruction during impact events.

Building on these capabilities, the GEEX approach to studying radial gravitational profiles of impact craters opens the door to a wide range of applications. Future research could explore less-dominant eigenvectors, expand to different crater size ranges (such as simple or basin-scale craters), examine specific geographic regions or other planetary bodies, and incorporate complementary datasets like topography, magnetics, or composition to enhance interpretation.

While our study focuses on Principal Components Analysis to provide an accessible starting point for the integration of GEEX into planetary science studies, other dimensionality reduction techniques may yield additional insights, such as Factor Analysis, manifold learning (e.g., t-SNE), and Non-negative Matrix Factorization (NMF). Future work could assess the utility of these other dimensionality reduction techniques when applied to gravity and other kinds of planetary data, using as a basis studies such as those by Tarnas et al. (2019) on the utility of diverse dimensionality reduction techniques to laboratory spectroscopy. Additional methodological improvements to GEEX may also involve refining its underlying machine learning framework, particularly through rigorous separation of test and validation datasets and hyperparameter tuning to optimize performance.

Given the significant improvements in precision and interpretive power offered by GEEX over simpler statistical analysis methods such as area averaging, we expect this methodology can be applied to a wide range of planetary science questions involving repeated physical or data structures, such as impact craters or mineral signatures, as in this and previous work. The GEEX framework may be immediately applicable to a variety of crater profile analyses, including those using topographic, magnetic, and spectral datasets. The size and complexity of modern planetary data presents a significant challenge to the understanding of planetary evolution. However, by developing applied statistical approaches like GEEX, we can further realize the promise of these datasets and continue to push forward on diverse questions in planetary science.

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AI Statement

During the preparation of this work the author(s) used generative AI tools (e.g., ChatGPT) to assist with language refinement and organization of visual materials. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Table 2-1. Crater features corresponding to radius-normalized distances used in this study. Based on scaling laws in Pike (1977) and Kruger et al. (2018) for the size range of craters considered in this study ($D=27\text{-}201\text{ km}$).

R-norm distance	0R	0.333R	0.667R	1R	1.333R	1.667R	2 R
Feature	Central Peak	Crater Floor	Rim Wall ($D < 123\text{ km}$)* or Floor ($D > 123\text{ km}$)	Rim	Rim Flank	Ejecta/Regional Baseline	Ejecta/Regional Baseline

* 97% percent of craters in our dataset have diameters (D) less than 123 km. Consequently, 0.667R corresponds to the rim wall for nearly the vast majority of craters studied herein.

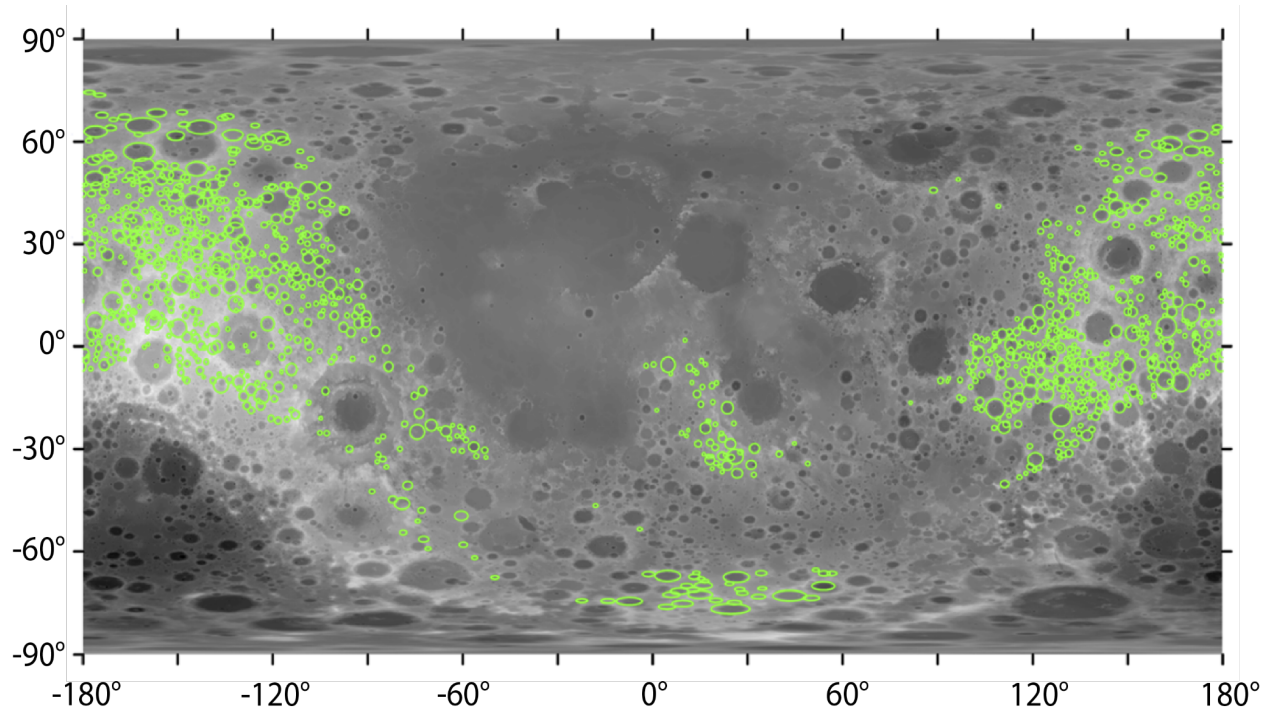


Figure 2-1. Locations of $N = 1184$ complex highland craters (green) analyzed using GEEX and presented on a grayscale topographic basemap of LOLA data (Smith et al., 2010). These craters were previously studied using conventional area-averaging techniques in Soderblom et al. (2015). After Soderblom et al. (2015).

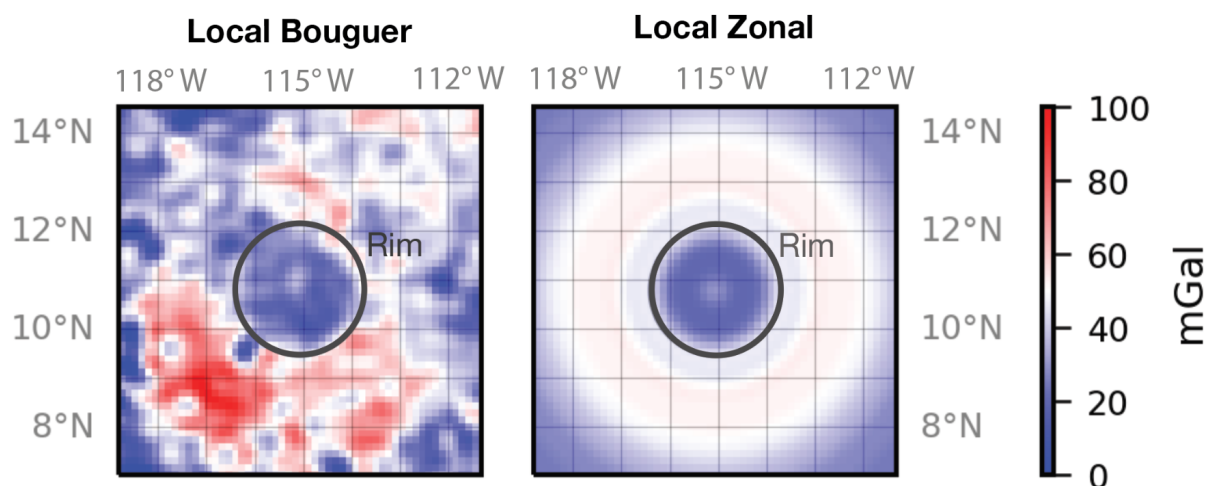
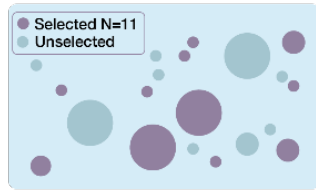
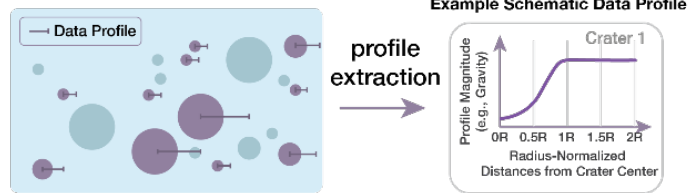


Figure 2-2. Bouguer anomaly of an example crater before (left) and after (right) reducing to zonal harmonics (Crater 1028, see crater IDs in Table T2 of the Supplementary Materials). Crater rim is indicated by a grey circle.

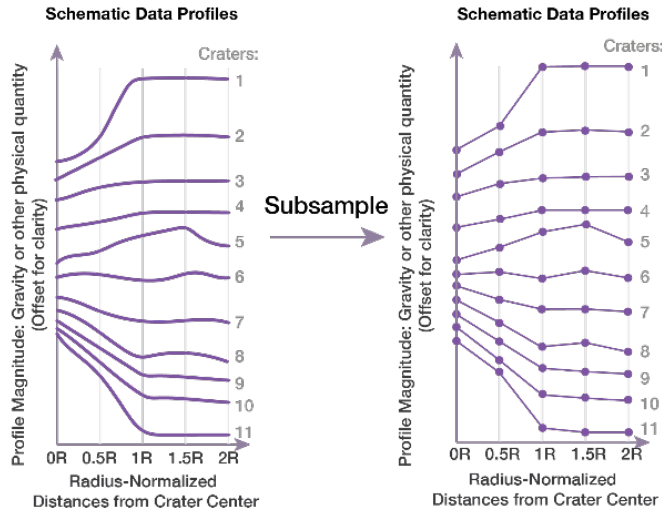
Step 1: Select Features



Step 2: Select Data in Signal Space



Step 2, continued: Subsample Data Profiles



Step 3: Standardize Data

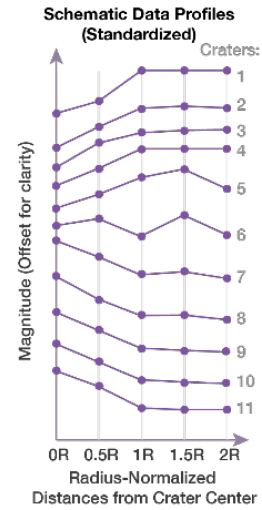


Figure 2-3. Conceptual workflow summarizing Steps 1-3 of the GEEX framework on a simplified example study of crater gravity profiles. All maps and graphs are schematic and meant only for illustrative purposes. In Step 1, physical features are selected for study, which in this example are $N = 11$ impact craters chosen for an unspecified physical affinity. In Step 2, data are selected in signal space. In this example, relative gravity profiles are extracted for each selected crater. Next in Step 3, data profiles are subsampled, in this case to 5 measurements per profile. All data profiles are standardized in the vertical/magnitude dimension.

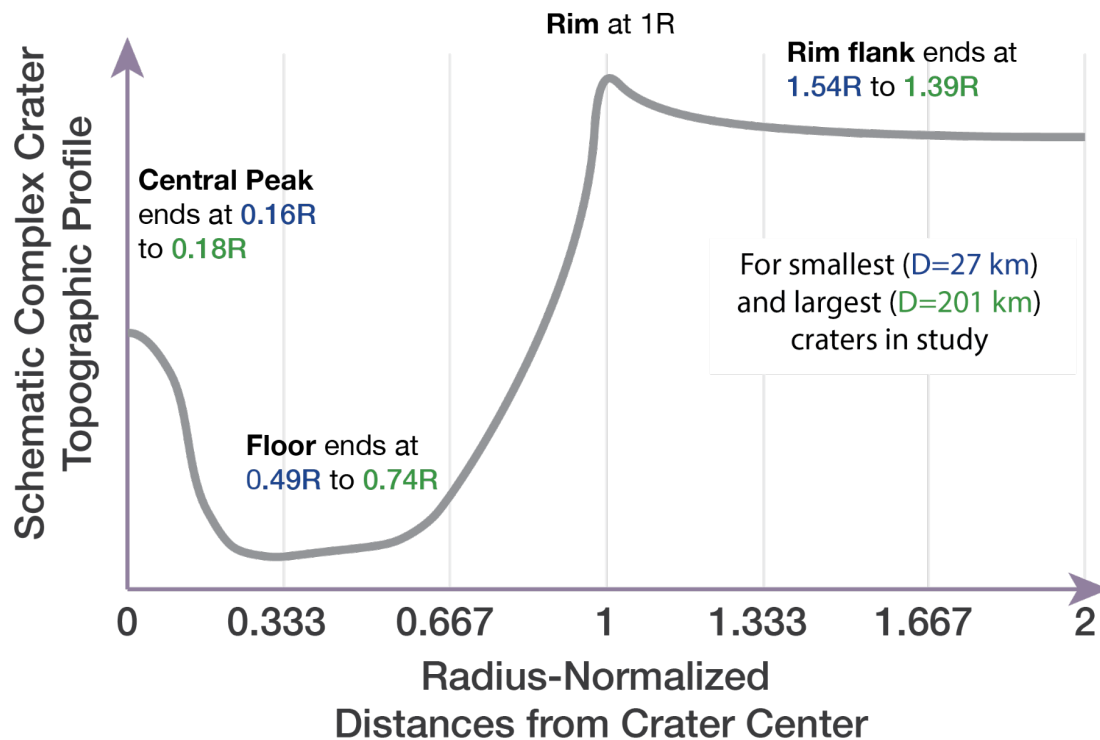
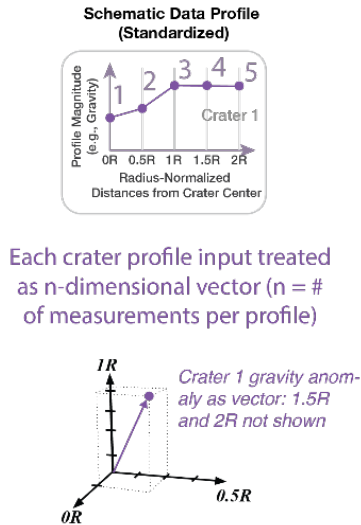


Figure 2-4. Radius-normalized distances of morphological features from the crater center for the size range considered in this study. Distance ranges are based on scaling laws from Pike (1977) and Kruger et al. (2018). X-axis highlights the seven radius-normalized distances used throughout our study: 0R, 0.333R, 0.667R, 1R, 1.333R, 1.667R, and 2R.

Step 4

A Dimensionality Reduction (e.g., PCA): Inputs



5 measurements
per profile

5 eigenvectors
for whole dataset
(Craters 1-11)

B Dimensionality Reduction: Outputs

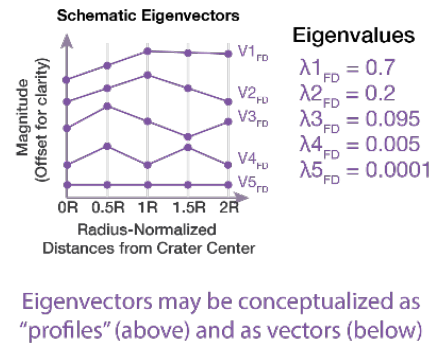
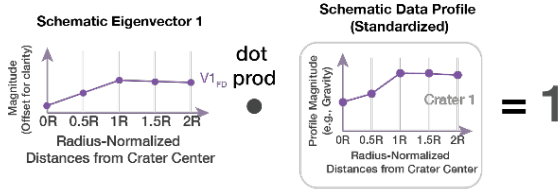


Figure 2-5. Conceptual workflow for Step 4 of the GEEX framework, using the example of gravity profiles of craters, as in our lunar crater gravity anomaly study. All profiles are schematic and meant only for illustrative purposes. Dimensionality reduction calculation is performed on all data profiles. (A) In this formulation, each input data profile is represented as an n-dimensional vector, where n corresponds to the number of element measurements assigned to specific coordinates within the profile. As an example, measurements for Crater 1 are shown in two graphical formats: as a profile and as a vector in Cartesian space. (B) The number of resultant eigenvectors for the full dataset (FD) equals the number of measurements for each profile, which is 5 in this example (7 are used in our full study below). The first eigenvector ($V1_{FD}$) is shown in two graphical formats: as a profile and as a vector in Cartesian space.

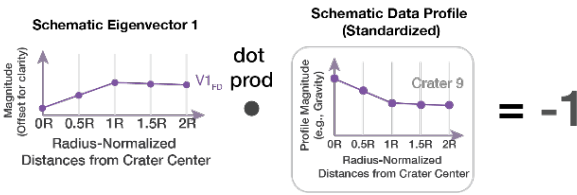
Step 5

A Example Dot Product Value (DPV) Analyses

example: data profile same as eigenvector



example: data profile inverse of eigenvector



B DPV Analyses for Eigenvector 1 of Full Dataset

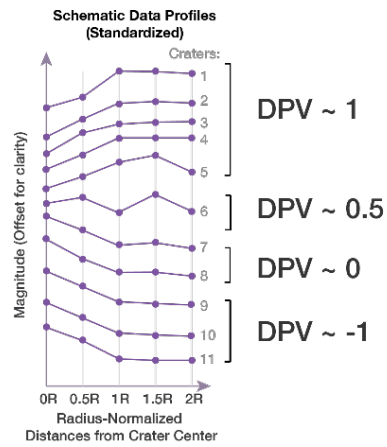
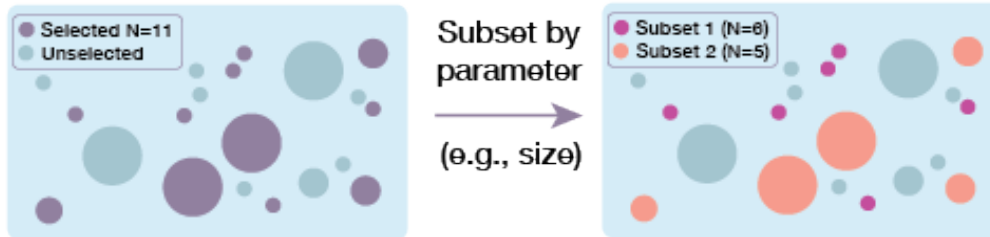


Figure 2-6. Conceptual workflow for Step 5 of the GEEX framework, continuing with the simplified example of impact craters from Figure 5. All profiles are schematic and meant only for illustrative purposes. (A) The dot product reflects the orientation and shape of each profile, with similar profiles yielding values near one, and profiles aligned with the negative orientation of the eigenvector yielding values near negative one. (B) A DPV is calculated for each of the profiles in the dataset, characterizing their orientation with respect to the first eigenvector.

Step 6

A Further Subsetting



B Eigendecomposition for Subsetted Data

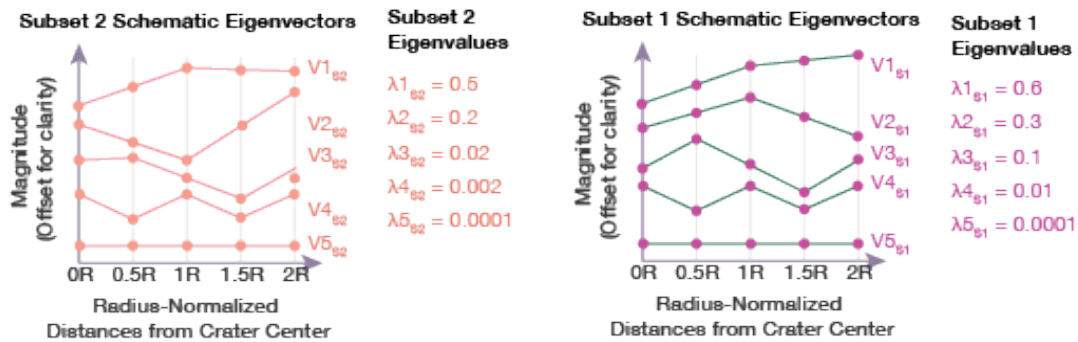
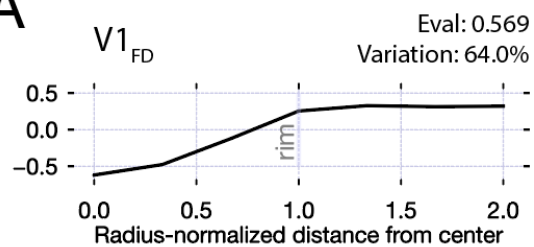


Figure 2-7. Conceptual workflow for Step 6 of the GEEX framework, continuing with the simplified example of impact craters from Figure 6. All maps and graphs are schematic and meant only for illustrative purposes. (A) An example of further subsetting of the full dataset for deeper interrogation of data. In this example, the 11 craters are subsetting into two groups of different diameters. (B) Eigenvector decomposition as described in Step 4 is performed, resulting in 5 eigenvectors and eigenvalues for each subset. As in Step 4, the number of eigenvectors is determined by the number of measurements in a data profile.

Eigenvectors of the Full Dataset ($V1_{FD} - V7_{FD}$)

A



B

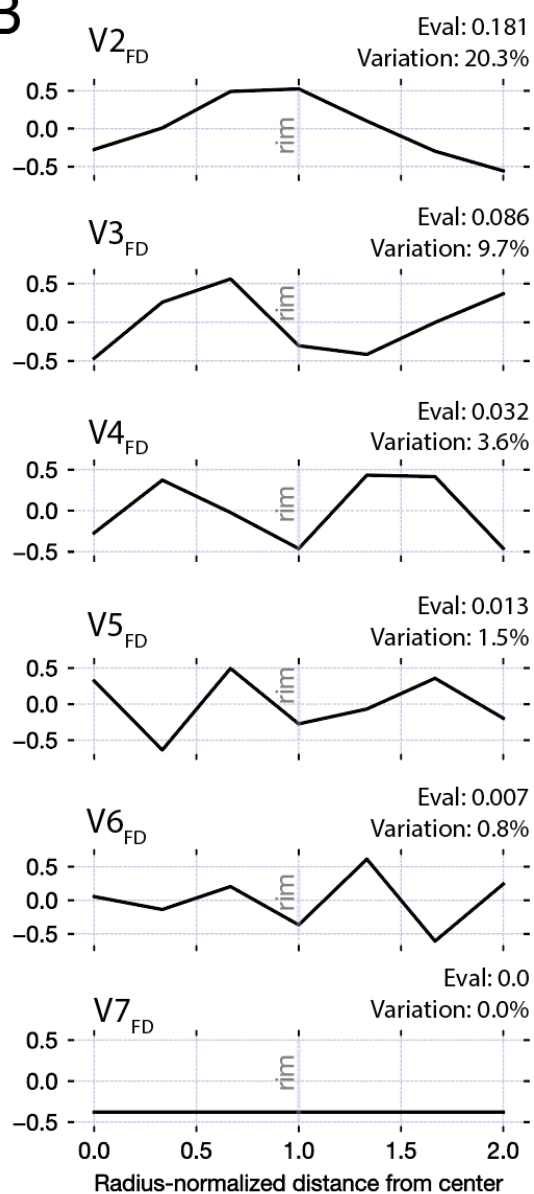


Figure 2-8. Eigenvectors 1-7 (V_{1FD} - V_{7FD}) for the full dataset of $N = 1184$ complex highland lunar crater gravity profiles. (A) Eigenvector 1 (V_{1FD}) captures 64% of the total variation in the dataset, as determined by the eigenvalue (λ_{1FD}) (see Section 3), making it the most useful eigenvector for interpreting the full dataset, and is therefore shown apart from the other eigenvectors. (B) The remaining six eigenvectors (V_{2FD} - V_{7FD}) are shown with associated eigenvalues (λ_{2FD} - λ_{7FD}) and percent variation captured for the full dataset. Seven eigenvectors are produced because each input profile was resampled to seven points due to resolution constraints (see Section 3). Y-axis is relative gravity; x-axis is radius-normalized distance from the crater center. The rim is indicated as a grey vertical line in each plot.

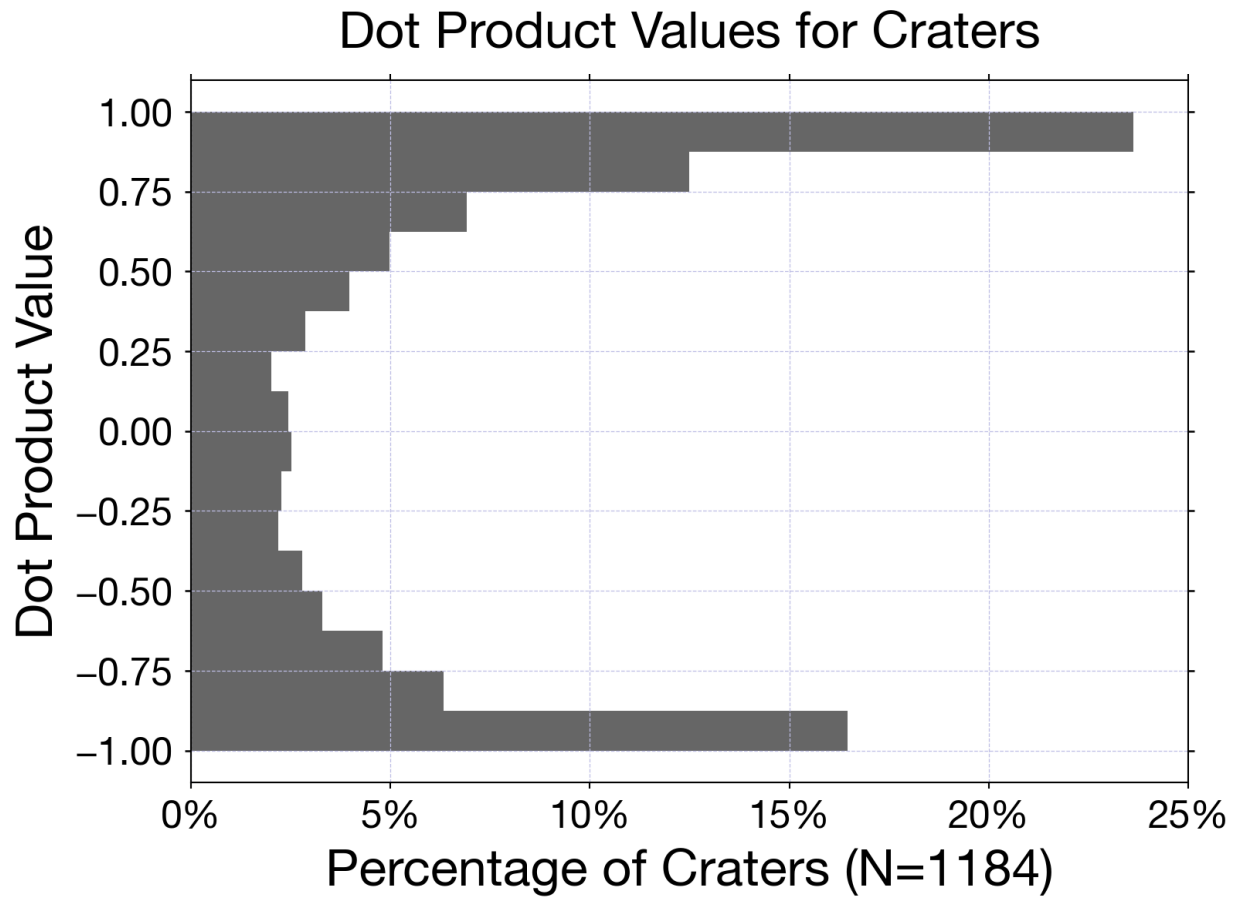


Figure 2-9. Histogram of crater Dot Product Values (DPVs) for our full dataset ($N = 1184$). DPVs are calculated with respect to Eigenvector 1 for the full dataset ($V1_{FD}$). See Figure 6 in methods for how DPVs are calculated.

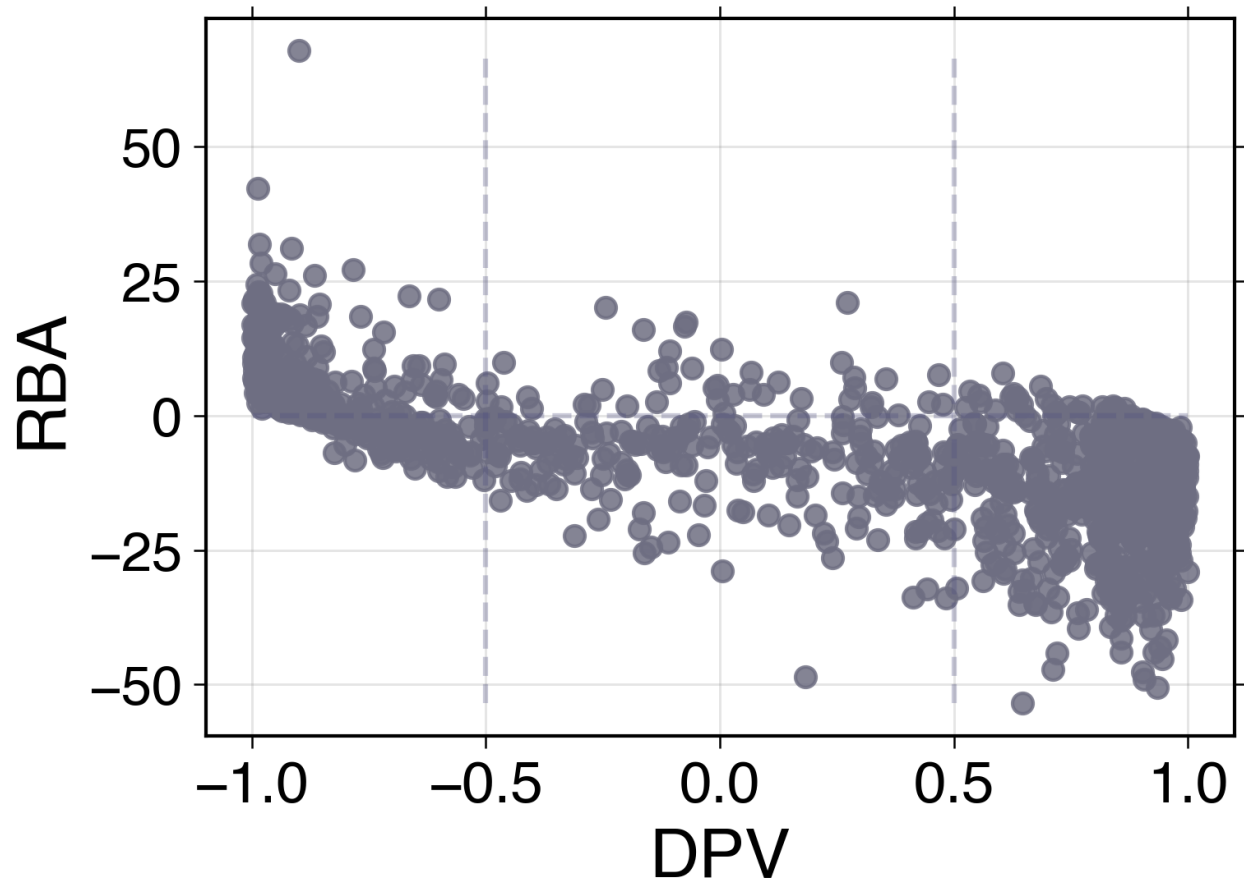
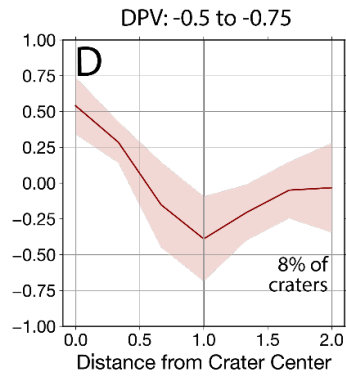
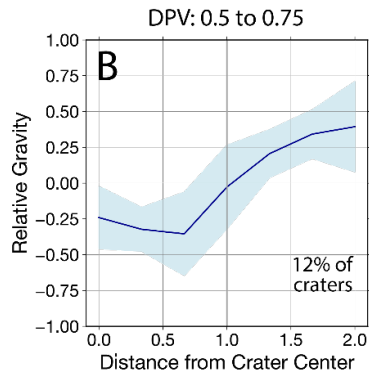
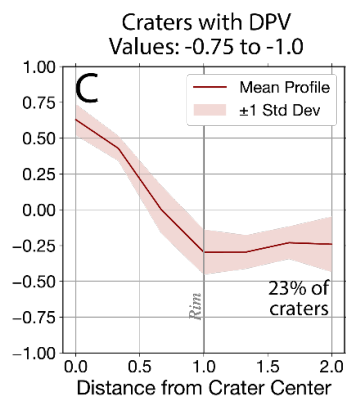
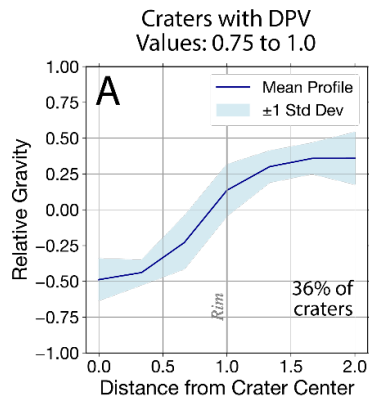


Figure 2-10. Relationship between Residual Bouguer Anomaly (RBA), which characterizes the net gravitational effect of a crater on its local region, and DPV, which characterizes a gravity profile's likeness to V_{1FD} . Each point represents a single crater in our $N = 1184$ dataset.

Negative Gravity Anomalies

Positive Gravity Anomalies



Ambiguous Gravity Anomalies

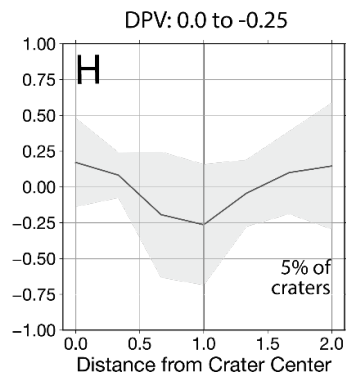
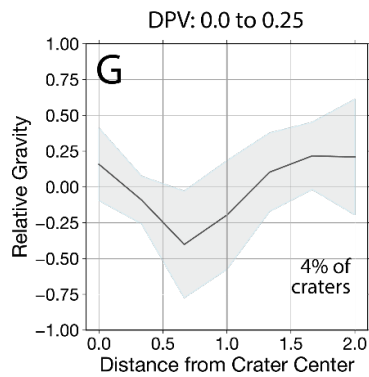
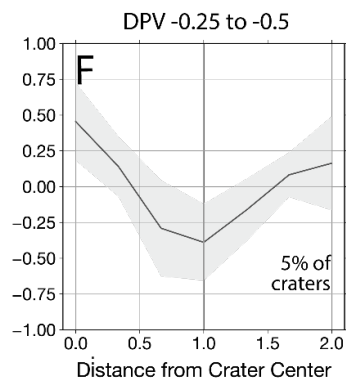
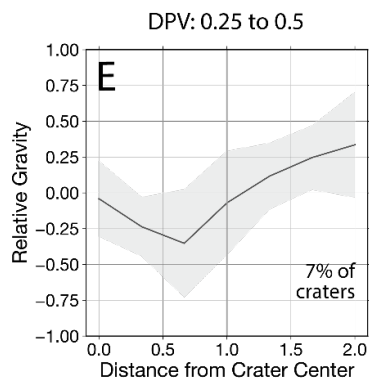
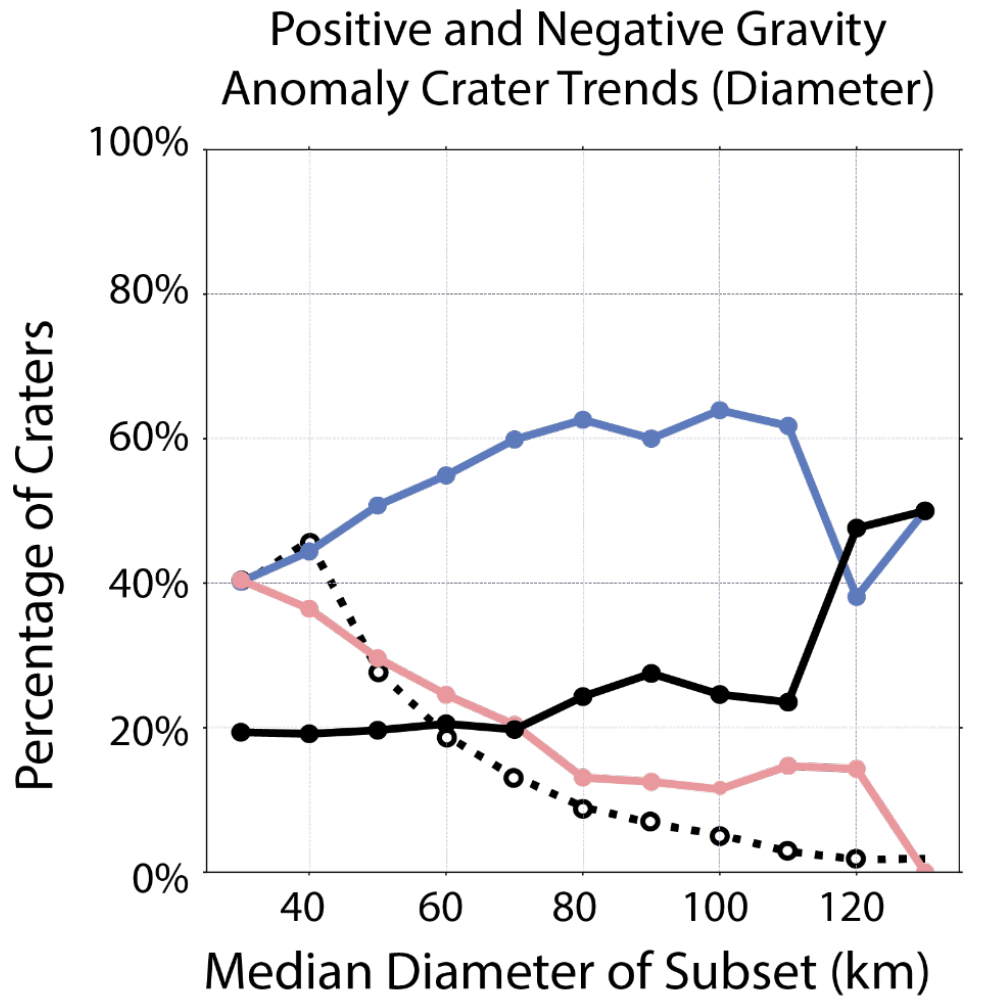


Figure 2-11. Radial gravitational profiles for craters from the N=1184 full dataset, grouped by dot product value (DPV) ranges calculated with respect to V_{1FD} for each crater. (A,B) Craters with DPV values > 0.5 (blue) have negative gravity anomalies. (C, D) Craters with DPV values < -0.5 (red) have positive gravity anomalies. (E-H) Craters with $0.5 > \text{DPV values} > -0.5$ (grey) have ambiguous gravity anomalies. Crater rims are indicated in each plot by a vertical grey line. The percentage of craters from the full dataset that appear in each plot is given in bottom right.



Points represent crater diameter subset bins, 20km-wide window size

- Craters in porosity subset as % of n=1184
- Craters with **Neg** Anomaly (DPV>0.5) as % of subset
- Craters with **Pos** Anomaly (DPV<-0.5) as % of subset
- Craters with **Ambig** Anomaly (-0.5<DPV<0.5) as % of subset

Figure 2-12. Distributions of craters that exhibit positive, negative, or ambiguous gravity anomalies as function of crater diameter. Craters from the full dataset of N = 1184 craters were first grouped into subsets with a bin size of 20 km. For each subset, the percentage of the craters in that subset having a positive, negative, or ambiguous gravity anomaly was calculated and plotted at the midrange diameter of that subset.

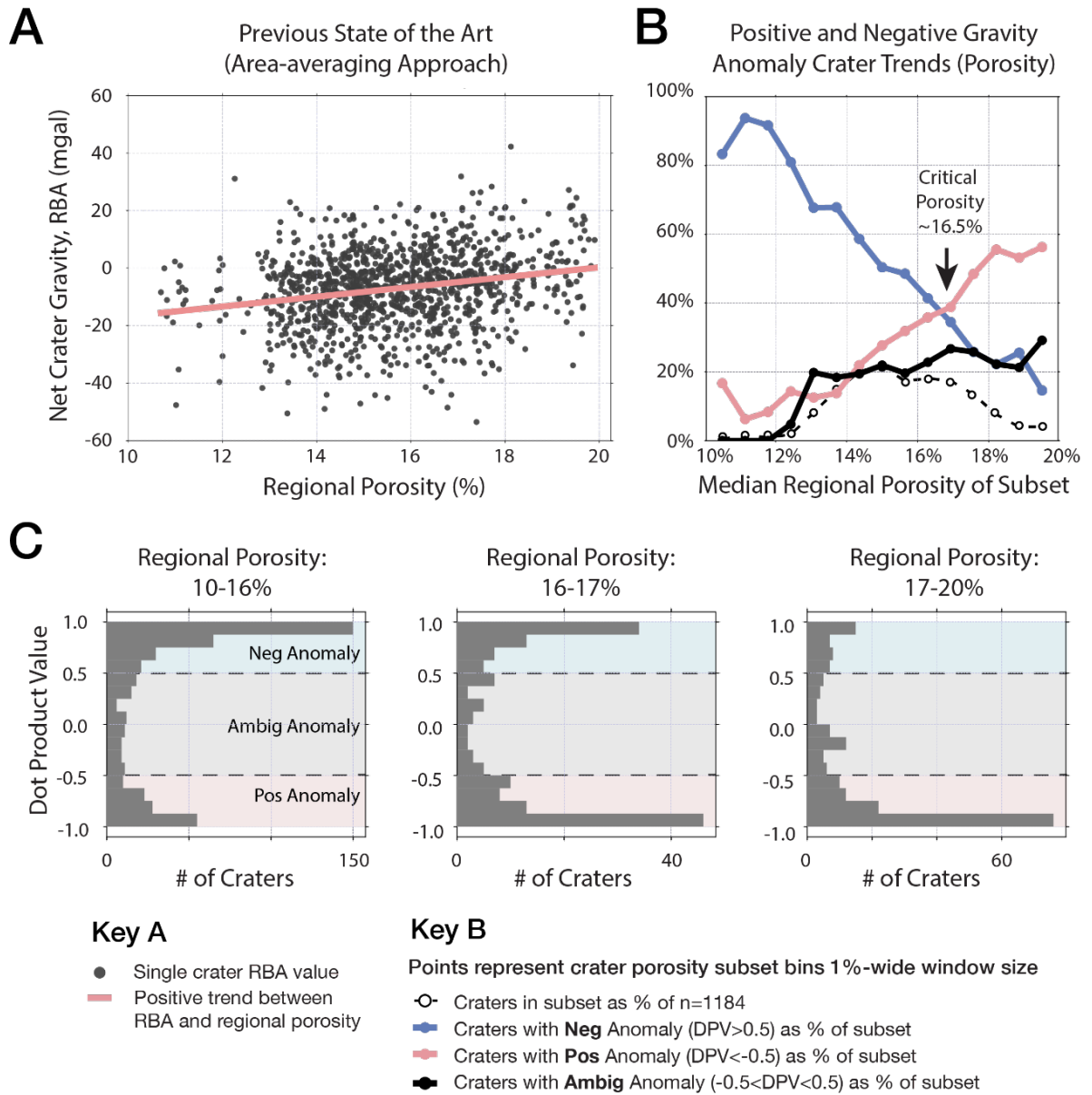


Figure 2-13. Crater gravity and regional porosity trends: comparing previous state-of-the-art and GEEX. (A) Plot of residual Bouguer anomaly (RBA) as function of regional porosity for impact craters, showing previous state-of-the-art approach based on area averaging for characterizing relationship of porosity and gravity for impact craters (after Soderblom et al., 2015). Linear fit to data given in red. (B) Craters from our study's full dataset of $N = 1184$ craters were grouped into subsets with a bin size of 1% porosity and the percentage of craters with positive, negative, or ambiguous gravity anomalies were likewise calculated and plotted. The "critical porosity" of ~16.5%, at which the fraction of craters with positive anomalies equals that of craters with negative gravity anomalies, is indicated. (C) Histograms of the dot product values (DPVs) of craters grouped by the craters' region porosity. DPVs corresponding to negative, ambiguous, and positive gravity anomalies are indicated with horizontal dashed lines.

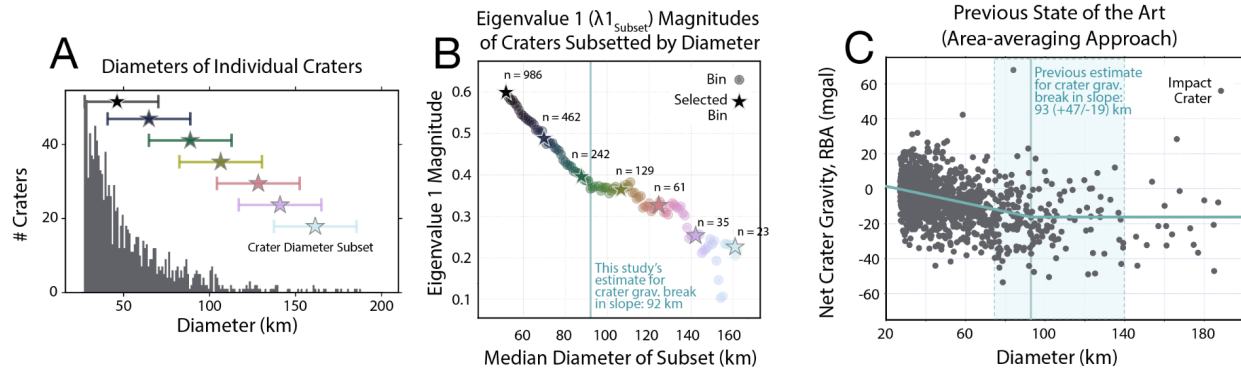


Figure 2-14. Gravity and diameter trends of impact craters: comparing previous state-of-the-art and GEEX. (A) Histogram of the full dataset of 1184 craters binned by diameter (1 km per bin). Above the histogram are the ranges (50 km) and midrange diameters (stars) of subsets of craters examined in panel B of this figure. Colors of stars in A correspond with colors of stars in B. (B) Plot of eigenvalue 1 ($\lambda_{1\text{Subset}}$) for subsets of the full dataset (bin size 50 km) as a function of diameter. The smaller selection of subsets shown in A and discussed below in Figure 15 are indicated with stars. Colors of stars and circles are keyed to diameter. The previously estimated location (light blue) of a break in slope of crater RBA at $D = 93^{+47}_{-19}$ km calculated using area-averaging techniques by Soderblom et al. (2015) coincides with a plainly visible break in slope in our own data. (C) Plot of residual Bouguer anomaly (RBA) as function of crater diameter, which was the previous state of the art approach to analyzing gravity of impact craters (after Soderblom et al., 2015). Linear two-slope Bayesian fit to data and estimates for location of break in slope with 95% confidence interval (vertical lines) are given in light blue.

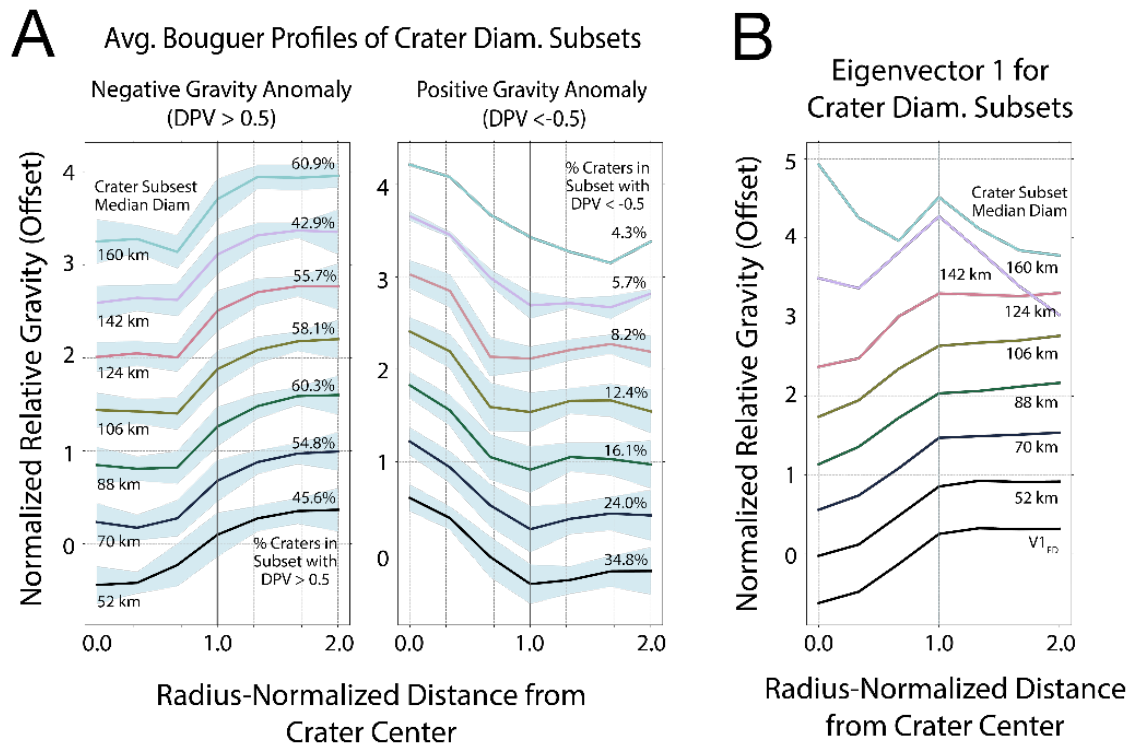


Figure 2-15. Eigenvector 1 ($V1_{\text{Subset}}$) and eigenvalue 1 ($\lambda1_{\text{Subset}}$) trends for subsets of craters derived from the seven 20 km-wide diameter ranges shown in Figure 14A, using consistent color coding. (A) Mean standardized relative gravity profiles for selected subsets of craters, grouped by the dot product value (DPV) calculated for each crater. DPVs are calculated with respect to $V1_{\text{FD}}$. Light blue region indicates 1σ variation of each diameter bin. Midrange diameter of each subset and the percentage of the 1184 craters in the full dataset appearing in each subset are given. Location of crater rim given by grey vertical line. (B) Eigenvector 1 profiles ($V1_{\text{Subset}}$) for the same selected subsets as shown in (A). Eigenvector 1 for the full dataset ($V1_{\text{FD}}$) is also shown for comparison purposes as the bottom-most profile.

CHAPTER 3: Gravitational Trends with Crustal Thickness for Complex Lunar Impact Craters

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Abstract

Gravity signatures of complex lunar craters offer insight into crustal structure (e.g., depth of pore closure) and impact porosity generation, but the variation in these gravity signatures has only been partially characterized ($<10\%$). While impact models have suggested that crustal thickness affects crater gravitational profiles, variables beyond diameter and pre-impact porosity have not been found to improve statistical models of variations in observed gravity signatures of complex craters.

Here, we searched for the effect of crustal thickness in Gravity Recovery and Interior Laboratory (GRAIL) gravity data using a recently developed analytical framework called Guided Endmember EXtraction (GEEX), pronounced "geeks" (Hundal et al., in review). Using GEEX, for the first time, we present evidence suggesting crustal thickness's influence on the gravitational signatures of complex craters, indicating (a) with increasing crustal thickness, complex craters produce a wider range of profile shapes that favor negative relative gravity anomalies over positive relative gravity anomalies and (b) the presence of a homogeneous domain that exists at a depths of $\sim 5\text{-}20$ km in shallow low porosity ($10\text{-}16\%$), intermediate-thickness ($40\text{-}48$ km) crusts.

1 Introduction

Impact cratering evolves planetary crustal structure on a wide range of spatial and temporal scales, altering thermal conductivity, promoting magmatic and volatile transport, enhancing geochemical cycling, and creating niches for subsurface habitability. The Moon is an ideal natural laboratory for studying impact processes due to the dominance of impact cratering and absence of liquid water, life, or atmospheric processes. Due to the Moon's proximity to Earth, it has been extensively measured by a wide range of global and high-resolution planetary datasets, including

the Gravity Recovery and Interior Laboratory (GRAIL) mission (Zuber et al., 2013). Under an assumption of constant grain density (i.e., composition), variations in gravity can be used to infer changes in the porosity structure of the lunar crust. GRAIL gravity studies have enabled much recent work on how impact cratering evolves the crustal structure of the Moon (Besserer et al., 2014; Bierson et al., 2016; Izquierdo et al., 2021; Soderblom et al., 2015; Wahl et al., 2020, Huang et al. 2022).

The gravitational signatures of simple and complex craters are powerful probes into the lunar crust as well as the impact cratering process. They reveal key structural transitions, such as the depth of pore closure and megaregolith layering (Soderblom et al., 2015; Izquierdo et al., 2021), and show how variables like diameter and pre-impact porosity influence impact-generated gravitational signatures (Milbury et al., 2015; Soderblom et al., 2015). However, despite a significant number of studies on complex crater gravity signatures (Soderblom et al. 2015, Bierson et al. 2016, Izquierdo et al. 2021), variables beyond diameter and pre-impact porosity have not been found to statistically affect our current models of impact generated signatures, even as those same models account for only about 10% of the observed variation in complex crater gravitational signatures (Bierson et al. 2016).

Crustal thickness has been shown in modeling to be an additional geophysical variable affecting the generation of impact-induced porosity for complex craters (Milbury et al., 2015; Rajsic et al., 2025). However, despite efforts using advanced frequency filtering and area-averaging methods, the effect of crustal thickness has remained elusive in observational gravity data (Bierson et al., 2016).

Here, we searched for the effect of crustal thickness in GRAIL gravity data using a recently developed analytical framework called Guided Endmember EXtraction (GEEX), pronounced

"geeks" (Hundal et al. in review). GEEX uses dimensionality reduction to (a) quantify variations in radial gravitational profile shapes and (b) track how these variations change with underlying geophysical parameters. GEEX has reproduced the lunar depth of pore closure with an order-of-magnitude higher precision and revealed novel findings from GRAIL data, including characteristic positive and negative anomaly shapes for complex craters and evidence that the shallow porosity of the Moon is not in equilibrium (Hundal et al., in review).

In Section 2 we review background on dimensionality reduction techniques. In Section 3 we describe our GEEX framework and how we apply it to our crater gravity profile dataset. In Section 4 we use GEEX to derive a set of eigenvectors and eigenvalues, which capture statistically significant shapes of variation in Bouguer gravity profiles and their relative importances. We observe how eigenvalue varies with crustal thickness. In Section 5 we interpret the geologic significance of these trends for the impact cratering process and the structure of the lunar crust. In Section 6 we summarize our conclusions, discuss the implications of this work.

2 Background

GEEX is a framework for the analysis of correlated and repeatable structures in geophysical data using dimensionality reduction techniques. GEEX has six steps: (1) selection of data in physical space, (2) selection of data in signal space, (3) data standardization for correlated data, and (4) dimensionality reduction, (5) Dot Product Values (DPVs), and (6) subsetting by geophysical variables. A detailed description of the GEEX methodology can be read in Hundal et al. (in review).

While GEEX can theoretically use any dimensionality reduction technique, here we employ Principal Components Analysis (PCA; R. A. Johnson & Wichern, 2007). PCA is one of the simplest and most well-established forms of dimensionality reduction, used in a wide variety

of fields such as meteorology, spectroscopy, engineering, and many more (e.g., Lorenz, 1956; Kourti & MacGregor, 1996; Wold et al., 1987; Jolliffe & Cadima, 2016). Because PCA produces completely independent axes or "shapes" of variation in a dataset, called eigenvectors, it is useful for the interpretation of complex data. This is particularly helpful for datasets subject to significant variations, such as impact craters in ancient terranes (Hundal et al. in review). PCA starts by creating a covariance matrix, which expresses the degree to which different variables, like gravity and different distances from a crater center, change together. From this matrix, we calculate eigenvectors, which show the main patterns of variation in the data. Eigenvector 1 describes the shape of greatest variation in a dataset, indicating a strong predominance in the data of profile shapes resembling (a) eigenvector 1 as well as (b) eigenvector 1's vertical flip.

2.1 Interpreting eigenvalues

Our study makes extensive use and interpretation of eigenvalue 1s with increasing crustal thickness. Therefore, we first focus on an in-depth explanation of how the magnitude of eigenvalue 1 correlates with the distribution of shapes and orientations in each set of profile data.

Figure 1 shows simplified examples of how variations in the sign and shape of profiles may influence eigenvectors and eigenvalues. Eigenvectors will have the same dimensions as their gravitational profile input data: their x-axes will be radial distance from the crater center, and their y-axes will be relative normalized gravity. Eigenvectors are sign-agnostic, meaning they describe a range of shapes including any positive or negative vertical stretch of the eigenvector. This sign-agnostic quality is shown in Figure 1 as solid blue line (positive orientation of the eigenvector) and dotted blue lines (negative orientation).

Each eigenvector comes with an associated eigenvalue that indicates how much variation there is along vertical multiples of an eigenvector's shape in the data. The eigenvalue depends on

two factors: (a) whether profiles match a given eigenvector shape well and (b) how much vertical variation of that shape is expressed in the data. In Figure 1B, all profiles are similar except for one profile, which is in the same shape but vertically flipped with respect to the others. Because only one out of ten profiles is flipped, the vertical variation described by eigenvector 1 is low in the data, and therefore, the eigenvalue is small. However, in Figure 1C, where again all profiles are roughly the same shape, about half of the profiles are in one orientation and remaining profiles are vertically flipped. In this case, the eigenvalue is near its maximum of 1 for input normalized profiles of length 1.

The first eigenvector captures the dominant shape of variation across a set of profiles but does not necessarily correspond 1:1 to the shape of any individual profile. This distinction is illustrated in Figure 1D and E. In panel D, the dataset is composed primarily of similar profiles, with a single outlier of contrasting shape. As a result, the first eigenvector reflects a compromise between the two shapes and does not resemble any single profile. In panel E, the distribution of shapes is more balanced, yet the eigenvector shape remains essentially unchanged. However, the corresponding eigenvalue increases, reflecting the fact that the contrasting shape now constitutes a larger fraction of the dataset. Thus, while the eigenvector shape describes the shape of variation, the eigenvalue quantifies the extent to which that variation is expressed across the group.

The number of eigenvectors produced during PCA corresponds to the dimensionality of the data. In this study, the dimensionality of the dataset is seven because we extract seven points from crater gravitational profiles. Seven points are extracted due to the resolution constraints of GRAIL data on our smallest craters (see Section 3).

Each following orthogonal eigenvector after the first describes decreasing amounts of variation. Orthogonality implies that each eigenvector is mathematically perpendicular to all others

in n -dimensional space. That is, the dot product between any pair of eigenvectors is zero, ensuring that each represents an independent mode of variation. Because of this orthogonality, any profile in the dataset can be expressed as a linear combination of these eigenvectors, each weighted with appropriate coefficients, with no redundancy or overlap in the directions they span. In the context of gravitational profiles, this means that each eigenvector captures a unique pattern of variation, uncorrelated with the others, enabling a clean separation of signal components in high-dimensional feature space.

Hundal et al. (in review) calculated a set of eigenvectors and eigenvalues for the entire Soderblom et al. (2015) database of lunar highland complex craters, the database from which our study also draws. These eigenvectors describe the dominant shapes of variation that are at play in our study. In particular, we compare the shapes of gravitational profiles in our study to the first eigenvector of the full Soderblom dataset, abbreviated as V_{1FD} . V_{1FD} exhibits a ramp shape: a steady slope from a distance of $0R$ (center) to $1R$ (rim) and then flat exterior to a distance of $2R$ (crater exterior).

Eigenvalue break-in-slopes identify specific parameter values or ranges where significant changes in the underlying data structure occur. This enables precise detection of transitions across geophysical variables. For example, Hundal et al. (in review) uses a break in slope in eigenvalue $1s$ across groups of craters of increasing diameter to identify the depth of pore closure on the Moon.

To learn more about what orientations and shapes of the individual craters in the groups summarized by eigenvalues, we calculate Dot Product Values (DPVs) for all the craters in our study. A DPV is calculated by taking the dot product between an individual profile and a reference profile shape, giving information on whether that profile is (a) whether the profile is similar in shape to a given reference vector, and if so (b) what sign orientation that profile is in with respect

to the reference vector. All the DPV values calculated in this study are with respect to eigenvector 1 for the full Soderblom database of highland complex craters (V_{1FD}). For an in-depth analysis on how DPV values correspond to profile shapes, please see Hundal et al. (in review).

3 Data/Methods

Details of the GEEX method are described in Hundal et al. (in review). Here, we provide a brief summary of our data and GEEX application to different crater subsets.

We draw the craters of our study from the Soderblom et al. (2015) dataset of complex highland lunar craters, hereafter referred to as the Soderblom dataset. The Soderblom dataset contains 1184 complex highland craters $D = 27\text{--}201$ km, selected from the Head et al. (2010) crater database. Highland craters are defined as those located outside the rim of the South Pole–Aitken basin with a mean regional elevation, measured from an annulus extending from the rim flank to $2R$, exceeding 0.5 km. The minimum diameter of 27 km exceeds that of the largest simple craters on the Moon, and the maximum diameter is smaller than craters that show gravitational evidence of mantle uplift (Soderblom et al. 2015).

We use Bouguer gravity data from the GRGM1200B RM1 model with $\lambda = 1$, calculated to degree and order 1200 by Goossens et al. (2020). Following the example of Izquierdo et al. 2021, we conservatively limit our analysis to degrees 7–650. Degrees 1–6 are excluded to remove long-wavelength features such as the crustal dichotomy. Degrees greater than 650 are removed to reduce noise. We apply a cosine taper from degrees 600–650 to limit ringing. This gravity field corresponds to a half wavelength resolution of ~ 8 km. Analyses of spherical harmonic data were done using Pyshtools (Wieczorek & Meschede, 2018). Following the approach of Hundal et al. (in review), we extracted zonal profile data from each crater center to a distance of $2R$, interpolating to seven radial distances: $0R$, $0.333R$, $0.667R$, $1R$, $1.333R$, $1.667R$, and $2R$.

While seven eigenvectors are created for each group of craters analyzed by PCA in this study, we only show results for eigenvector 1. This approach allows us to assess whether crustal thickness exerts any influence on the shape of gravitational profiles, and if so, to identify the first-order trends associated with that variability.

Craters in our study's size range excavate to depths of 5–50 km (Holsapple, 1993), overlapping the 25–60 km crustal thickness of the lunar highlands (Wieczorek et al 2013). However, an overwhelming majority of our craters (>90%) excavate to depths less than 25 km. Our analyses therefore use the shallow porosity model for the Moon derived by Besserer et al. (2014). Crustal thicknesses for this study are derived from Crustal Thickness Model 1 calculated by Wieczorek et al. (2013).

Crustal thickness and porosity are loosely correlated as shown in Figure S10 of the supplementary materials. For this reason, we examine crustal thickness trends at a variety of porosities and include versions of our main text figures color coded for porosity in the supplementary materials.

3.1 Subsetting

The power of GEEX is enhanced by comparing the results of PCA on many groups of craters with slightly differing geophysical parameter ranges. To assess whether crustal thickness affects the first-order variability of gravitational profiles, we divided our dataset into thirty-one finely spaced crustal thickness bins, each ten kilometers wide and with midranges separated by one kilometer. To isolate the effects of crustal thickness from those of diameter and porosity, both previously shown to influence crater gravity signals, we further subdivided each crustal thickness bin by diameter and porosity ranges, as detailed below.

Figure 2 shows the parameter ranges used for subsetting. Data were subset into every possible combination of ranges for porosity (three bins), diameter (six bins), and crustal thickness (31 bins) that each contained at least eight craters, the minimum required to produce all non-zero eigenvalues for PCA eigenvectors (see Section 4). While 558 combinations are possible, only 396 ranges contained at least the minimum number of craters.

Diameter bins were defined first. We used six overlapping 20 km-wide ranges, with midpoints advancing by 10 km from 40 ± 10 km to 90 ± 10 km. While our original dataset includes crater diameters extending up to 201 km, we are only able to perform subsetting on craters with diameters up to 100 km due to the limited crater numbers beyond this size.

We show results from craters in low-porosity terranes (10-16%, $N = 681$ craters), as opposed to the full range of porosity terranes (10-20%, $N = 1185$) available from the Soderblom et al. (2015) database of complex highland lunar craters. Groups of craters in higher porosity terranes ($>16\%$ porosity) do not show unambiguous trends with crustal thickness in our analyses and, instead, are dominated by changes that correlate with diameter and porosity. Even so, we still include the results of our crustal thickness analyses in higher porosity terranes in the supplemental materials (Supplemental Section 7.3).

Within 10-16% porosity, we additionally observed variations in preliminary analyses binned by the slightly narrower porosity ranges 10–15% ($N = 462$) and 14–16% ($N = 468$). The significant overlap between craters (50%+) in each porosity bin (10-16%, 10-15%, and 14-16%) is necessary to provide sufficient numbers of craters for our analysis in each bin after further subsetting by crustal thickness and diameter. And so, each diameter subset was further divided into three low-porosity bins: 10–15%, 14–16%, and 10–16%, yielding a total of 18 diameter/porosity subsets.

Finally, we further subset these diameter/porosity groups based on crustal thickness in narrow, 10 km-wide crustal thickness ranges that advance their mid-range by 1 km between sets. The minimum and maximum crustal thickness is based on the range of thicknesses in each of the eighteen diameter and porosity ranges described above. In cases where there were fewer than eight craters in a given crustal thickness, diameter, and porosity range, PCA was not performed due to dimensionality constraints (see Section 2). In all, this produced 396 distinct subsets, each with a specific crustal thickness, diameter, and porosity range.

4 Results

Here we examine the results of our GEEX analysis with a focus on Eigenvalue 1 (λ_1) and Dot Product Value (DPV) trends with crustal thickness for craters in low porosity terranes (10–16%).

Figure 3 shows eigenvalue 1 results from our low-porosity crater groups, arranged by shallow regional porosity (columns: 10–15%, 14–16%, and 10–16%) and diameter (rows: 40±10 km to 90±10 km in 10 km increments). The associated eigenvector 1s of the group of craters evaluated shown in Figure 3 are shown in Figure S2 of the supplemental materials.

In all subplots of Figure 3A–C, we observe two important trends with increasing crustal thickness: (a) a general negative slope in eigenvalue 1s over the full range of crustal thicknesses (30–56±5 km) that is particularly strong in thin crusts (30–40±5 km) and (b) relatively flat slopes for eigenvalue 1s at intermediate crusts (40–48±5 km).

The general negative trend of eigenvalue 1s with crustal thickness is demonstrated in Figure 3D, which shows the sign of the best-fit slope taken from the 18 subplots of Figure 3A–C. All panels are red, indicating that all subplots exhibit negative slopes. Decreases in eigenvalue 1 indicate a decreasing contribution of that group's first eigenvector's shape to the total variability of

gravity profiles in a group of craters—either because fewer profiles resemble the first eigenvector's shape, or because profiles that resemble that shape are becoming more strongly oriented in a single direction.

Negative trends between eigenvalue 1 and crustal thickness generally become even more negative with increasing diameter up to $D = 80 \pm 10$ km; however, for the largest diameter plots ($D = 90 \pm 10$ km, bottom row), the overall trend of plots become less steeply negative for groups of craters that include slightly higher porosities ($> 15\%$, B,C).

The values of eigenvalue 1 decrease most rapidly with crustal thickness in thin crusts ($30-40 \pm 5$ km thick) for all subplots in Figure 3A-C. As noted above, this indicates that the shapes and/or orientations of gravitational profiles are changing significantly with crustal thickness for thin crusts.

Eigenvalue 1s tend to remain relatively constant at intermediate crustal thicknesses ($40-48 \pm 5$ km, shaded region in Figure 3A-C). Figure 3E shows the best-fit slope between crustal thicknesses of 40-48 km for the 18 subplots in Figure 3A-C. In 13 of the 18 subplots, eigenvalue 1s remain constant or decline only slightly across this range (indicated by light-toned panels in Figure 3E). The remaining five subplots exhibit steeper eigenvalue changes between $40-48 \pm 5$ km thickness (indicated by crossed, dark red panels in Figure 3E). These five steeply-sloped subplots are all at larger crater diameters ($70-90 \pm 10$ km). However, if a subplot is steeply sloped at intermediate crustal thicknesses in one of the three porosity range, it is not steeply sloped at all porosity ranges. Slopes at intermediate crustal thicknesses are not uniformly expressed across the three porosity ranges. For example, in the bottom-most row of subplots, showing the largest craters ($D = 90 \pm 10$ km), the slope of eigenvalue 1 at intermediate crustal thicknesses ($40-48 \pm 5$ km) is sharply negative for the left-most column ($10-15\%$ porosity), but this slope is relatively flat in the

right-two columns, where higher-porosity craters are included (14–16% and 10–16%).

While trends between eigenvalue 1 and crustal thickness are well defined for thin crusts (30-40±5 km, steeply negative slopes) and intermediate crusts (40-48±5 km, flat slopes), in the thickest crusts (>50 km), the slopes of eigenvalue 1s with increasing crustal thickness are variable. In some cases, eigenvalue 1s decrease significantly after 50±5 km thickness, as is the case for the $D = 50 \pm 10$ km row of subplots, where eigenvalues drop by over half (~65%) across just five kilometers of change in crustal thickness. Conversely, the effect is reversed for the $D = 70 \pm 10$ km row, which shows a modest increase in eigenvalue of 0.1 (unitless) over the same five kilometers.

If we examine the associated eigenvector 1s of those shown in Figure 3 in the supplemental materials (Figure S2), they typically resemble the shape of $V1_{FD}$ at thin crusts (steady slope upward from the center to the rim, indicated by a vertical line, then flat in the exterior region of the crater out to $2R$). However, for craters $D \geq 60 \pm 10$ km, eigenvector 1s tend to change in shape away from that of $V1_{FD}$ with increasing crustal thickness, and instead resemble one or a combination of two following lower-order eigenvectors from the Soderblom database ($V2_{FD}$ - $V3_{FD}$, see Hundal et al. in review).

Eigenvalue 1 is a powerful tool for precisely indicating important geophysical values and ranges at which transitions in the shapes and orientations of gravitational profiles occur (e.g., 40-48 CTs); however, it does not specify what particular shapes and orientations are dominating and changing within a given geophysical value range. To address this, we apply Step 5 of the GEEX framework, Dot Product Value (DPV) analyses. By taking the dot product of our gravitational profiles with a single standard profile shape, we can track how profiles change in their shape-likeness and orientation with respect to a standard profile. In this case, our standard profile is the first eigenvector of the full Soderblom dataset of complex highland craters $V1_{FD}$ (see Figure 4D,

Hundal et al. in review). $V1_{FD}$ is the most important shape of variation for the Soderblom dataset, and therefore provides an excellent profile against which we can track changes in orientation and shape in our dataset. Furthermore, DPVs with respect to $V1_{FD}$ broadly indicate whether an crater's gravitational anomaly is positive ($DPV < -0.5$), negative ($DPV > 0.5$), or ambiguous ($-0.5 < DPV < 0.5$) (Hundal et al. in review).

In the Discussion below (Section 5), we will use the DPVs with respect to $V1_{FD}$ in Figure 4 to further examine two of the trends observed in Figure 3: (a) the broad negative slope of eigenvalue 1 with increasing crustal thickness across all crustal thicknesses ($30-56 \pm 5$ km) and (b) the flat areas of consistent eigenvalue 1s with crustal thickness in intermediate crusts ($40-48 \pm 5$ km).

Figure 4 shows crustal thickness vs. Dot Product Value trends with respect to the first eigenvector of the full Soderblom et al. (2015) dataset of complex lunar highland craters ($V1_{FD}$, see Figure 4D). Figure 4E demonstrates how DPV endmembers relate to the shape and orientation of a given profile, as well as whether that crater is likely a positive or negative anomaly (for more information on the correspondence between profile shape and DPV, please see Hundal et al. in review). Figures 4A-C show the same diameter (row), porosity (column), and crustal thickness (x-position) ranges used to calculate eigenvalue 1s in Figure 3. The number of craters indicated for a group in Figure 3 is split amongst the three DPV range colors in 4A-C.

DPV trends observed across all crustal thicknesses include (a) profiles different in shape from $V1_{FD}$ (indicated by black) generally increase in their fraction with increasing crustal thickness, and (b) the fraction of positive-anomaly profiles tends to decrease with increasing crustal thickness.

We also observe that most of the variation in DPV fractions occurs outside of intermediate

crustal thicknesses ($40\text{-}48\pm 5$ km). Exceptions to this include the five greyed-out plots of Figure 4, corresponding to the same geophysical ranges that produced steep eigenvalue 1 slopes at intermediate crusts in Figure 3.

There are several additional trends in the fractions of positive, negative, and ambiguous anomalies across all crustal thicknesses that have a strong diameter dependence. First, DPV fractions of larger craters ($D\geq 70\pm 10$ km) are more sensitive to changes with crustal thickness (sometimes changing by up to 0.6) than smaller craters ($D\leq 60\pm 10$ km), where changes are about half as significant (up to 0.3). For larger craters ($D\geq 70\pm 10$ km), the proportion of negative anomaly craters typically reaches a maximum around 48 km crustal thickness. At intermediate diameters ($50\text{-}60\pm 10$ km), positive anomaly fraction trends are very similar, being relatively constant at a value of 0.2 with increasing crustal thickness, then decreasing abruptly at 48 km to roughly zero between 52 and 55 km crustal thickness. For the largest craters ($D=80\text{-}90\pm 10$ km), the proportion of positive anomalies decreases rapidly in thin crusts (<40 km) and is roughly zero in intermediate and thicker crusts (>40 km). This is likely because V_{IFD} best characterizes smaller complex impact craters ($D < \sim 70$ km, Hundal et al. in review).

5 Discussion

Here we discuss potential geophysical interpretations for the trends observed in the Results (Section 4), including the overall negative trend between eigenvalue 1 and crustal thickness, especially at thin crusts (25-40 km thick), as well as the "flat" ($|\text{slope}| < 0.01$) slopes typically observed in eigenvalue 1s with crustal thickness for groups of craters in intermediate crusts (40-48 km thick). Our observations and interpretations are summarized in Figure 5.

Porosity is anti-correlated with crustal thickness (Figure S10) and porosity has already been established to affect gravitational anomalies, with positive anomalies being more likely to form in high porosity terranes and negative anomalies being more likely to form in low porosity terranes (Soderblom et al. 2015, Milbury et al. 2015, Hundal et al. in review). However, examining eigenvalue 1 trends with crustal thickness color-coded for mean group porosity (Figure S3), shows that the mean porosity of our groups of craters do not change significantly across crustal thicknesses, varying by less than 1% percent (0.7-0.9% at most). In several panels of Figure S3, local porosity minima and maxima do not appreciably affect eigenvalue 1. We therefore suggest that the observed downward negative trends are not simply a byproduct of changing porosity. Sharp changes in eigenvalue 1 slope occur at 40 km and/or 48 km in every porosity–diameter combination tested, indicating that these crustal thickness values are more important than porosity for this trend.

The negative eigenvalue 1 trend with crustal thickness in Figure 3 is matched by systematic trends in the shape of eigenvector 1s (Figure S2) and DPV analyses (Figure 4) with crustal thickness. The shape of associated eigenvector 1s with crustal thickness (Figure S2) typically resemble the shape of $V1_{FD}$ in thin crusts but change to different shapes (often resembling $V2_{FD}$ and/or $V3_{FD}$) with increasing crustal thickness, an effect that is much stronger at larger diameters ($D \geq 70 \pm 10$ km). These changes are also correlated with observed increases in the proportions of negative and ambiguous gravity anomalies relative to $V1_{FD}$ with crustal thickness, and with decreases in the proportions of positive gravity anomalies with crustal thickness (Figure 4).

Systematic trends with increasing crustal thickness in eigenvalue 1, eigenvector 1, and DPVs may relate to differences in the strength, temperature, and porosity structure of crusts with thickness. Johnson et al. (2018) has shown in iSALE hydrocode modeling that thinner crusts tend

to be stronger than thicker crusts due to differences in overburden pressure. Previous work has also shown that thinner crusts have generally experienced hotter thermal histories due to a given depth's increased proximity to the mantle and increased abundances of thermogenic elements (Miljković et al., 2013). As mentioned above, previous authors have also documented that thin crusts also tend to have higher porosities. This and increased temperatures promote compaction via impacts that result in more positive anomalies and fewer negative anomalies (Soderblom et al. 2015, Milbury et al. 2015, Hundal et al. in review).

Eigenvalues are high ($\sim 0.6\text{--}0.8$) for thin crusts ($30\text{--}40 \pm 5$ km), indicating profiles are consistent in shape and evenly distributed in their orientations (as supported by DPV trends). From this, we infer that thinner, stronger, and more porous crusts favor consistent profile shapes that resemble V_{1FD} and well-balanced proportions of positive and negative gravity anomalies. With increasing crustal thickness, eigenvalue 1s in thin crusts ($<40 \pm 5$ km) decline sharply, which may indicate that the effect of crustal thickness on gravitational profile shape is changing rapidly in thin crusts. In contrast, eigenvalue 1s are low (typically .1 to .4) in thicker (>48 km), colder, and weaker crusts, producing a wider range of profile shapes that favor negative anomalies over positive anomalies. While reduced eigenvalues are especially pronounced at large diameters ($D \geq 70 \pm 10$ km), this likely arises from reduced representativeness of V_{1FD} for craters larger than $D \sim 70$ km.

Intermediate crustal thicknesses between $40\text{--}48 \pm 5$ km typically exhibit relatively constant eigenvalue 1s. Similarly, most of the variation in eigenvector 1 shape (Figure S2) and DPV fractions (Figure 4) for positive, negative, and ambiguous anomalies occurs outside of this intermediate crustal thickness range. However, this is not true for the geophysical ranges corresponding to five of the nine larger diameter ($D \geq 70 \pm 10$ km) panels in Figure 3 that do not show flatness in the intermediate crustal thickness range. For those the geophysical ranges

corresponding to those five panels, eigenvalues, eigenvectors, and DPV fractions do change appreciably in intermediate ($40\text{-}48\pm 5$ km) crusts.

Therefore, we suggest the presence of a uniquely homogenous 3D volume within the lunar crust at a depths of 7-21 km, and potentially shallower, corresponding to shallow low-porosity (10-16%) and intermediate-thickness crusts (40-48 km). This region covers an area of roughly 2.3 million km^2 , or 6% of the lunar surface, and a volume of 32 million km^3 .

6 Conclusions

Here, we present the first observational evidence of crustal thickness's first-order effects on the variability of impact-induced gravity signals for low porosity (10-16%) craters.

We find the following:

1. The first-order variability in the shape and orientation of gravitational profiles generally decreases with increasing crustal thickness. This effect is most pronounced at thin crusts <40 km thick.
2. At intermediate crustal thicknesses (40-48 km), the first-order variability in the shape and orientations of gravitational profiles remains relatively constant for small craters ($D\leq 60\pm 10$ km).

This may suggest the presence of a uniquely homogenous 3D volume of ~ 30 million km^3 within the lunar crust, surrounding proximal to the northern and western edges of the central highlands north of SPA at depths of 7-21 km.

These effects may be due to changes in the strength of the lunar crust with thickness, and/or they may be due to lateral variations across the lunar crust that due to crustal differences in geochemistry, structure, and thermal history.

Future work may examine changes in the shape of eigenvector 1 as well as eigenvectors beyond the first to determine finer scale variations that may be caused by crustal thickness.

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PCA Eigenvector and Eigenvalue 1 results from schematic profiles

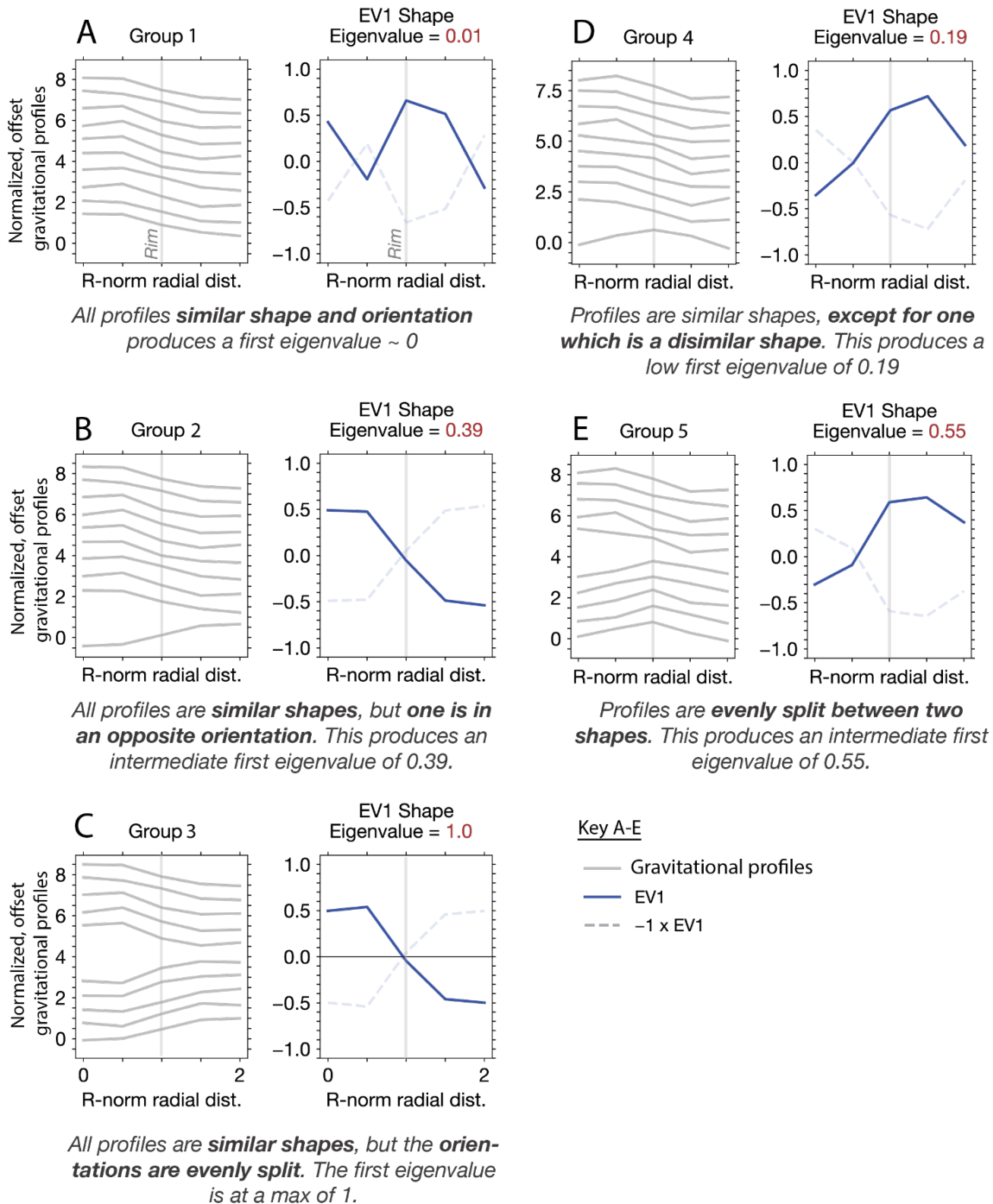


Figure 3-1. Schematic example calculations of eigenvector 1 (EV1) and eigenvalue 1 from gravity profiles. Each example (a-e) shows groups of hypothetical, resampled gravity profiles, and

highlights how variations in the sign and shape of the profiles may influence eigenvectors and eigenvalues. Examples (a-c) show gravity profiles with similar shapes but differing proportions of sign-orientation. (a) Group of craters with no variation in the shape or sign of craters, which is unrealistic for studies of craters. This hypothetical edge-case has an eigenvalue near 0, indicating little variation in the shape and orientation of profiles. Eigenvector 1 merely highlights noise. (b) Group of craters with a single crater exhibiting an inverted sign with respect to the remaining profiles. The eigenvalue is intermediate and the eigenvector shows the shape of variation in the data. (c) Group of craters with roughly half of crater profiles showing inverted sign. Because half are in one orientation, and the remaining exhibit an inverted sign, and there are no other shapes to account for, the eigenvalue is as high as it can be for norm-1 profiles (EValue ~ 1). The shape of eigenvector 1 is the same as in the previous example (b). Examples (d-e) show profiles of two different shapes, but no variation in sign-orientation. (d) Profiles of the same shape, roughly sigmoidal, except for one, which is pyramid shaped. The resulting eigenvector is a 50-50 representation of the two shapes. The eigenvalue is low because most of the profiles are similar to one-another. (e) Profiles of half roughly sigmoidal shapes and half pyramid shapes. Despite pyramid shapes making up a higher proportion of the profiles, the shape of the eigenvector remains the same. However, the eigenvalue is higher (~ 0.5) because the variation is more evenly split among the profiles. The eigenvalue is not as high as in (c) because the shape of eigenvector 1 is different from the shapes of any of the profiles used to calculate it.

Geophysical parameter ranges used to define PCA subsets

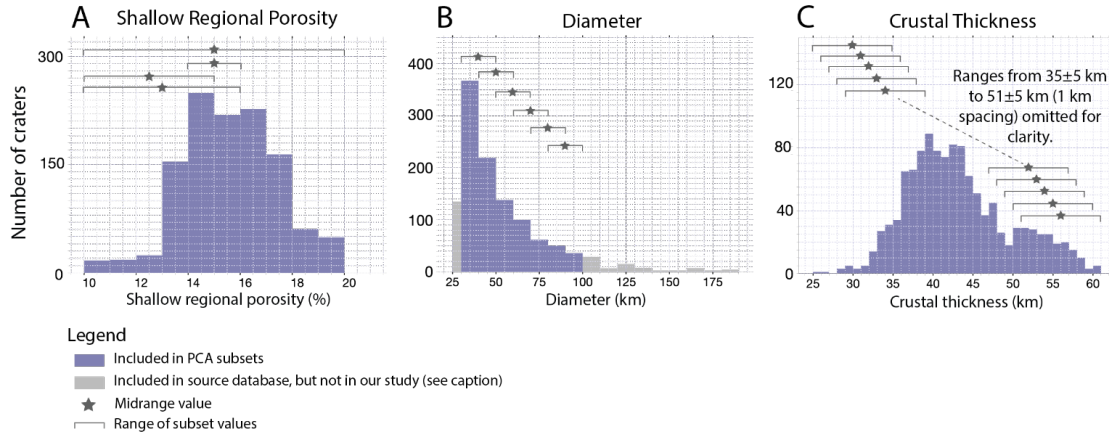


Figure 3-2. Geophysical parameter ranges used to define the 396 crater groups analyzed with PCA. Brackets denote range limits; stars mark midrange values. Of 558 possible combinations of these porosity, diameter, and crustal thickness bins, 396 met the minimum crater count ($N \geq 8$) required for PCA and were included in this study. (A) Porosity histogram for lunar highland craters from Soderblom et al. (2015). Craters were subset into three porosity bins: 10–15%, 14–16%, 10–16%, and 10–20%. (B) Histogram of diameters from our source crater database. Six ranges were defined by 20 km-wide diameter bins, with midranges separated by 10 km. Craters with diameters $D > 100$ km did not contain the minimum number of craters necessary, eight, to run PCA when additionally subset by the two other variables shown. Small craters $D < 30$ km were not included to maintain the equal spacing of each range. (C) Histogram of crustal thicknesses beneath craters in our source database. Brackets indicate 31 ranges of crustal thickness, each 10 km-wide, with the midrange of each separated by one kilometer.

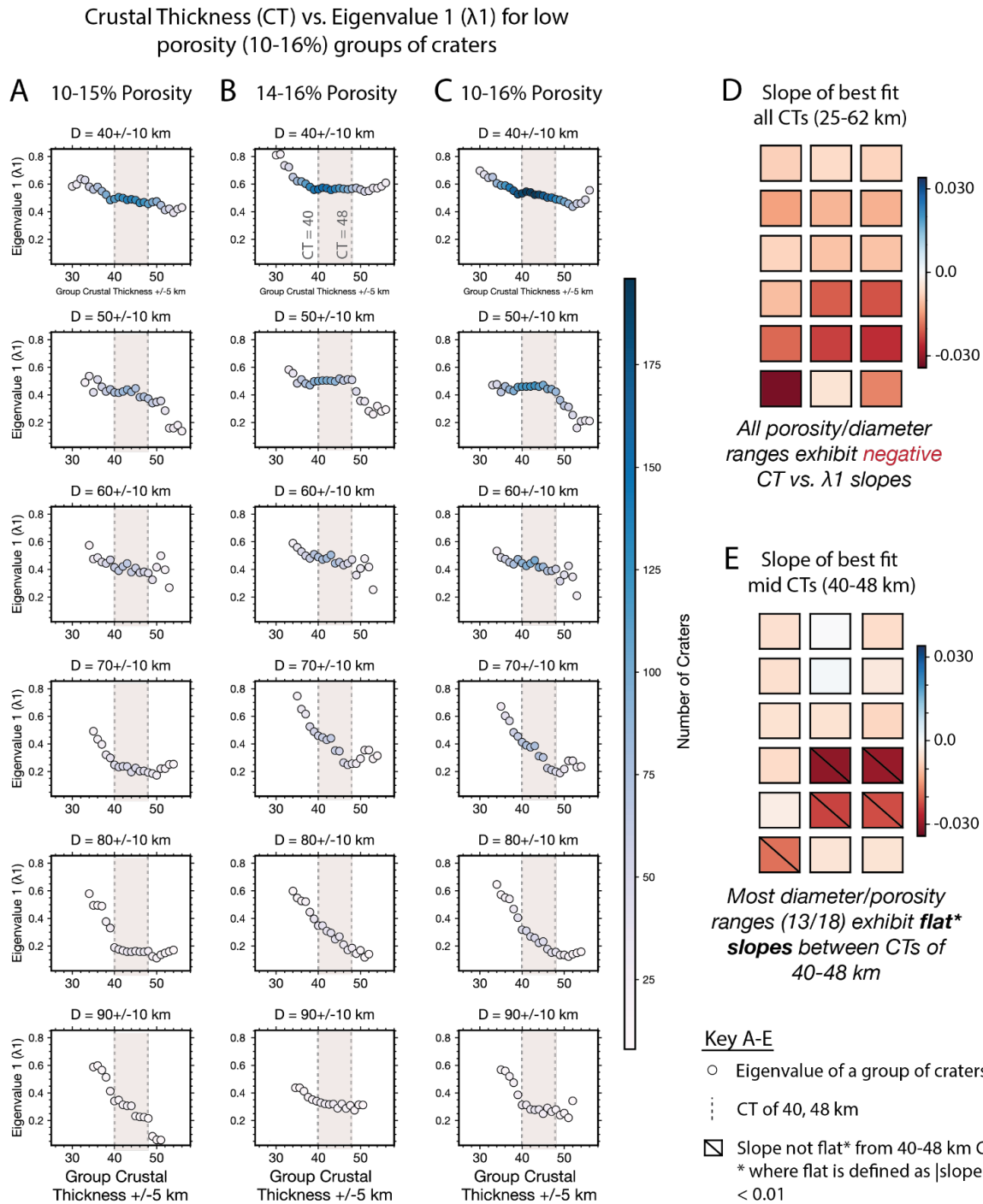


Figure 3-3. Eigenvalue 1 (λ_1) trends with crustal thickness for low-porosity (10–16%) crater groups, divided into three porosity columns: 10–15%, 14–16%, and 10–16%. Each circle

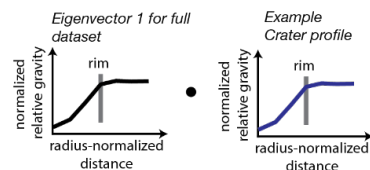
represents a group of craters within a specific combination of porosity, diameter, and crustal thickness ranges. Columns show porosity bins, rows show 20 km-wide diameter bins ($D = 40 \pm 10$ km to 90 ± 10 km, increasing downward). In each subplot, λ_1 is plotted against the midrange crustal thickness bin (± 5 km). The shaded region between $40\text{-}48 \pm 5$ km crustal thickness highlights where eigenvalues are sometimes constant in value (see text). (D) Best-fit slopes of each subplot in (a-c). Red values show all subplots are negative in slope and that slopes generally become more negative with increasing diameter. (E) Best-fit slopes for the $40\text{-}48 \pm 5$ km range of crustal thicknesses. Light-toned, uncrossed plots exhibit relatively constant eigenvalues in the $40\text{-}48 \pm 5$ km crustal thickness range.

CT of 40-48 km

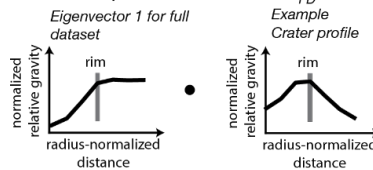
- Fraction of craters w/ neg. grav. anom. (DPV > 0.5)
- Fraction of craters w/ pos. grav. anom. (DPV < -0.5)
- Fraction of craters w/ ambig. grav. anom. (-0.5 < DPV < 0.5)

Graph of normalized relative gravity vs. radius-normalized distance for a thin shell. The curve starts at the origin, rises linearly to a point labeled 'rim' at distance 1, and then remains constant.

DPV = 1
Profile shape AND orientation similar to V1_{FD} (negative anomaly in crater)



Profile shape dissimilar to V1_{FD}



Profile shape similar to $V1_{FD}$, but vert. flipped (**positive anomaly** in crater)

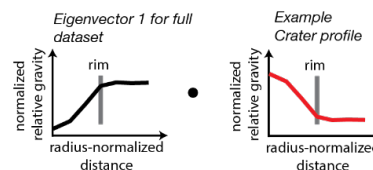
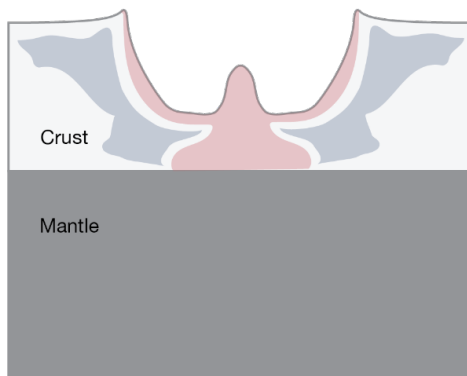


Figure 3-4. (A-C) Fraction of craters, within a specific combination of porosity and diameter ranges, that exhibit positive, negative, or ambiguous gravity anomalies with crustal thickness. Regional porosity ranges are divided by column (10–15%, 14–16%, and 10–16%). Rows show craters within 20 km-wide diameter bins ($D = 40 \pm 10$ km to 90 ± 10 km, increasing downward). The blue, red, and black colors of circles at each crustal-thickness midrange value together contain the same data as the single circle in the corresponding crustal thickness and subplot of Figure 4. Five subplots with desaturated colors are the same combinations of geophysical ranges that led to steep eigenvalue 1 slopes with crustal thickness in Figure 4, indicated there by crossed panels in Figure 4E. (D) Eigenvector 1 for the full Soderblom et al. (2015) dataset of complex craters in the lunar highlands ($V1_{FD}$). All DPVs are calculated with respect to this eigenvector. (E) Summary explanation of how profile shapes correlate with DPV values. For a more in-depth explanation of how profile shape changes with DPVs with respect to $V1_{FD}$, please see Figure 11 of Hundal et al. (in review).

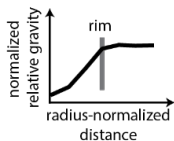
A Thin crusts (25-40 km)



Consistent grav. profile shapes

Eigenvector 1s resemble $V1_{FD}$

*Eigenvector 1 for full
Soderblom dataset ($V1_{FD}$)*



More positive anomaly craters

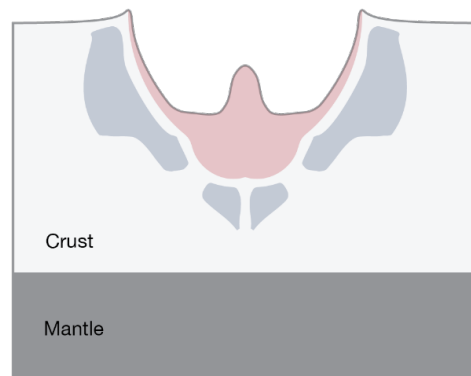
Larger positive anomaly craters

Higher porosity

Greater strength

Warmer thermal history

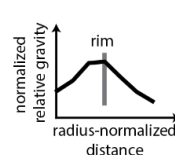
B Thick crusts (48-60 km)



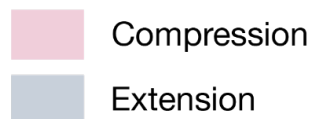
Wider range grav. profile shapes

Eigenvector 1s resemble $V2_{FD}$

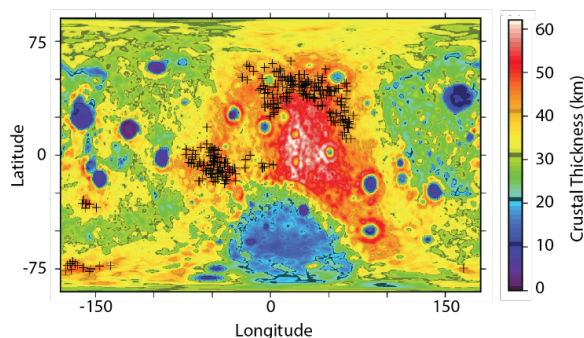
*Eigenvector 2 for full
Soderblom dataset ($V2_{FD}$)*



Key A, B



C Intermediate crusts (40-48 km)



Eigenvalue 1s consistent
Eigenvector 1s consistent
Corresponding to 7-21 km depth

*Potentially indicates a uniquely
homogenous volume within
lunar crust ~30 million km³*

+ = one crater

Figure 3-5. Conceptual figure summarizing observations and interpretations for how complex crater gravitational profiles vary with crustal thickness. Panels show (A) thin (25–40 km), (B) thick

(48–62 km), and (C) intermediate (40–48 km) crusts. (A) and (B) sketch the first-order trends with crustal thickness. (C) maps craters with consistent eigenvalue and eigenvector 1 behavior at intermediate thicknesses, potentially suggesting a homogeneous 3D crustal volume. Compression/extension schematics in (A) and (B) adapted from Rajšić et al. (2025).

CHAPTER 4: Deep Porosity of Farside Lunar Basins Revealed by Guided Endmember Extraction

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Abstract

High-resolution gravity data from NASA's Gravity Recovery and Interior Laboratory (GRAIL) mission has enabled direct investigation of the Moon's crustal porosity. Numerical models suggest that deep, basin-induced porosity plays a critical role in establishing the Moon's present-day porosity structure, yet previous gravity studies have not simultaneously resolved (a) lateral porosity variations at the basin scale and (b) porosity at depths greater than ~ 10 km. Because basin-forming impacts are the dominant process generating porosity in the lunar crust, and likely in the early crusts of Earth, Mars, and Venus, understanding how this porosity forms, redistributes, and collapses over time provides key constraints on planetary thermal evolution, magmatic localization, and volatile storage.

Here we apply a new statistical framework, Guided Endmember Extraction (GEEX), to the gravity signatures of complex craters, enabling porosity analyses at depths of ~ 5 – 20 km and at finer spatial scales than previous approaches (Wahl et al., 2020; Soderblom et al., 2015). Using the fraction of low-Dot Product Value ($DPV < -0.5$) complex craters as a proxy for deep crustal porosity, we quantify its distribution around seven farside impact basins. We find that basin rims preserve deep porosity, whereas basin centers exhibit a progressive loss of porosity from Imbrium-aged to Pre-Nectarian basins. This pattern suggests that deep basin porosity relaxes over geologic time, likely driven by viscous crustal flow and enhanced thermal gradients near basin centers.

Our results provide the first observational evidence for the deep fragmentation predicted by numerical models, and they indicate that deep and shallow basin porosity evolve independently, with distinct mechanisms dominating their long-term preservation and compaction.

1 Introduction

The Moon provides the clearest record of how impact cratering affects the generation and evolution of porosity in planetary crusts in the absence of significant atmospheric, hydrologic, and tectonic processes. High-resolution gravity data from the Gravity Recovery and Interior Laboratory (GRAIL) mission has permitted direct analysis of the Moon's current porosity structure and its long-term evolution (Zuber et al., 2013; Besserer et al., 2014). Porosity strongly controls magmatic ascent, thermal conductivity, and permeability of planetary crusts (Warren & Rasmussen, 1987; Shearer & al, 2006; Head & al, 2020).

Modeling studies have shown that basin-forming impacts play a dominant role in establishing the Moon's porosity structure, which has notably high porosity at the surface (up to 20%) and extends deep into the crust and potentially the mantle (4% porosity at 20 km depth) (Wiggins et al., 2019, 2022; Huang et al., 2022). Wiggins et al. (2019, 2022) suggest that the very high porosities observed in the surface and at depth the lunar crust are due to widespread tensile fragmentation caused by basin-forming impacts. Huang et al. (2022) recreates the porosity structure of the Moon using (a) basin-forming impacts that initially increase porosity at great depths and distances from the impact origin and (b) smaller impacts that subsequently drive compression over geologic time. Understanding porosity's impact-driven evolution therefore offers direct implications for the magmatic and thermal evolution of early planetary crusts, the cycling and long-term retention of volatiles, and the development of subsurface habitats relevant to the origin and persistence of life.

However, previous gravitational studies of crustal porosity have not simultaneously resolved (a) lateral variations in porosity at the basin scale and (b) porosity at depths greater than ~10 km.

For example, while the direct gravity analysis of Wahl et al. (2020) has the necessary lateral resolution to study basin-scale porosity, they are restricted to spherical harmonic degrees ≤ 150 , meaning they largely sample the shallow crust (up to ~ 10 km). Meanwhile, studies of deeper porosity (>10 km) are permitted by examining gravity signatures of complex craters which are modulated by the porosity of their target terranes. In this vein, Soderblom et al. (2015) used the gravity signatures of complex craters to infer a depth of pore closure near 20–25 km. However, these observations were made over the entire lunar highlands, precluding an ability to resolve subregional porosity variations necessary for basin-scale analyses.

A lack of observational data on deep, basin-induced porosity limits our ability to address key questions about crustal evolution. These questions include: Do the shallow (<10 km) and deep (~ 10 – 20 km) layers beneath impact basins evolve together or independently through time? Where in a basin's anatomy does deep porosity persist, and where does it collapse over geologic time? Because basin-forming impacts are the dominant process generating crustal porosity on the Moon, and likely in the early crusts of Earth, Mars, and Venus, understanding how this impact-induced porosity forms and persists directly informs models of a planetary thermal history, the localization of subsurface magmatism, and the long-term storage and migration of volatiles.

A new statistical framework called Guided Endmember Extraction (GEEX) enables complex-crater gravity analyses of crustal porosity at greater depths than Wahl et al. (2020), as well as at finer regional scales than Soderblom et al. (2015) (Hundal et al. 2025a). GEEX utilizes a dimensionless number called Dot Product Value (DPV) that quantifies how closely a crater's radial gravity profile matches the first eigenvector of the gravitational profiles of all complex crater in the highlands. This first eigenvector is the dominant mode of variation in gravitational profiles in global dataset of highland complex craters and is referred to here as V1FD (Hundal et al.,

2025a). DPVs range from -1 to 1 , with values near either extreme indicating strong similarity to the characteristic profile shape of VIFD.

Hundal et al. (2025a) used DPVs to identify a subset of highland complex craters whose presence can be used as a more accurate proxy for deep crustal porosity on the Moon than the more general datasets used previously. They found that craters in lower-porosity regions correspond with low DPVs (< -0.5), while those in higher-porosity regions correspond with high DPVs (> 0.5). Craters with high DPVs typically display negative Residual Bouguer Anomalies (RBAs), consistent with reduced density and increased porosity, whereas low-DPV craters typically show positive RBAs, indicating denser, less porous crust. In a given area, higher concentrations of complex craters with low DPVs ($DPV < -0.5$) correlates with higher regional porosities.

Therefore, in this study, we quantify the distribution of low DPV (< -0.5) complex craters superimposed around seven basins in the lunar highlands. We find that, at depths of ~ 5 - 20 km, basins retain porosity in their rims, while porosity in their centers diminishes from very high in Imbrium-aged basins to very low in Pre-Nectarian/Nectarian aged basins, potentially due to crustal relaxation that is most pronounced at basin centers.

2 Background

Here we provide background information on porosity generation/compaction via impacts, gravitational signatures of craters, and the statistical framework of Guided Endmember Extraction (GEEX) used to identify craters for our analysis.

Impact craters generate and erase crustal porosity through several processes that operate across the crater structure and over a wide range of timescales, spanning from projectile contact to late-stage modification. Porosity is generated by impacts via several mechanisms. Following the initial compressive shockwave, rarefaction waves generate widespread tensile fracturing that

extends to considerable depths (>10 km) and several radii from the crater center (Wiggins et al., 2019, 2022). Shear stresses further increase pore space through dilatant bulking (Collins, 2014). Ejecta redistribution during crater excavation further increases porosity, particularly around the rim, with continuous ejecta blankets extending approximately one crater radius from the rim (Melosh, 1989). Meanwhile, impacts reduce pore space through compressive shockwaves (Ding et al. 2020), localized heating (Davison et al., 2012), melt production (Wünnemann et al., 2008), and changes in overburden pressure (Gyalay & al, 2020). Subsequent bombardment by smaller impacts further compacts the crust through further shock compression (Wünnemann et al., 2006) seismic shaking (Richardson et al., 2004; Güldemeister & Wünnemann, 2017), and thermal annealing (Davison et al. 2012).

The relationship between crustal porosity and a crater's gravity signature arises from how impact energy is partitioned between compaction and fracturing during crater formation (Love et al. 1993). Bouguer gravity represents the gravitational signal after removing the contribution of topography using an assumed uniform crustal density. Higher Bouguer gravity within a crater relative to its surroundings, resulting in a positive RBA, arises from compaction of the underlying crust, an effect that becomes more pronounced in higher porosity target terranes. When a crater forms in a highly porous terrane, much of the energy of the impact is lost to compaction and relatively less is transmitted into further fracturing material. Compaction also increases the heat generated by an impact, leading to further porosity compaction. Therefore, craters that form in high porosity terranes are more likely to result in a bouguer gravity excess in the crater center with respect to their surroundings. Inversely, when an impact crater forms in a relatively less porous terrane, energy is more efficiently transmitted through the crust, resulting in more fracturing. This

increased fracturing leads to less dense materials below the impact crater, resulting in a negative bouguer gravity anomaly with respect to the surroundings.

Recent work has demonstrated that the Bouguer gravity signatures of complex craters provide a powerful tool for characterizing subsurface porosity, both laterally and with depth (Milbury et al., 2015; Soderblom et al., 2015; Bierson et al., 2016; Izquierdo et al., 2021; Hundal et al. 2025). This approach has been used to constrain the depth of pore closure (Soderblom et al., 2015; Hundal et al., 2025) and to identify stratified porosity within the megaregolith (Izquierdo et al., 2021). Because the transient cavity of each crater excavates material from a characteristic depth, the gravity signature of a crater provides sensitivity to porosity variations at those depths, allowing smaller craters to probe shallower levels and larger ones to probe deeper crustal regions.

Across the lunar highlands, terranes with higher crustal porosity tend to host a larger fraction of complex craters exhibiting positive Residual Bouguer Anomalies (RBAs), where a positive RBA indicates a net gravity increase within the crater relative to its surroundings (Soderblom et al. 2015, Milbury et al. 2015, Bierson et al. 2016, Hundal et al. 2025a). The strength of this relationship, however, depends on the specific shape of a crater's gravity profile (Hundal et al. 2025a).

Wahl et al. (2020) produced radial porosity profiles for major lunar basins; however, the spherical harmonic degrees used in Wahl et al.'s gravity analysis ($l = 150-700$) correspond to e-folding depths of only 2-11 km. Wahl et al. indicate that, given the shallow nature of their analysis, their results are not an appropriate observational constraint on the hypothesis of deep fragmentation introduced by Wiggins et al. (2019, 2022).

Hundal et al. (2025) used a dimensionality reduction framework called Guided Endmember Extraction (GEEX) to show that the correlation between crater gravity and regional porosity is strongest for a distinct subset of positive-RBA craters whose gravity profiles share a common shape that represents the dominant mode of variation across highland complex craters. This characteristic shape corresponds to the first eigenvector derived from the Full Dataset (FD) of the Soderblom et al. (2015) highlands crater catalog, denoted $V1_{FD}$ (Hundal et al. 2025). $V1_{FD}$ represents the dominant first-order shape of crater gravity profiles, the principal contrast between crater interiors and exteriors, with a shape that decreases linearly from the crater center to the rim and remains flat beyond the rim where gravity is relatively consistent with the background field.

The similarity of each crater's gravity profile to $V1_{FD}$ can be expressed by a Dot Product Value (DPV), a dimensionless quantity ranging from -1 to 1 that measures how closely a profile aligns with the shape of $V1_{FD}$, where 0 indicates a profile that is orthogonal to $V1_{FD}$ (that is, does not look like that shape at all), and -1 indicates the opposite vertical orientation of $V1_{FD}$. Craters with $DPV < -0.5$ define a narrow family of gravity profiles common in the highlands and consistent with the most significant pattern of variation in the global dataset. Consequently, the fraction of $DPV < -0.5$ craters in a given region serves as a proxy for deep-seated porosity, sensitive to the crustal depths sampled by the transient cavities of the craters analyzed.

3 Data

We analyzed Bouguer gravity derived from the GRGM1200B RM1 field (Goossens et al., 2020) computed to spherical-harmonic degree 1200 and assuming a crustal density of 2550 kg m^{-3} . To minimize the influence of long- and short-wavelength features and noise, only degrees 7–650 were retained following Izquierdo et al. (2021). Lower degrees (1–6) capture large-scale

asymmetries such as the farside–nearside crustal dichotomy, whereas higher degrees (> 650) contribute predominantly noise. A cosine taper between $l = 600$ – 650 was applied to smooth the transition and suppress spectral ringing. The resulting field has an effective half-wavelength spatial resolution of roughly 8 km. All spherical-harmonic operations and map transformations were performed using the `pyshtools` package (Wieczorek & Meschede, 2018). Radial zonal gravity profiles were extracted from crater centers to twice the crater radius ($2 R$) and resampled at seven evenly spaced distances (0 – $2 R$) following Hundal et al. (2025).

For consistency with previous GEEX applications, we analyze complex highland craters drawn from the Soderblom et al. (2015) catalog, which comprises 1185 entries from Head et al. (2010) spanning 27–201 km in diameter. The sample is restricted to highland regions with mean surrounding elevations > 0.5 km (measured between the rim flank and $2 R$) and excludes the South Pole–Aitken basin and mare terranes. These criteria remove craters affected by large-scale compositional or structural heterogeneity and isolate a population for which residual Bouguer anomalies primarily reflect porosity-driven density variations. No complex craters in this dataset intersect published maps of mare (cite) or cryptomare (cite). This approach also enables a direct comparison for GEEX-derived DPV cut-offs of the same dataset.

The locations of our complex craters constrains the selection of basins for this study to seven farside basins. We only used basins for which highland complex craters were abundant to all sides. Nectaris basin was considered, but not included because very few (<15) highland complex craters were available and only to the SW of the basin. From youngest to oldest, the chosen basins are Orientale, Moscoviense North, Hertzprung, Korolev, Freundlich-Sharonov, and Coulomb-Sarton. Table 1 lists the abbreviations and ages of these basins. Moscoviense and Moscoviense North are theorized to be a double impact basin, with Moscoviense being the

younger and smaller basin, and Moscoviense North being larger and older to the Northeast. We use the larger basin radius of Moscoviense North in our analysis. While Orientale and Moscoviense North contain mare in their interiors, none of these mare intersect our complex crater dataset.

4 Methods

To serve as a proxy for deep porosity, we construct radial profiles for each of this study's seven farside basins, where the value of the profile corresponds to the fraction of complex craters at given ± 0.25 basin radii (R_b) intervals that exhibit DPVs < -0.5 . Higher fractions correspond to greater relative porosity at depth. Profiles are calculated out to three basin radii (R_b) following the example of Wahl et al. 2020, where the profile from $2-3R_b$ serves as a background comparison for the profile.

The depths probed by the craters in this analysis define the depth interval of the lunar crust to which our results apply. To calculate the depth that these radial profiles are sensitive to, we calculate a range based on the transient depth of the craters in each basin profile. The depth to which a crater structurally disturbs the crust is approximately equal to the depth of its transient crater, the bowl-shaped cavity formed when the impact excavates to its maximum depth. This transient cavity typically reaches a depth about one-third to one-fourth of its diameter (Melosh & Ivanov, 1999). Immediately following its formation, the transient cavity undergoes gravitational collapse, producing a final crater that is broader and shallower than the original structure. The final crater radius (R) is related to the transient crater radius (R_{T}) by the scaling relation $R/R_T = 1.02 (R_T/R_*)^{0.079}$, where $R_* \approx 9$ km represents the simple-to-complex transition radius on the Moon (Holsapple, 1993). To estimate the depth range sampled by each fractional profile, we first calculated the mean and standard deviation of the crater diameters within each profile. The lower bound of the sampled depth range was then defined as one-fourth of the transient crater

diameter corresponding to the mean diameter minus one standard deviation. The upper bound was defined as one-third of the transient crater diameter corresponding to the mean diameter plus one standard deviation.

Uncertainties on the fractional profiles were quantified using 95% Wilson confidence intervals (Brown et al., 2001), which provide binomial proportion confidence limits based on the number of positive-anomaly complex craters ($DPV < -0.5$) and the total number of complex craters within each distance interval. The Wilson interval treats each crater as an independent Bernoulli trial with two possible outcomes: either exhibiting or not exhibiting a positive gravity anomaly of the characteristic shape. Under this framework, the number of “successes” (positive anomalies) out of a fixed total number of trials follows a binomial distribution. The Wilson interval provides more accurate bounds than a normal approximation in this case, given that this study employs small sample sizes and proportions near 0 and 1.

To compare basin radial profile shapes, we compute an area-weighted, bounded contrast ratio C that quantifies whether porosity is concentrated near the basin center ($<0.5R_B$) or the rim ($1.0R_B$ - $1.2R_B$):

$$C = (\text{rim} - \text{center}) / (\text{rim} + \text{center}).$$

Values approaching 1 indicate profiles with elevated porosity at the rim and depressed values at the center, whereas values approaching -1 indicate high porosity at the center and low values near the rim.

5 Results

Here we review the results of our analysis of deep porosity evolution of farside impact basins, reviewing changes in deep crustal profiles with distance from basin centers and with increasing basin age.

Figure 1 shows the deep crustal profiles of the seven farside basins analyzed in this study, illustrating the fraction of positive-anomaly complex craters ($DPV < -0.5$) as a function of normalized distance from each basin center. These profiles serve as a proxy for relative changes in deep porosity with distance from basin centers. Orientale exhibits its highest values near the basin center and a relatively steady decline outward to $\sim 1.5 R_b$, indicating substantial porosity within the basin interior at depth. Moscoviense shows an intermediate morphology, peaking near $1.2 R_b$ like the older basins but also retaining elevated values within the basin rim. The profiles of Hertzprung through Coulomb-Sarton share a consistent form, remaining near zero from the basin center to $\sim 0.5 R_b$, rising sharply to a maximum at $1.0\text{--}1.2 R_b$, then declining monotonically to $\sim 2 R_b$ before leveling off. This pattern indicates that deep porosity is preserved near the basin rim. Together, these profiles indicate a progressive transition from interior-dominated porosity in young farside basins to rim-focused porosity in older ones. The timescale for this interior compaction falls between the formation ages of Moscoviense and Hertzprung.

Figure 2 summarizes the trends of Figure 1 using a bounded contrast ratio, where values near -1 indicate a profile that peaks much more strongly at its center than at its rim, and values near 1 indicate that a profile peaks much more strongly at its rim than at its center. Orientale exhibits profile that peaks in its center, whereas Moscoviense shows a moderate, rim-weighted contrast. Hertzprung through Coulomb–Sarton display consistently rim-focused profiles, reflecting the progressive migration of deep porosity from basin interiors to rims with increasing age.

6 Discussion

This study extends prior gravitational analyses by probing the Moon’s crustal porosity at depths (>10 km) that have remained beyond the reach of most previous observations. While Wahl

et al. (2020)'s analysis of basin porosity profiles primarily samples the upper ~ 10 km of the crust, our approach leverages the gravity signatures of complex craters, whose transient excavation depths provide sensitivity to deeper (~ 5 -20 km) structural layers. This method allows the first observational test of the deep tensile fragmentation predicted by numerical models (Wiggins et al., 2019, 2022) and enables direct assessment of how deep basin porosity varies with age and radial position.

We find that farside basins display a systematic transition from center-focused porosity in younger basins, such as Orientale, to rim-focused porosity in older, Pre-Nectarian examples. This pattern implies that deep porosity within basin interiors collapses over time, whereas rim porosity remains preserved. The timing of this transition, between the formation of Moscoviense and Hertzsprung, marks the interval over which deep crustal porosity becomes redistributed or compacted.

These results suggest that the shallow and deep components of basin-induced porosity evolve through distinct mechanisms. Shallow porosity (< 10 km), accessible to direct gravitational analysis (Wahl et al., 2020), likely diminishes through processes such as repeated smaller impacts, impact-induced seismic shaking, redistribution of fines, localized heating, and shock compression. In contrast, the compaction of deep porosity (~ 10 –20 km) is more plausibly driven by crustal relaxation near basin centers, elevated thermal gradients associated with proximity to the mantle, and the long-term effects of overburden pressure.

Our findings therefore indicate that the evolution of basin porosity is depth-dependent and multi-stage: immediately after formation, basin interiors are highly porous due to bulking and tensile fracturing, while over geologic timescales relaxation and thermal annealing preferentially reduce centrally-focused porosity at depth. Basin rims, being cooler, mechanically stronger, and a

further distance from the central relaxation of the impact structure, preserve their deep porosity structure over time.

By establishing an observational link between impact-generated deep porosity and its subsequent compaction, this work provides the first empirical validation of deep fragmentation models and constrains the processes that govern porosity retention in planetary crusts. These insights not only refine our understanding of the Moon's crustal evolution but also carries implications for broader questions of crustal permeability, magmatic transport, and volatile migration across the terrestrial planets.

7 Conclusions

This study provides the first observational evidence that the deep porosity of lunar basins persists along their rims (1-1.2 R_b) while diminishing substantially in their centers (0-0.5 R_b). The timescale of this interior compaction falls between the formation of Moscoviense North (Nectarian) and Hertzprung (Nectarian–Pre-Nectarian). This compaction may be consistent with enhanced crustal movement and thermal annealing of pore space near basin centers. The trend is not observed in shallower radial porosity profiles of farside basins, implying that deep and shallow porosity evolve independently over time. This framework provides the first observational test of the deep tensile fragmentation predicted by numerical models (Wiggins et al., 2019, 2022), suggesting that such deep fracturing becomes compacted in basin interiors but endures over geologic timescales in their rims. By identifying craters most sensitive to porosity variations via GEEX, this work extends gravity analyses to greater crustal depths than previous studies and establishes a pathway for quantifying deep porosity evolution across planetary bodies.

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Table 4-1. Lunar highland basins in this study in their order of formation

Basin Name and abbreviation	Period ^a	Mare Infill
Oriente (O)	Imbrium	Yes ^b
Moscoviense North (M)	Nectarian	Yes ^b
Hertzprung (H)	Pre-Nectarian/Nectarian	No
Korolev (K)	Pre-Nectarian/Nectarian	No
Freundlich-Sharonov (F)	Pre-Nectarian/Nectarian	No
Dirichlet-Jackson (D)	Pre-Nectarian	No
Coulomb-Sarton (C)	Pre-Nectarian	No

^a Fassett et al. (2012); ^b None of the complex craters used in this study intersect mare

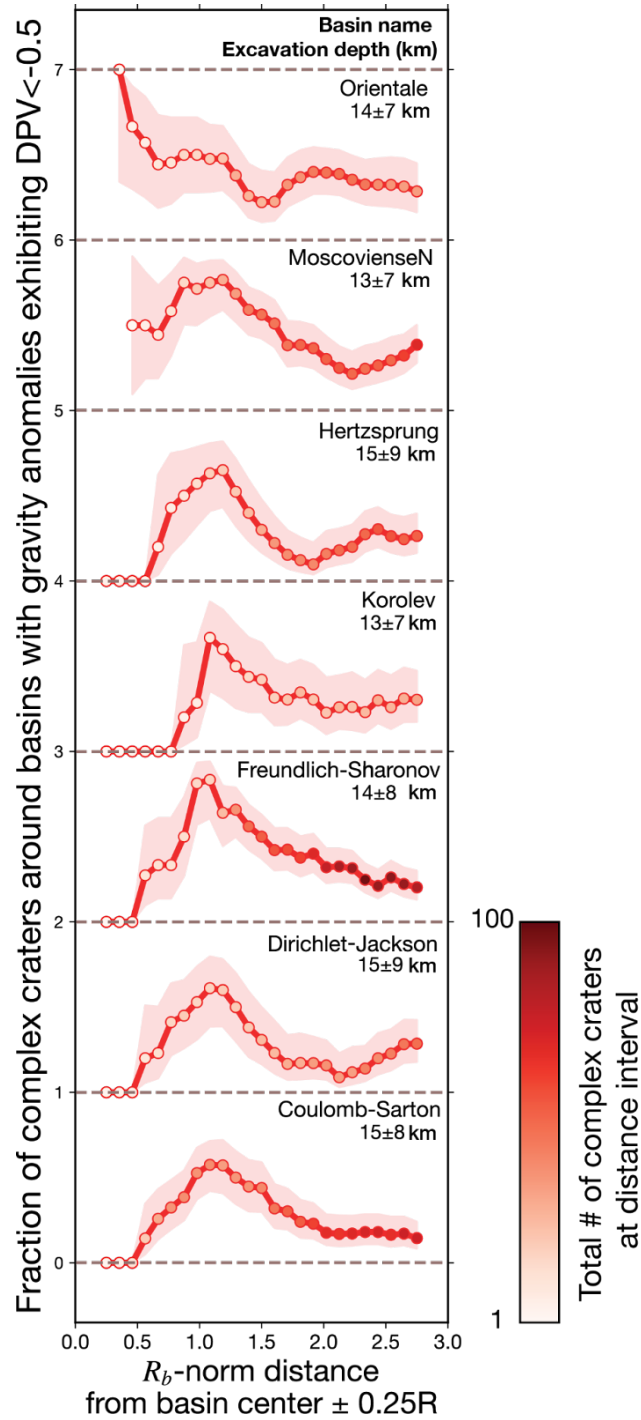


Figure 4-1. Fraction of positive-anomaly complex craters ($DPV < -0.5$) as a function of normalized distance from the centers of seven farside basins, offset vertically for clarity. Each point represents this fraction within an annulus ± 0.25 basin radii (RB) wide. Higher fractions correspond to greater relative porosity at depth. Basins are ordered from youngest (Orientale) to oldest (Coulomb–Sarton). Shaded regions show 95% Wilson confidence intervals; point color

denotes the total number of complex craters at a given distance interval. Dashed lines mark fractions of 0 and 1.0. At basin centers where no profile is shown, zero highland complex craters from our database occur within that distance interval.

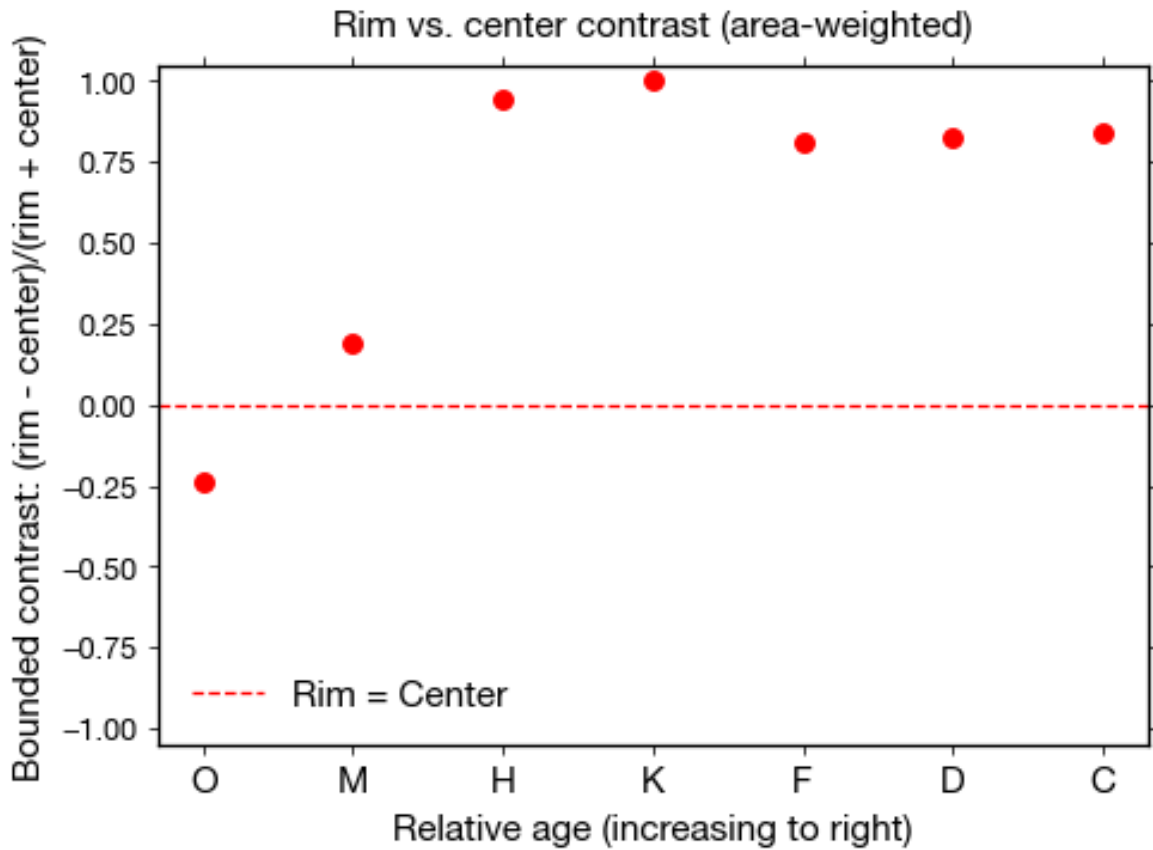


Figure 4-2. Area-weighted contrast between basin-center ($0-0.5R_b$) and basin-rim ($1.0-1.2R_b$) regions of the fractional profiles shown in Figure 1. Values near +1 indicate rim-focused profiles, while values near -1 indicate center-focused profiles. Basins are arranged on the x-axis in their order of formation, with age increasing to the right. Orientale exhibits a strongly center-focused signature, whereas Moscoviense shows a moderate, rim-weighted contrast. Hertzprung through Coulomb–Sarton display consistently rim-focused profiles, reflecting the progressive migration of deep porosity from basin interiors to rims with increasing age.

FUTURE WORK

The preceding chapters demonstrate that Guided Endmember Extraction (GEEX) provides a powerful framework for identifying meaningful structures in complex planetary datasets. While the applications shown here focus on translating dimensionality reduction in spectroscopy to application in gravity-derived measurements of lunar crustal architecture, the utility of GEEX extends well beyond this initial domain. This dissertation opens up more avenues than it has been able to explore directly, particularly regarding the dimensional, methodological, and planetary breadth of problems to which GEEX can be applied.

1 Beyond the First Eigenvector

Future work may explore how information encoded in eigenvectors beyond the first reveals subtler but geophysically meaningful patterns. Higher-order eigenvectors, those beyond the first-order variation described by the first eigenvector, may contain variance associated with secondary impact processes, such as rim-focused fracturing or post-impact modification, that remain unexplored in this work.

2 Applying GEEX to Other Datasets and Planetary Structures

GEEX is readily transferable to a wide range of planetary datasets. Immediate extensions include its application to crater profiles derived from topography, magnetic, or spectral data, enabling comparison of morphological, compositional, and gravitational modes of variation within a unified analytical framework. GEEX can conceivably be applied to any planetary dataset, regardless of its dimensionality (e.g., 2D profile data, 3D geospatial data, 1000+D hyperspectral data...).

Beyond craters, GEEX can be adapted to repeated or quasi-periodic physical structures across the Solar System, including double ridges on Europa, polygonal terrains on Pluto, atmospheric features on the gas and ice giants of the solar system, as well as dune fields, gullies, banded ice and rock stratigraphy on Mars, and many other self-similar features shaped by physical surface, subsurface, and atmospheric processes.

3 Methodological Refinements

GEEX can be improved upon in many ways. Future work could investigate the influence of dimensionality reduction algorithm choice and optimization (e.g., testing nonlinear techniques such as t-SNE within a GEEX-style guided framework). GEEX could incorporate additional hyperparameter tuning and separation of training, test, and validation datasets to further enhance the interpretability and robustness of results. Expanding GEEX to handle multi-modal datasets, where gravity, topography, and composition are analyzed jointly, could bridge the gap between surface and subsurface observations in a novel and quantitatively rigorous way.

4 GEEX: A Step Forward, and Onward

GEEX offers a template for dimensionality reduction applications in planetary science: an interpretable, flexible framework capable of distilling structure from high-dimensional measurements. Its design is not limited to a single dataset, dimensionality, or planet. As planetary datasets grow in size and resolution, the capacity of analytical techniques to extract physically meaningful modes of variation across scales will be essential. This dissertation thus provides a step forward upon which future analyses can build, whether aimed at understanding the porosity structure of the Moon, or more broadly, the processes that shaped the Earth and the other planets of the Solar System.

APPENDIX A: Supporting Information for Chapter 1

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Introduction

This document provides more in-depth information concerning the data and methods used in the main manuscript as well as further discussion comparing the Capping Unit to other rock formations in the same stratigraphic position. Tables S1 through S9 provide full observation and spectra ID numbers, locations, and processing information.

Laboratory spectra included here may be acquired from the NASA/Keck Reflectance Experiment Laboratory (RELAB) at Brown University (<https://pds-specilib.rsl.wustl.edu/search.aspx>). HiRISE images may be downloaded from the mission's website (<https://hirise-pds.lpl.arizona.edu/PDS/>). The CTX image mosaics can be found at the Murray Lab at Caltech (<http://murray-lab.caltech.edu/CTX/tiles/beta01/>). CRISM images and the MOLA map are available from the Planetary Data System Geosciences Node (<https://pds-geosciences.wustl.edu/missions/mro/crism.html> and <https://pds-geosciences.wustl.edu/missions/mgs/mola.html>, respectively).

Dataset 01 is a collection of all the data associated with this study including shapefiles, spectra, ROIs, DEMs, images is available at the following link:

<https://zenodo.org/record/6354669#.YmA8K9rMJ9M>

Measuring outcrop orientation

The vertical precision of HiRISE DEMs (Digital Elevation Models) is on the order of <1 m (McEwen et al., 2007). Outcrop orientations were obtained by extracting 3D profiles from DEMs taken over the edges of the stratigraphic layers/beds. A plane was fitted to these non-collinear point clouds by Principal Component Analysis in a house-made Python program. The orientation

of the third principal component of the data represents the dip of the outcrop. We measured orientations only from well-exposed stratigraphic contacts or beds. Dips were calculated with three measurements of each outcrop and averaged. The standard deviation of these measurements were approximately one degree. It should be noted that the top surface of the Capping Unit is eroded as evidenced by impacts/pits and yardangs. However, should this surface be within error ($\pm 1^\circ$) of the other dips, this implies that the uppermost surface maintained its original depositional orientation at the outcrop-scale. The contact between the Capping and Olivine-Rich Units was made where boulder-rich bands transition to smooth bands (see Figure S2).

Spectral Noise Reduction Techniques

Endmember extraction uses Factor Analysis, a statistical method that calculates eigenvectors (or “endmembers”) representative of independent variance in a dataset. The first eigenvector accounts for the greatest spectral variance, while each successive eigenvector describes less. Low-order eigenvectors—those describing the most variance—tend to have spectral shapes that can be interpreted as surface/sample spectral signals and varying degrees of structured noise (e.g., Tarnas et al., (2021)). While eigenvectors are useful for identifying the presence of spectral classes, they should not be interpreted as exact 1:1 surface/sample signals (e.g., Tarnas et al., (2021)). Endmember extraction has been applied to Mars spectral data to identify mineral components with both narrow (e.g., Amador et al., 2018; Das et al., 2022; Tarnas et al., 2019; Thomas & Bandfield, 2017) and broad absorption features (Glotch et al., 2006). Here, we use the HySime algorithm instead of the R-mode algorithm because laboratory studies have shown it to be more reliable due to HySime's separation and exclusion of noise

subspaces, though non-gaussian noise can still be present in resultant eigenvectors (Tarnas et al., 2021).

Following endmember extraction, we implemented a method called Dot Product Mapping to identify areas where each endmember is most strongly represented in the data (Das et al., 2022). This involves calculating the dot-product of an eigenvector of interest with each pixel in an ROI (Region of Interest), creating a full dot-product map. Areas that have a spectral shape corresponding to that eigenvector will have higher positive values, and those that have the inverse shape will have more negative values. This technique aids the interpretation of what may be causing variation in the data, such as mineral components (e.g., spatially correlated deposits), structured noise (e.g., noisy columns), etc.

To further improve the quality of eigenvectors produced from endmember extraction, we finally employed Dot-Product Noise Removal to further improve the quality of eigenvectors produced from endmember extraction. Here, we examined the dot-product maps of eigenvectors with high amounts of structured or atmospheric noise and removed highlighted areas from the ROI before re-running endmember extraction (see Figure S1A,B). Figure S3C shows an example where, after re-running factor analysis, the fourth eigenvector has significantly less noise, allowing for later comparison to mineral components such as pyroxene. Dot-Product Noise Removal was not necessary for high-quality data such as CRISM's Map Projected Targeted Reduced Data Record (MTRDR) images which are already well-corrected for atmospheric and certain types of structured noise (Seelos et al., 2012).

Comparison to the Pitted Capping Unit of Goudge et al., (2015)

We find that the Pitted Capping Unit of Goudge et al., (2015) is morphologically and geographically distinct from the Capping Unit of the present study. Figure S1A, B show the Capping Unit is a crater-preserving rock that erodes into mesas with steep scarps and lobate margins. Exposures of the Olivine-Rich Unit are often visible at the base of these mesas. The Capping Unit's craters and pits have distinct rims and are variably filled with aeolian sediments. The Pitted Capping Unit also has craters, but they appear significantly more eroded: rims and cavities are often indistinct or only partially preserved. The unit does not erode into mesas but is instead geographically continuous. The Olivine-Rich and the Capping Units are not regionally co-extensive with the Pitted Capping Unit.

Guided Endmember Extraction and Dot Product Mapping in the Laboratory

To show how Factor Analysis eigenvectors (or “endmembers”) compare to averaged ROI spectra in a laboratory setting, we imaged an olivine-rich basalt from Hawaii on the Brown University Headwall Imager. This sample bears abundant, spatially localized olivine phenocrysts that are roughly .5 cm in size. The headwall imager has a spatial resolution of .34 mm/pixel and 178 spectral bands from 0.4-2.6 microns (the spectral resolution is 8.0 nm and spectral sampling is 9.62 nm).

The second endmember eigenvector extracted from this sample resembles a typical olivine spectrum: a broad absorption at 1 μm , and a relatively steady spectrum after $\sim 1.6 \mu\text{m}$ (Figure S4D). The algorithm also produced Dot-Product Maps of each eigenvector, showing areas where each eigenvector was most strongly represented. In the second eigenvector Dot-Product Map (Figure S4B), we found high spatial correlation to the olivine phenocrysts. This Dot-Product Map was used to create a thresholded ROI over the olivine crystals (Figure S3C), which we then used to extract the “averaged spectrum” in Figure S4D. It is highly encouraging that the broad shape of

the second eigenvector is consistent with the average spectrum. More detailed nuances of the averaged spectrum, such as the alteration feature at 1.9 μm and the upward slope after 2 μm are both contained in the third and fourth eigenvectors. This emphasizes that an eigenvector is not a 1:1 indicator of a surface/sample signal, but that their shapes can be used to indicate the presence of diagnostic spectral features within a dataset. The first five eigenvectors and dot product maps used in this experiment are documented in Figure S5.

Table S1-1. HiRISE Observation IDs or Locations for Figures 2 and 3.

Figures	HiRISE Observation ID or Location
2A	HiRISE PSP_011841_2005
2B	HiRISE ESP_016931_1980
2C	HiRISE ESP_039493_2030
2D	HiRISE ESP_016522_1830
2E	HiRISE PSP_009718_2005
2F	Murray Lab Global CTX Mosaic* [77.38E, 20.10N]
2G	HiRISE ESP0601301985
2H	HiRISE ESP0489081985
2I	Murray Lab Global CTX Mosaic* [77.55E, 18.22N]
2J	HiRISE ESP0460601985
3A	DTEEC_002756_1830_002822_1830_A01

* Dickson et al., 2018

Table S1-2. All HiRISE-Stereopair IDs used in study

Generated by HiRISE/University of Arizona	
DTEEC_002888_2025_002176_2025	DTEEC_002756_1830_002822_1830
DTEEC_045994_1985_046060_1985	
Generated In-House	
ESP_016931_1980_ESP_017076_1980	ESP_015942_1980_ESP_016443_1980
ESP_026992_2025_ESP_027691_2025	ESP_026280_1975_ESP_027902_1975

Table S1-3. Outcrop orientations (measured on HiRISE DEMs).

Outcrop Number	Location (°E, °N)	Cap Surface Dip (°)	Error ^a	Cap/Olv ^b contact Dip (°)	Error	Olv band 1 Dip (°)	Error	Olv band 2 Dip (°)	Error	Olv Band 3 Dip (°)	Error	Basement / Olv contact Dip (°)	Error
1	77.040 , 17.758	2	0	1	1							1	1
2	77.059 , 17.770	1	1	1	1	3	1	1	1			3	2
3	77.599 , 20.790	3	1	2	1							2	1
4	77.628 , 20.797	2	1	3	1							1	1
5	77.615 , 20.843	3	0	3	0							1	1
6	77.600 , 20.883	2	0	1	1	2	1	2	1	2	1	3	1
7	22.198 , 22.267	7	1	5	1	5	2	4	1			4	1

^a Standard Deviation of three measurements

^b Olv = Olivine Rich Unit

Table S1-4. RELAB IDs for Laboratory spectra in Figure 4. *

Lab Spectrum	Spectrum ID	Sample ID	Sample Name
Shergotty Meteorite	C1LM21	LM-LAM-021	Shergotty
High-Ca Pyroxene	NBPP22	PP-CMP-022	Cpx 75
Low-Ca Pyroxene	LAPP47b	PP-EAC-047-B	PYX110 45-90 um

* More information about the samples and measurement conditions of the spectra can be found in Table S9.

Table S1-5. Full CRISM Observation IDs and paper CIDs used in Figure 4.

Figure 4 CID	Full CRISM Observation ID
1	HRL0000D0C707IF183LTRR3
2	FRT000199C707IF166JTER3
3	FRT0002372807IF166JTER3
4	FRT0001953807IF166JTER3
5	HRL000047D807IF174JTER3
6	HRL000040FF07IF183JTER3

Table S1-6. Columns removed from CRISM ROIs during Dot Product Noise Removal.

CID in Figure 4	Filename in ds01 ^a	Columns removed ^b	Horizontal displacement ^c	Smoothing window size
1	hrl0000d0c7-nilifossae_cap	-	-	3
2	frt000199c7-niliplanum_cap	[152 158; 312 322; 338 363; 422 432]	31	-
2	frt000199c7-niliplanum_olv	[104 112]	44	-
3	frt00023728-niliplanum_cap	[51 116; 222 238; 245 256; 271 283; 288 305; 410 414; 419 423; 425 429; 445 450]	31	-
4	frt00019538-niliplanum_cap	-	-	-
4	frt00019538-niliplanum_olv	-	-	-
5	hrs000047d8-libyamontes_cap	[106 107; 111 111; 113 113; 118 118; 124 124; 134 134; 149 152; 197 198; 201 202; 210 210; 212 216]	17	-
5	hrs000047d8-libyamontes_olv	-	-	-
6	hrl000040ff-jezero_floor	-	-	-

^a Files ending in .txt are spectra and those ending in .img are subsets of CRISM images used to create spectra

^b For example, [48 50; 109 114] means columns 48-50 and 109-114 were removed from the CRISM image.

^c Width of NoData border in CRISM images when displayed in ENVI.

Table S1-7. Proposed Hypotheses for the formation of the Capping Unit

Observation/Feature	Ash Fall	Lava Flow	Aeolian Erg	Impact Product	Igneous Intrusion
<i>Regional Characteristics</i>					
50,000 km ² geographic extent	✓	✓	✓	✓	✓
3000 m vertical extent	✓	✓	?	✓	✓
Uniform composition across 50,000 km ²	✓	✓	?	✓	?
<i>Draping Behavior</i>					
Apparent draping of topography	✓	✓	✓	✓	?
10:1 relief-to-thickness draping of bowl-shaped, kilometer-scale outcrops	✓	x	x	✓	x
Dips parallel to underlying topography	✓	?	?	✓	x
<i>Layering</i>					
Layering	✓	✓	✓	x	✓
Meter-scale layering	✓	✓	✓	x	?
Several layers of alternating tonality	✓	✓	?	x	?
regional, meter-scale tonal layering (~50,000 km ²)	✓	?	x	x	x
Same tonality/scale as ORU layers	✓	x	x	x	x
<i>Association with Olivine-Rich Unit (Ash)</i>					
Coextensive with ORU	✓	x	x	x	x
Shared pyroxene signal with ORU	✓	x	x	x	x
Conformable contact w/ friable ORU	✓	?	?	?	x

Table S1-8. All HiRISE image Observation IDs used in study

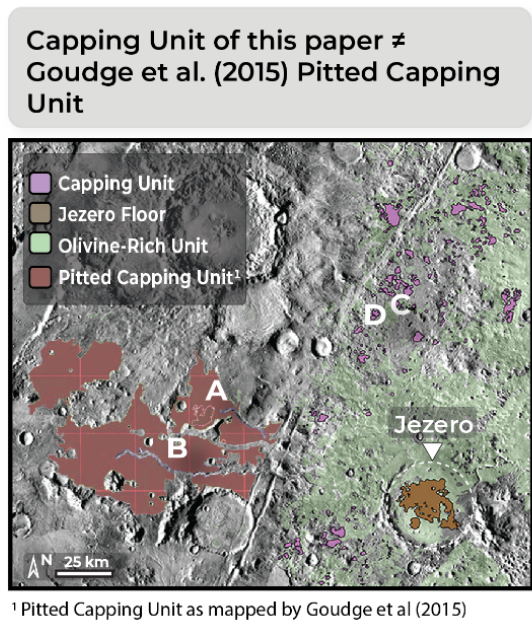
ESP_011841_2005_RED.JP2	ESP_039493_2030_RED.JP2
ESP_015955_1840_RED.JP2	ESP_046060_1985_RED.JP2
ESP_016522_1835_RED.JP2	ESP_048908_1985_RED.JP2
ESP_016786_1980_RED.JP2	ESP_055277_1990_RED.JP2
ESP_016931_1980_RED.JP2	ESP_060130_1985_RED.JP2
ESP_018988_1980_RED.JP2	PSP_002176_2025_RED.JP2
ESP_026280_1975_RED.JP2	PSP_002822_1830_RED.JP2
ESP_027691_2025_RED.JP2	PSP_002888_2025_RED.JP2
ESP_032794_1990_RED.JP2	PSP_008571_1995_RED.JP2
ESP_035917_1755_RED.JP2	

Table S1-9. All HiRISE-Stereopair IDs used in study

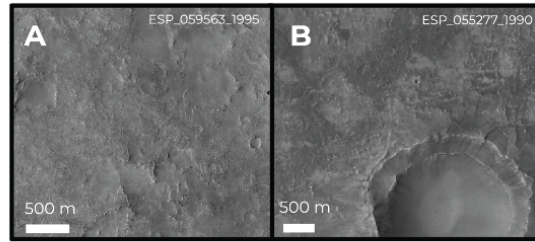
Generated by HiRISE/University of Arizona	
DTEEC_002888_2025_002176_2025	DTEEC_002756_1830_002822_1830
DTEEC_045994_1985_046060_1985	
Generated In-House	
ESP_016931_1980_ESP_017076_1980	ESP_015942_1980_ESP_016443_1980
ESP_026992_2025_ESP_027691_2025	ESP_026280_1975_ESP_027902_1975

Table S1-10. Additional information regarding the samples and measurement conditions of the laboratory spectra included in Figure 4. Due to its size, this table has been uploaded separately.

Data Set S1. A tarball of all supporting data including HiRISE images and DEMs, shapefiles, outcrop orientation point clouds, CRISM ROI subsets, and spectra. These data are available at <https://zenodo.org/record/6354669#.YmA8K9rMJ9M>



Goudge et al. (2015) Pitted Capping Unit



Capping Unit of this study

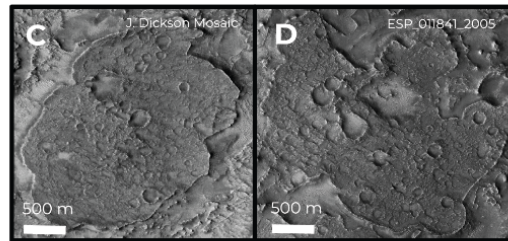


Figure S1-1. Morphological comparison of the Capping Unit of this study and the Pitted Capping Unit of Goudge et al., (2015).

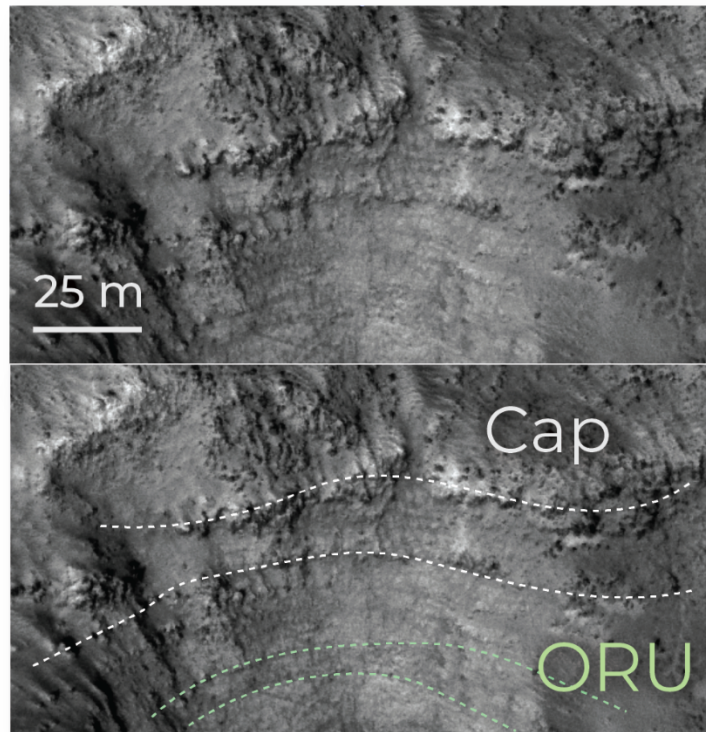


Figure S1-2. A close-up of the annotated/unannotated insets in Figure 2D, showing tonal layers in the Cap (bouldery) and the Olivine-Rich Unit (ORU; smooth).

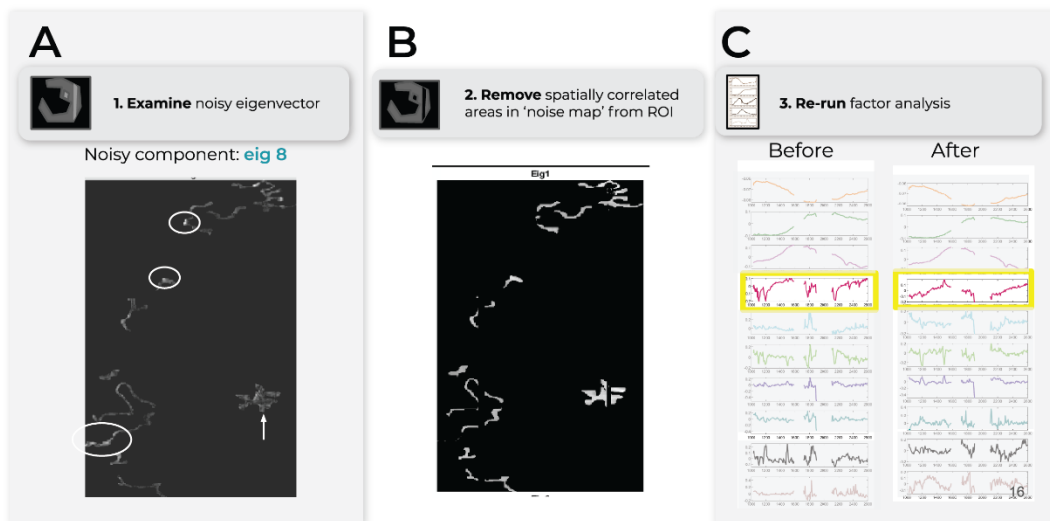


Figure S1-3. Dot-product noise removal for an ROI over the Olivine-Rich Unit in the Nili Fossae region (FRT00000D0C7). (A) Dot Product Map for the eighth eigenvector, which corresponds to structured noise. Highlighted areas in this map show where the noise is most strong. (B) Before re-running endmember extraction, we remove the areas highlighted in (A) from the data. (C) Eigenvectors before and after Dot-Product Noise Removal.

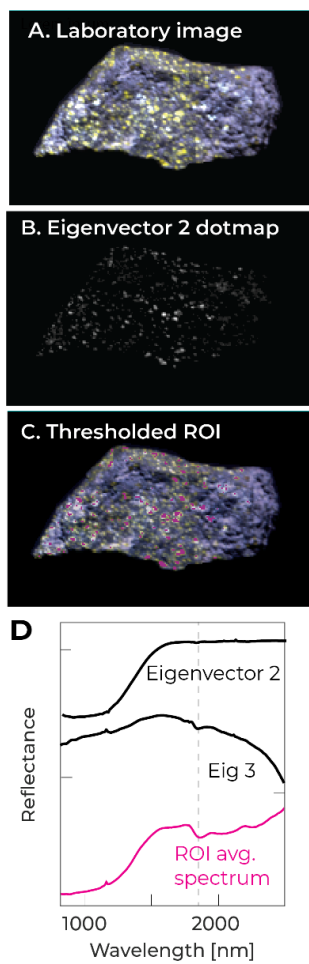
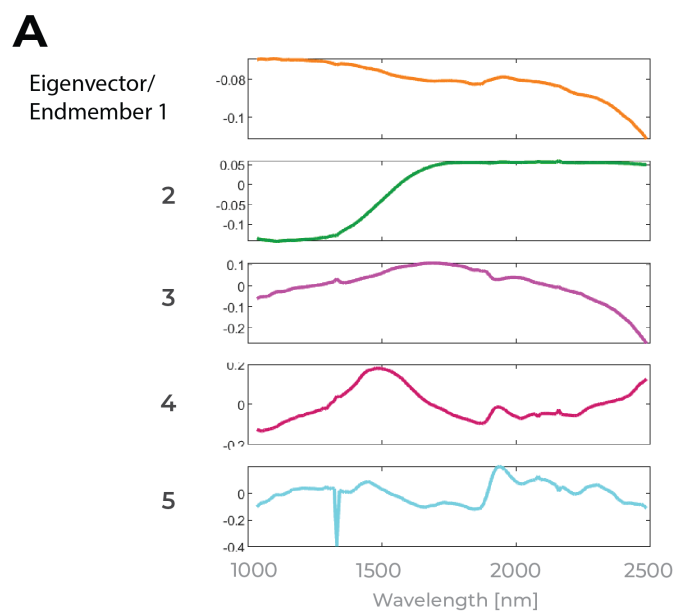


Figure S1-4. A laboratory proof-of-concept of Endmember Extraction and Dot Product Mapping with an olivine-rich porphyritic Hawaiian basalt.

Endmembers plotted against wavelength



Associated Dot Product Maps

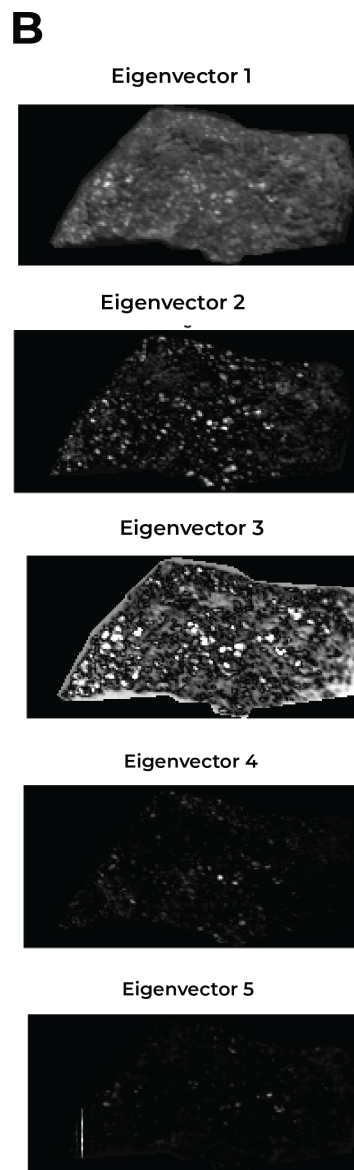


Figure S1-5. The first five endmembers and associated Dot Product Maps of the Hawaiian Basalt shown in Figure S4.

Capping Unit in bowl-shaped topography - Hashir Crater in Libya Montes

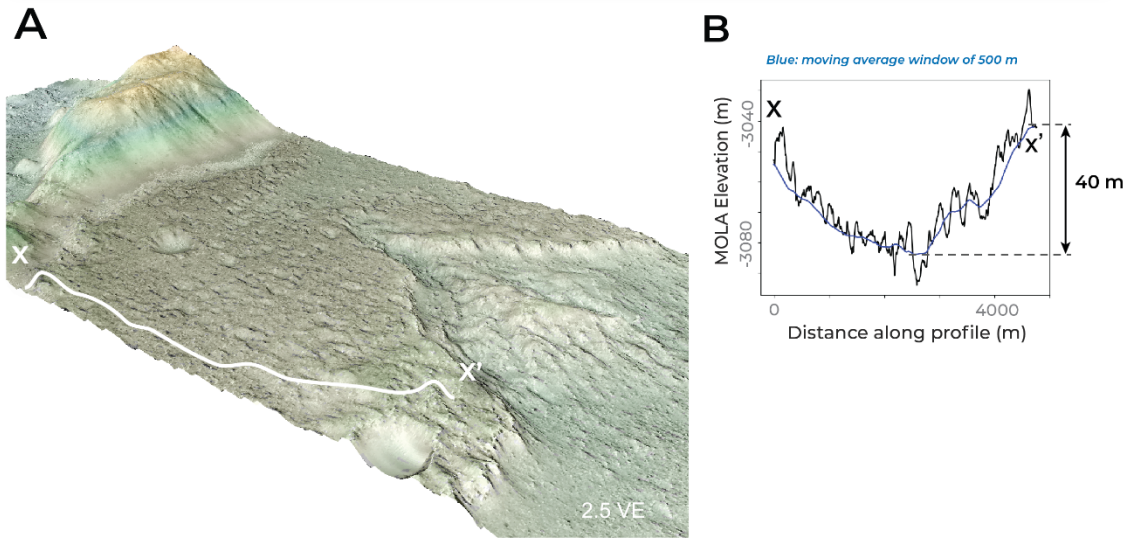


Figure S1-6. (A) A 3D view of the Capping Unit in the bowl-shaped topography between Hashir Crater's rim and its central mound (DTEEC_002756_1830_002822_1830_A01). (B) Profile X-X' shows 40 m of relief--far exceeding surface variations caused by weathering, which are on the order of ~10 m. Blue line indicates a smoothed moving average with a window size of 500 m.

APPENDIX B: Supporting Information for Chapter 2

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The noisy components of eigenvectors can be reduced using DPV-highlighted regions. Upon calculating an initial set of endmember components from a dataset, certain endmembers may correspond well to geologically meaningful structures (e.g., a mineral spectrum), whereas other endmembers may primarily reflect structured noise. By using DPVs of noise-dominated endmembers, one can create Dot Product Maps that highlight noisy data instances. Data instances above a certain DPV threshold can then be removed from the dataset for a subsequent iteration of endmember calculation, thereby reducing the contribution of structured noise to the calculated endmembers that reflect variability in geologically relevant structures. See Hundal et al. (2022) supplemental for an example of this technique applied to hyperspectral image data.

Table S2-1. Important acronyms and terms defined.

Term or Acronym	Definition	Additional Notes
GEEX	Guided Endmember EXtraction	Generalized framework for application of dimensionality reduction techniques to planetary science data of correlated, repeated features.
PCA	Principal Components Analysis	A simple form of dimensionality reduction. Produces mutually orthogonal components that are eigenvectors of a dataset's covariance matrix.
FA	Factor Analysis	A dimensionality reduction technique used in many spectroscopy studies.
DPV	Dot Product Value	A Dot Product Value characterizes how well a data profile aligns with the shape of an eigenvector/component using the dot product of the two vectors, $DPV = \mathbf{X} \cdot \mathbf{v}$, where $\mathbf{X}$ is a profile and $\mathbf{v}$ is an eigenvector or component.
Dot Product Mapping	A DPV technique that highlights where a specific component is strongly represented in a dataset.	
Eigenvector	A vector defining an invariant direction under a linear transformation, obtained via eigendecomposition of a matrix. Not all dimensionality reduction techniques yield eigenvectors.	
PCA Eigenvector	Eigenvectors of a dataset's covariance matrix. These eigenvectors are always orthogonal.	Intuitively, PCA eigenvectors represent the most important independent "shapes" of variation in a dataset. Their associated eigenvalues describe their relative importances.

Dimension	An axis along which measurements are recorded.
Component, endmember	A basis vector or mode of variation in a transformed space, representing a fundamental pattern extracted from the dataset through dimensionality reduction.
Data sample, feature, or instance	An n -dimensional observation of a structure.
Data Profile	A one-dimensional set of measurements.
Sample Measurement	A zero-dimensional scalar quantity representing the magnitude of an element at a defined coordinate, such as a position, wavelength, or time step.
R	Crater Radius
R_p	Planetary Radius
D	Crater Diameter

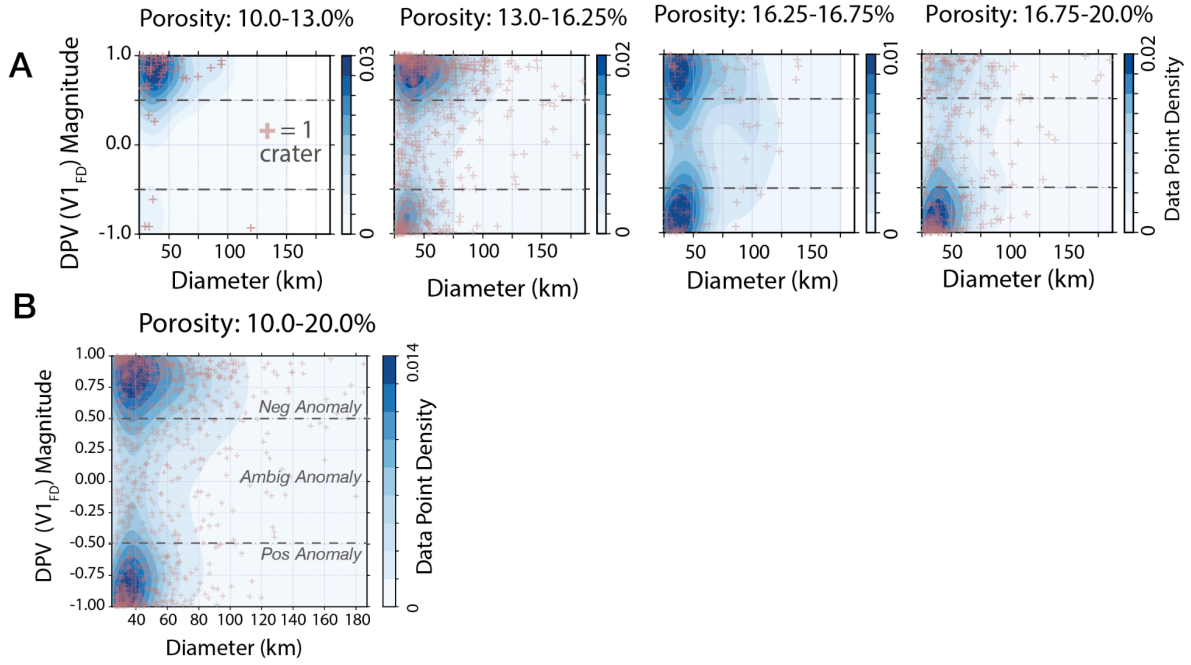


Figure S2-1. Plots of relationships between dot product values (DPV), calculated between crater gravitational profiles and eigenvector 1 of the full dataset ($V1_{FD}$), and crater diameter, for craters with varying (A) ranges of regional porosity and (B) the total range of porosity variability considered in our dataset. Of particular significance is the plot for craters with porosity of 16.25-16.75%, which includes the "critical porosity" of 16.5% described in Figure 13B of the main text, where the fraction of craters with positive gravity anomalies equals that of craters with negative gravity anomalies. Horizontal dashed lines indicate the DPV ranges of craters with negative, ambiguous, and positive gravity anomalies. Red crosses indicate individual craters, while blue regions indicate the density of data points.

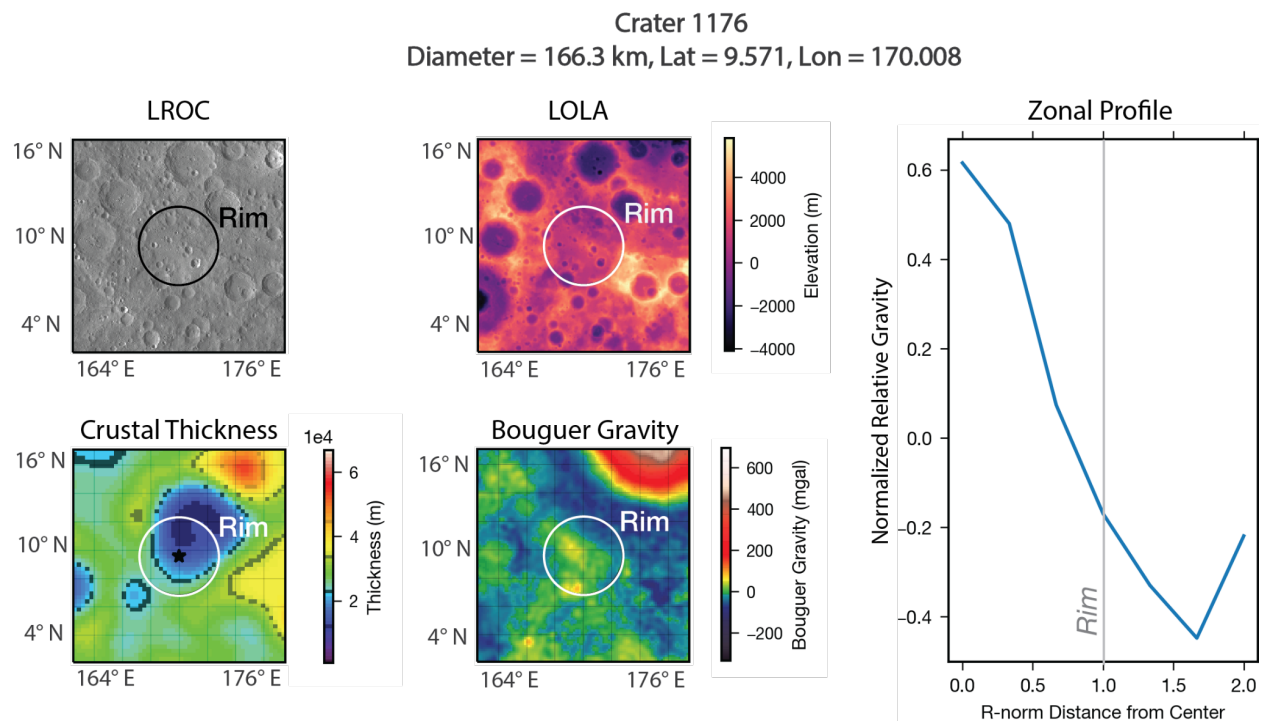


Figure S2-2. Diagnostic plots for Crater 1176. Basemaps for LROC (Lunar Reconnaissance Orbiter Camera; Robinson et al. 2010), Lunar Orbiter Laser Altimeter (Smith et al., 2010) Smith et al. 2010), crustal thickness (Wieczorek et al. 2013), and Bouguer gravity anomaly and included (Goossens et al. 2020).

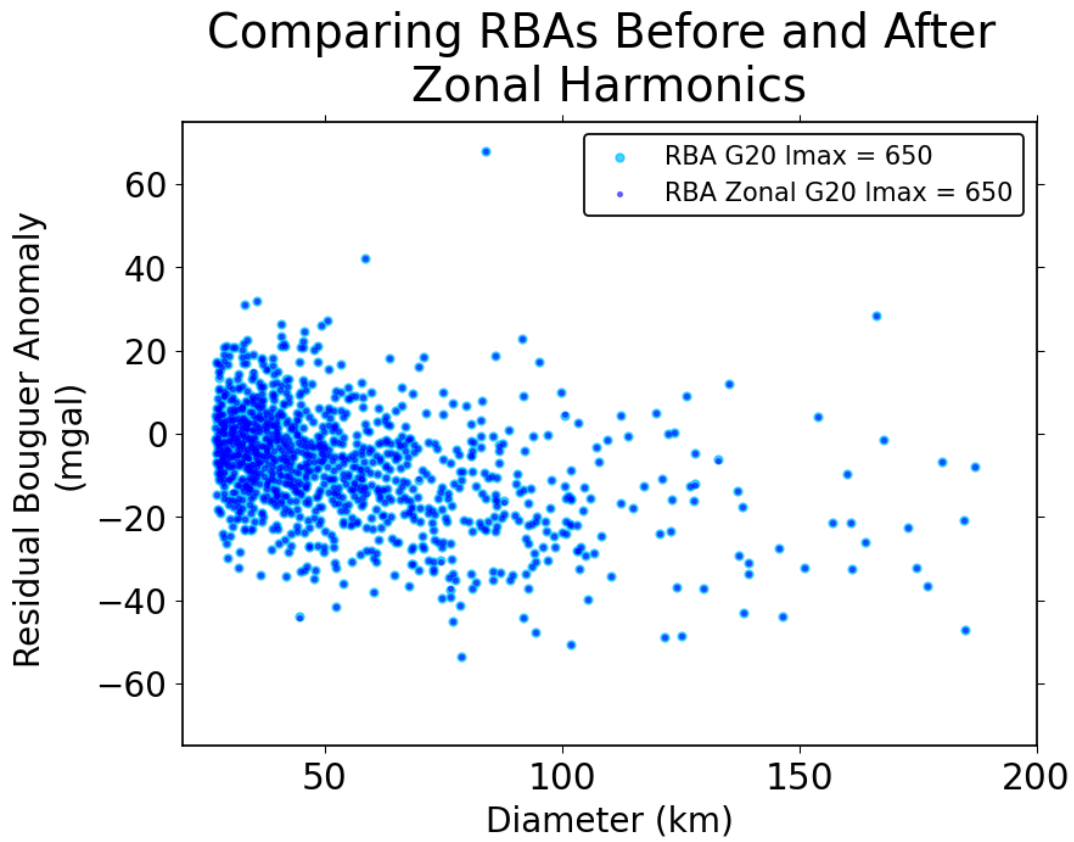


Figure S2-3. Residual Bouguer Anomaly (RBA) measurements using Goossens et al. (2020) (G20) gravity data before and after reducing to zonal harmonics.

APPENDIX C: Supporting Information for Chapter 3

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Crustal Thickness trends for craters of all porosities (10-20%)

Groups of craters from terranes of all porosities (10-20%) produce distinctly different eigenvalue 1 trends with increasing group crustal thickness as compared to those from exclusively low-porosity terranes (10-16% shallow porosity).

Figure S4 shows GEEX crustal thickness trends for groups of craters spanning the entire porosity range of our source database (10-20%) of lunar highland complex craters (Soderblom et al. 2015). Craters within each group fall within a unique combination of diameter and crustal thickness ranges: 20 km-wide diameter ranges, from 40 ± 10 km (top) to 90 ± 10 km (bottom), are indicated by subplot titles, while 10 km-wide crustal thickness ranges are indicated by the x-position of circles, with midranges separated by 1 km along the x-axis. The number of craters in each group varies from 8 (the minimum number of craters required to produce all non-zero eigenvalues) to a max of over 350, indicated by the depth of blue of each circle. Trends with crustal thickness produced by groups with relatively few craters may be more noisy than those with significantly more.

Figure S4A shows eigenvalue 1s calculated from these groups of craters, while Figure S4B shows the associated eigenvector 1s, though only one out of every four eigenvector 1s is plotted for visual clarity. Eigenvalue 1 characterizes the magnitude of the first-order variability in orientation and shape of each group's gravitational profiles. Eigenvector 1 characterizes the shape of first-order variability in each group's gravitational profiles.

One of the most important takeaways from Figure S4 is that there is an overall negative trend in eigenvalue 1 with increasing crustal thickness. This is demonstrated in Figure S4D which shows the sign of the best-fit slope taken from the six subplots of Figure S4A. All panels are red,

indicating that all diameter ranges exhibit negative slopes. Negative slopes generally become more negative with increasing diameter up to $D = 80 \pm 10$ km.

While the graphs of eigenvalue 1 vs. crustal thickness (Figure S4A) exhibit strongly negative overall slopes, they typically attain a minimum eigenvalue 1 at intermediate crustal thickness (45-53 km) and subsequently increase modestly toward greater thicknesses. The well-defined inflection in each eigenvalue 1 vs thickness graph creates an approximately "reverse checkmark" shape. These inflections are particularly sharp for diameters of 50 ± 10 km, 70 ± 10 km, 80 ± 10 km, and 90 ± 10 km (see vertical dashed lines in Figure S4A). These sharp inflections or slope-breaks occur at thinner crusts with increasing diameter.

Eigenvector 1 shapes are generally similar to each other across the diameter and crustal thickness ranges examined. The eigenvector 1 shapes in S4B resemble the shape of eigenvector 1 from the full database of lunar highland complex craters from Soderblom et al. (2015) (Hundal et al. in review, see Figure 4D of the main text).

The self-similarity of eigenvector 1 shapes indicates that the "reverse checkmark" shape in the eigenvalue 1 graphs, discussed above, is caused principally by differences the orientations of group profiles, more specifically, that the orientation of gravity profile shapes similar to eigenvector 1 within a group are more evenly distributed at thin crustal thicknesses, and more likely to be in one orientation versus another at thicker crustal thicknesses.

Eigenvector 1s define the shape patterns of the first-order variations in the gravitational profiles of each group. For clarity, eigenvectors are shown only at 4 km intervals, corresponding to groups of craters with midrange crustal thicknesses from 33 to 53 km. These shapes are similar to the eigenvector 1 of the full Soderblom highland complex crater database, abbreviated as $V1_{FD}$ (Hundal et al. in review). $V1_{FD}$ exhibits a "ramp shape" with a steady slope from the center of the

crater to the rim and then flat exterior to a distance of $2R$. This $V1_{FD}$ shape in the eigenvector 1s of our groups indicates that interior-exterior differences in gravity (i.e., craters that exhibit a clear positive or negative anomaly with their surroundings) make up the dominant variations in our data.

However, there are some exceptions: five of the eigenvectors shown do not look like $V1_{FD}$ and instead look like a pyramidal shape that highlights the rim. These pyramid-shaped eigenvector 1s include the two thickest-crust (49 and 53 km midrange thickness) eigenvectors shown for $D = 70 \pm 10$ km and $D = 80 \pm 10$ km, as well as the thickest crust (53 km midrange thickness) eigenvector for $D = 90 \pm 10$ km. The pyramid shape of these five eigenvectors suggests that, at these large diameters and very thick crusts, variations in profile shape related to the rim are more important than interior-exterior variations in shape.

We interpret the significance of both the overall decrease in eigenvalue 1 with crustal thickness and the sharp slope-breaks observed in Figure S4A by examining Dot Product Values (DPVs) of the individual craters that were used to make up the groups in each panel of Figure S4A. This crater-level comparison provides insight into how variations in profile shape and orientation contribute to the group-level trends in eigenvalue 1. All the DPV values calculated are with respect to $V1_{FD}$, the eigenvector 1 for the full Soderblom highland complex crater database (see Figure 4D of the main text). See Figure 4D in the main text to see the shape of $V1_{FD}$.

Figure S5A shows the results of our DPV analysis. Profiles with $DPVs > 0.5$ have a shape and orientation similar to $V1_{FD}$, while profiles with $DPVs < -0.5$ have a similar shape and opposite sign-orientation. These two ranges also generally correspond to negative ($DPVs > 0.5$) and positive ($DPVs < -0.5$) gravitational anomalies with respect to the region (Hundal et al. in review). Profiles with $DPVs$ between -0.5 and 0.5 are different in shape from $V1_{FD}$. In-depth analysis of profile shapes with respect to $DPVs$ are shown in Hundal et al. (in review).

Vertical lines of three different colors (blue, orchid, and lilac) in Figure S5A show the positions of three important shifts in the data with crustal thickness. The blue lines indicate the crustal thickness value of the sharp slope-breaks observed in Figure S3A. The orchid-colored lines indicate the mean thickness of the five thickest crusts for positive anomaly craters ($DPV < -0.5$). Figure S5B shows the crustal thickness values of these two quantities versus the midrange diameter of the panel from which they were taken. The crustal thickness value of the break in slope (blue) is correlated with the mean crustal thickness of the five thickest-crust craters with positive anomalies (orchid).

The lilac lines show the results of a test designed to evaluate whether the observed trends are driven by decreasing crater counts with increasing diameter. As diameter increases, fewer craters are available, which could bias the mean crustal thickness of the five thickest-crust craters with positive anomalies (orchid) toward thinner values. To test this, we ran 10,000 simulations in which we randomly selected 87 craters from each diameter bin (87 is the number of craters in the largest diameter bin, 90 ± 10 km), recalculating the mean thickness of the five thickest-crust positive-anomaly craters each time. The resulting means and standard deviations of our results from this 10k simulation are shown in lilac in both Figure S5A and B. These values closely track the original blue and orchid trends, indicating that the observed patterns are not an artifact of varying numbers of craters in each diameter bin. We therefore interpret the breaks in slope in Figure S4A as indicating a transitional crustal thickness after which positive crater anomalies are less well-represented in significant numbers in the data.

High shallow porosity (>16%) terranes do not show crustal thickness trends

We find that PCA subsets containing craters from high porosity terranes ($>16\%$ shallow porosity) do not show unambiguous eigenvalue 1 trends with crustal thickness. Here we explain how we determined this lack of correlation.

Eigenvalue 1s follow systematic trends with crustal thickness for groups of craters with low porosities (10–16%), exhibiting negative slopes in thin crust (25–40 km thick) and flat slopes in intermediate crust (40–48 km thick). However, these trends are significantly less distinct in crater groups with only slightly higher porosities (e.g., 14–16.5%; see Fig. S8). We interpret this difference to be due to differing proportions of positive and negative anomaly craters at higher porosities. Positive anomaly craters are more likely to form at higher porosities (Soderblom et al. 2015, Milbury et al. 2015, Hundal et al. in review). At a shallow porosity of 16.5%, positive anomaly craters and negative anomaly craters (those that resemble the shape and orientation of $V1_{FD}$) are evenly represented (Hundal et al. in review). Therefore, we interpret that the the variation between gravitational profiles that are similar in shape to $V1_{FD}$, but in different orientations, dominate the variations of profiles trends of eigenvalue 1 with crustal thickness are dominated by relationships with diameter and pre-impact porosity.

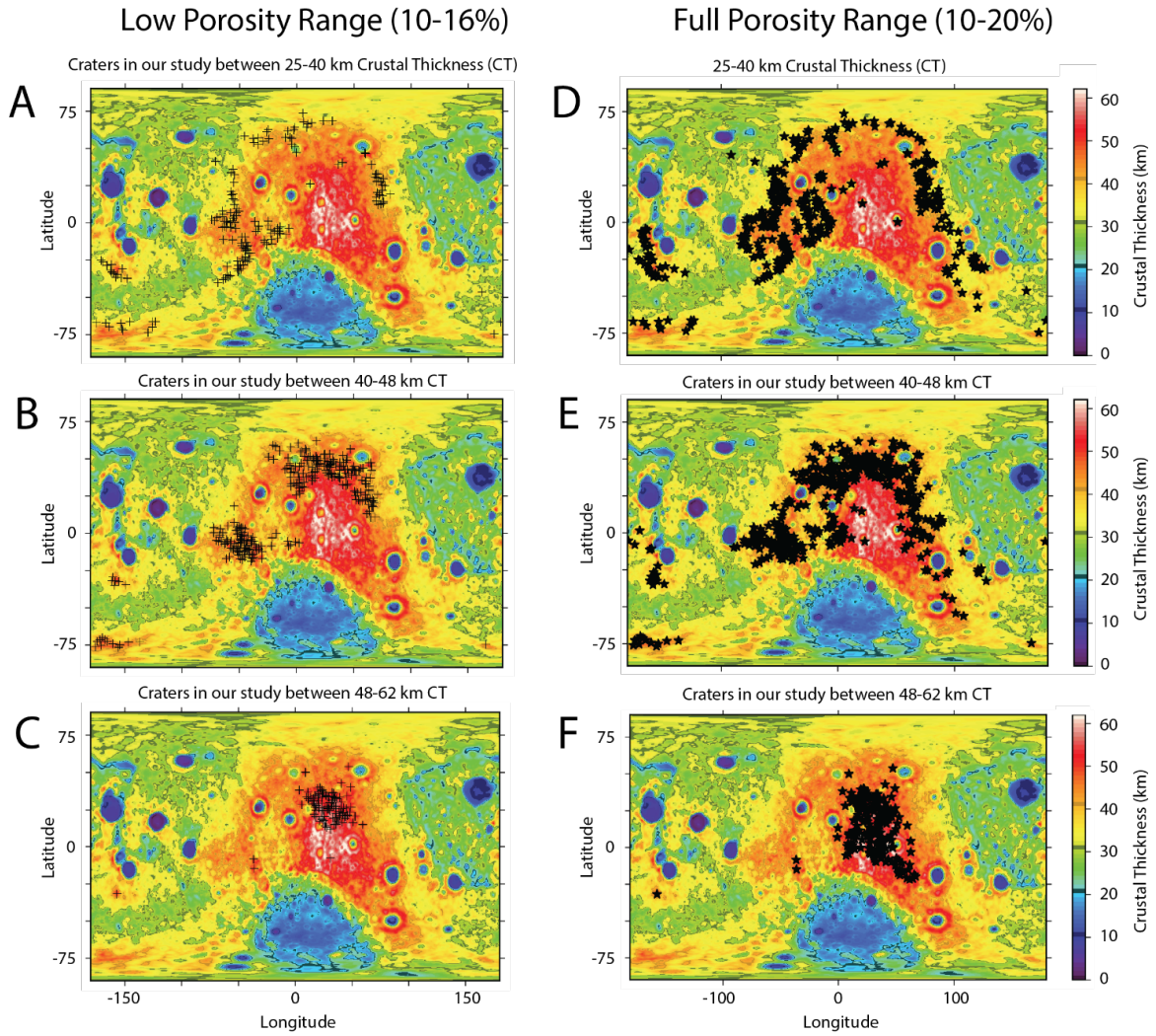


Figure S2-1. Location of craters in distinct crustal thickness (CT) ranges for all shallow porosities, 10-20% (A-C) and low shallow porosities, 10-16% (D-F). Each point (cross or star) represents a single crater. Rows show different crustal thickness ranges: CT = 25-40 km (A, D), CT = 40-48 km (B, E), CT = 48-62 km (C, F). Basemap is of crustal thickness from Wicczorek et al. (2013).

Crustal Thickness vs. Eigenvector 1 (V1)
for low porosity groups of craters

 Eigenvector of every 4th group of craters

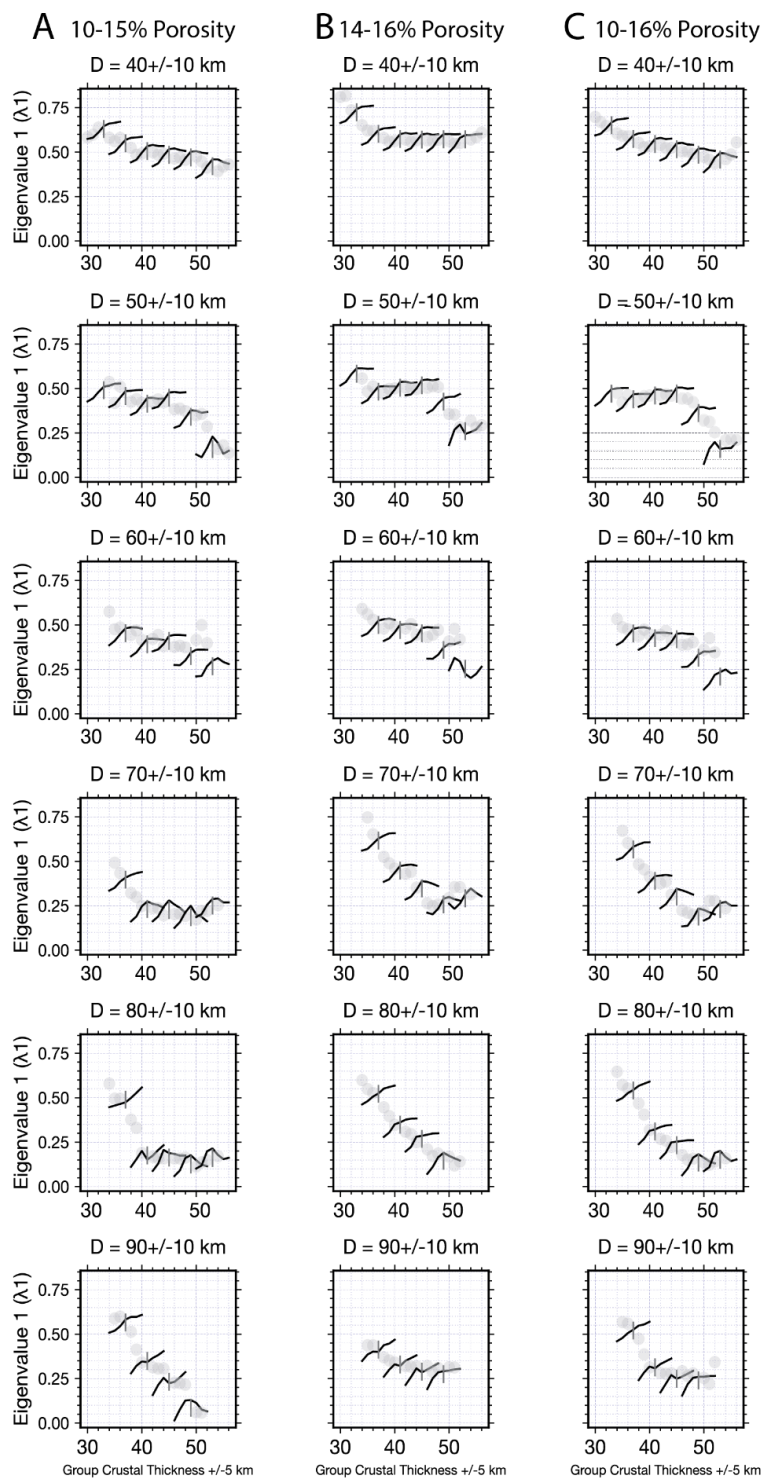


Figure S3-2. Crustal thickness trends with eigenvector 1s associated with eigenvalue 1s in Figure 3 of the main text.

Crustal Thickness vs. Eigenvalue 1 (λ_1)
for low porosity groups of craters

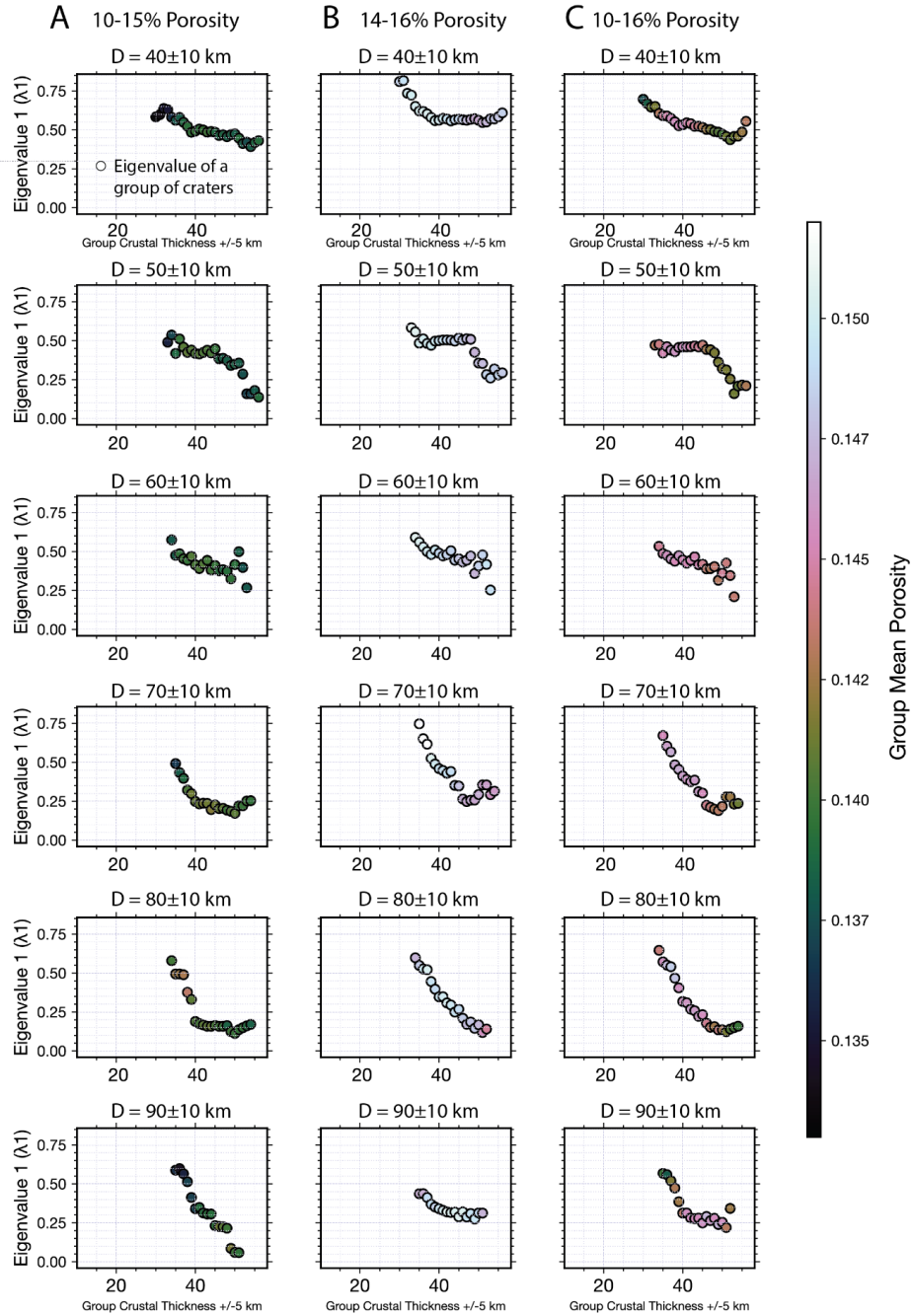


Figure S3-3. Eigenvalue 1s of Figure 3 in the main text color-coded for group mean regional shallow porosity.

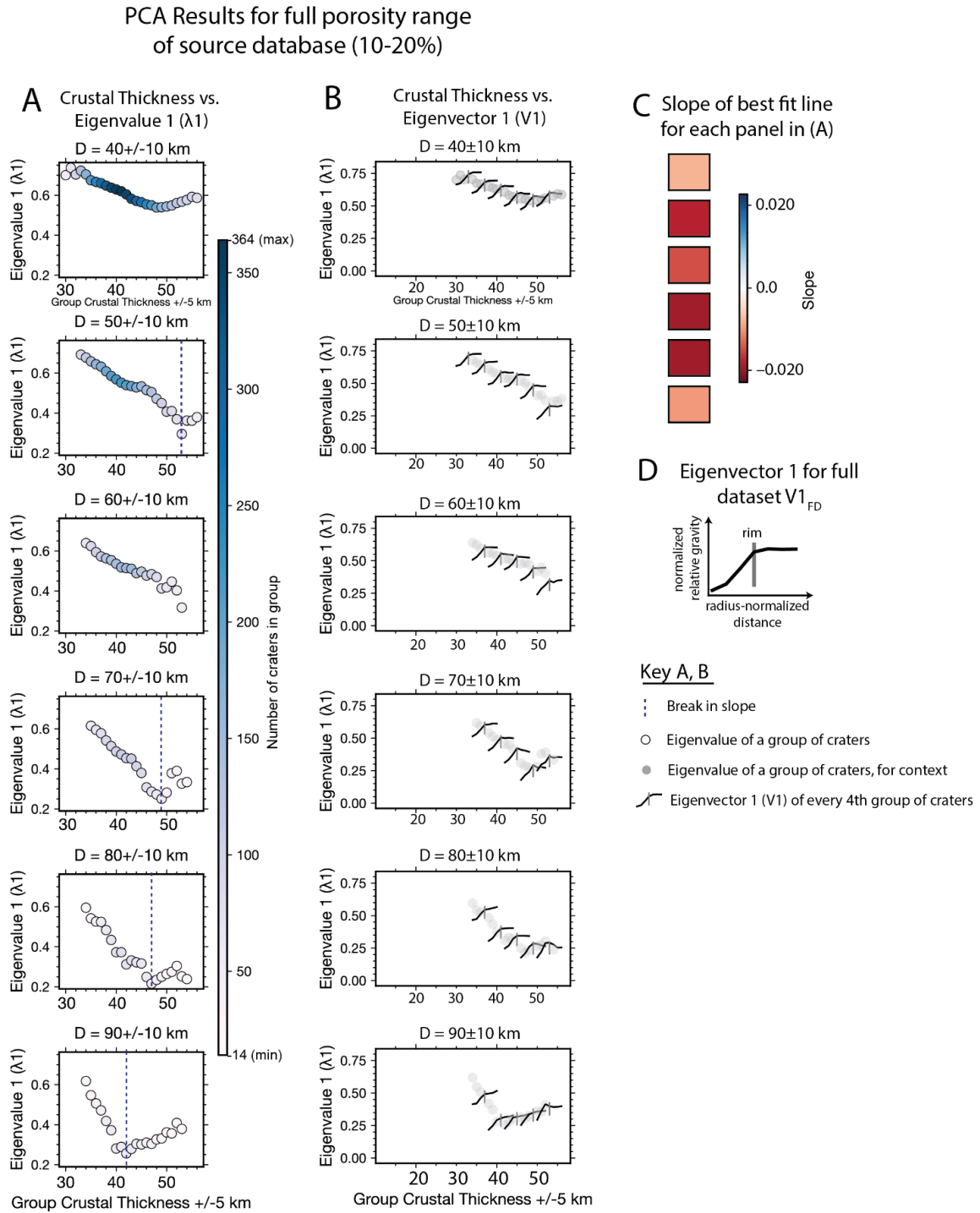
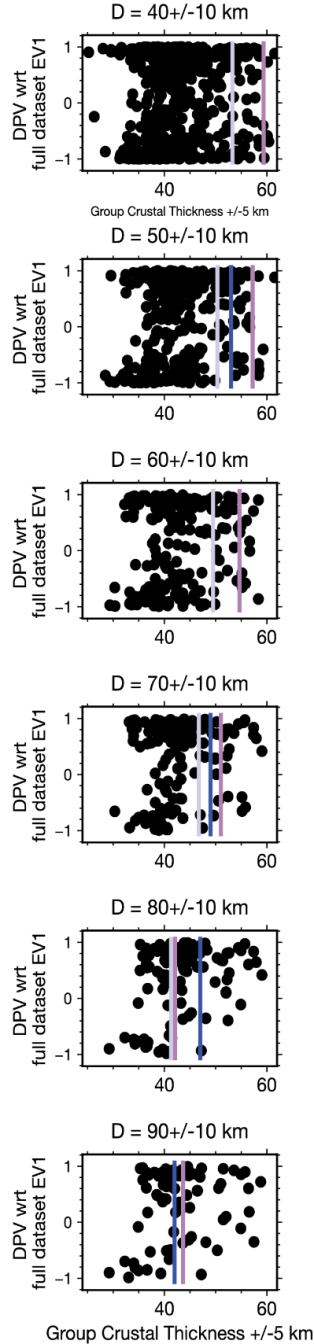


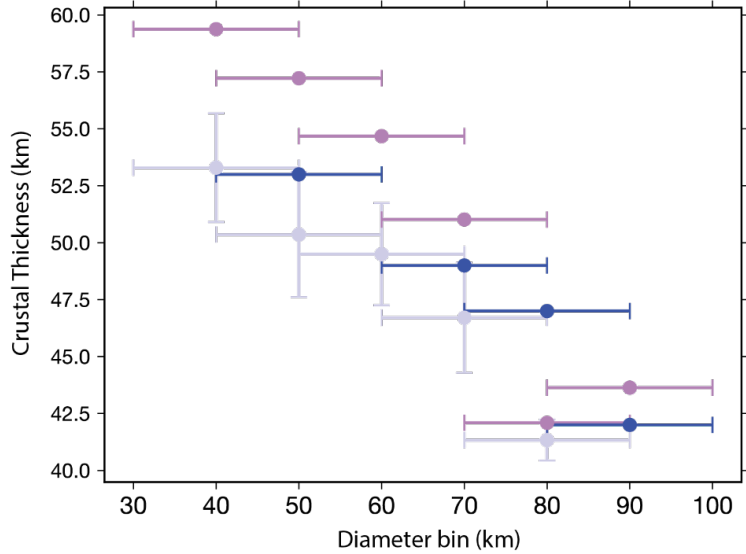
Figure S3-4. Crustal thickness vs. PCA results (eigenvalue 1s, eigenvector 1s) for groups of craters

spanning the entire porosity range of our source database (10-20%) of lunar highland complex craters (Soderblom et al. 2015). Each row shows results from groups of craters in constrained diameter ranges indicated by subplot titles. (A) Eigenvalue 1s of groups of craters. Each point represents a group of craters with a constrained crustal thickness within ± 5 km of the indicated midrange value. Points are separated by 1 km each. The greyscale darkness of the point indicates the number of craters in each group. The blue vertical dashed line shows breaks in slope of eigenvalue 1 with crustal thickness. (B) Eigenvector 1s of the same groups of craters shown in (A). For clarity, eigenvector 1s are shown at 4 km intervals for groups of craters with midrange crustal thicknesses from 33 km to 53 km. A vertical line in each eigenvector 1 profile shows the 1R position of the rim. Behind eigenvector 1s, semi-transparent grey circles show the same eigenvalue points in (A) for context. (C) Slope of best fit line for all data shown in each panel in (A). Note that all panels are red, indicating a negative overall slope for each panel. (D) Eigenvector 1 for the full Soderblom et al. (2015) dataset of lunar highland complex craters, abbreviated as $V1_{FD}$, shown for comparison with eigenvector 1 shapes calculated in this study.

A DPV results with respect to crustal thickness for craters of all porosities (10-20%)



B Breaks in eigenvalue/DPV behavior with crustal thickness for different diameter bins



Key A, B

- Dot Product Value of a single crater
- Break in slope of Crustal Thickness (CT) vs. Eigenvalue 1 (see caption)
- Mean CT of 5 pos. anom craters with greatest CT
- Mean CT of 5 thickest pos. anom craters when randomly downsampled to 87 craters in 10k simulation
- I Standard deviation of 10k simulation
- I Width of diameter bin

Dot Product Value (DPV)

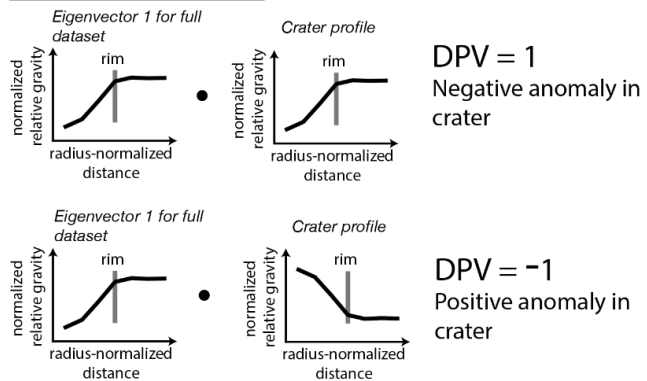


Figure S3-5. Dot Product Value (DPV) results compared to the crustal thickness of slope changes

in λ_1 values observed in Figure S4. (A) Crustal Thickness versus DPVs of individual craters. Each point corresponds to a single crater. DPVs are calculated by taking the dot product of individual profiles and first eigenvector of the full Soderblom et al. (2015) dataset (Hundal et al. in review). Eigenvector 1 for the full dataset ($EV1_{FD}$) is shown in the DPV insert on the bottom right. Dot products close to 1 indicate that profiles are similar in shape to $EV1_{FD}$, while dot products close to -1 indicate profiles are similar to the opposite sign-orientation of the eigenvector. Hundal et al. (in review) established that $DPVs < -0.5$ correspond to positive anomaly craters. Here we explore the relationship between the position of the λ_1 break-in-slope observed in Figure S4 (dark blue vertical line) and the mean thickness of the five thickest positive anomaly impact craters (orchid-colored vertical line). Note that, as diameter increases, both the dark blue and orchid-colored vertical lines move to thinner crusts. To address concerns that the reduced number of craters with increasing diameter was creating the trend observed, we ran a 10k simulation randomly selecting only 87 craters in each diameter bin, equivalent to the number of craters present in the 90 ± 10 km diameter bin. (B) Crustal thickness positions of the three parameters shown in (A) for different diameter bins. Note the general trend toward thinner crusts for larger diameters expressed by all parameters.

Crustal Thickness vs. Eigenvalue 1 (λ_1) for full porosity groups of craters

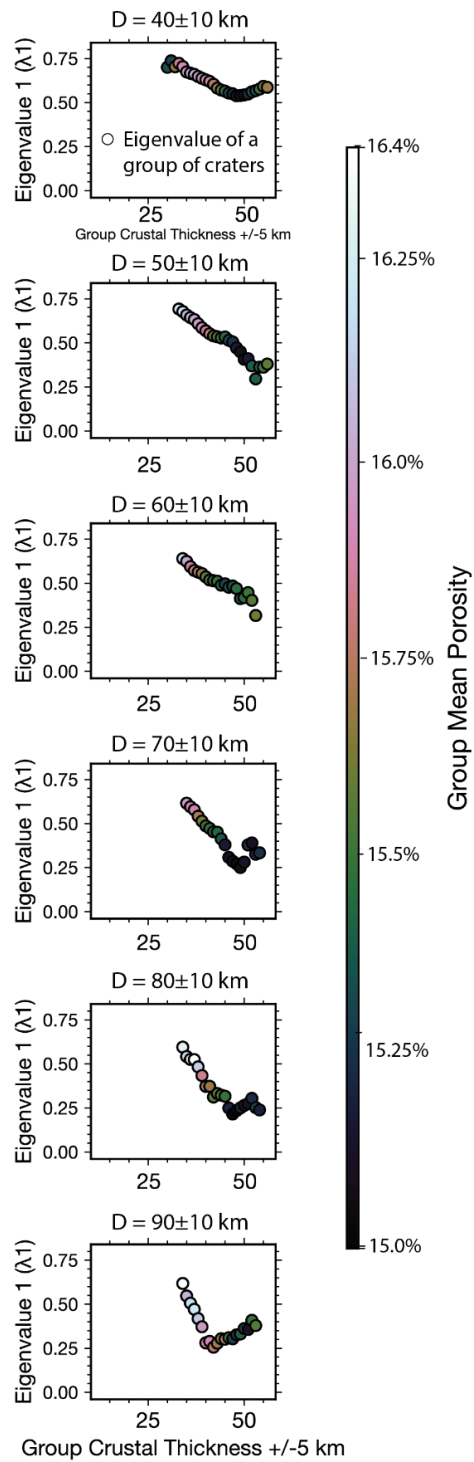


Figure S3-6. Eigenvalue 1s for craters from all shallow regional porosity terranes (10-20%), color coded for porosity.

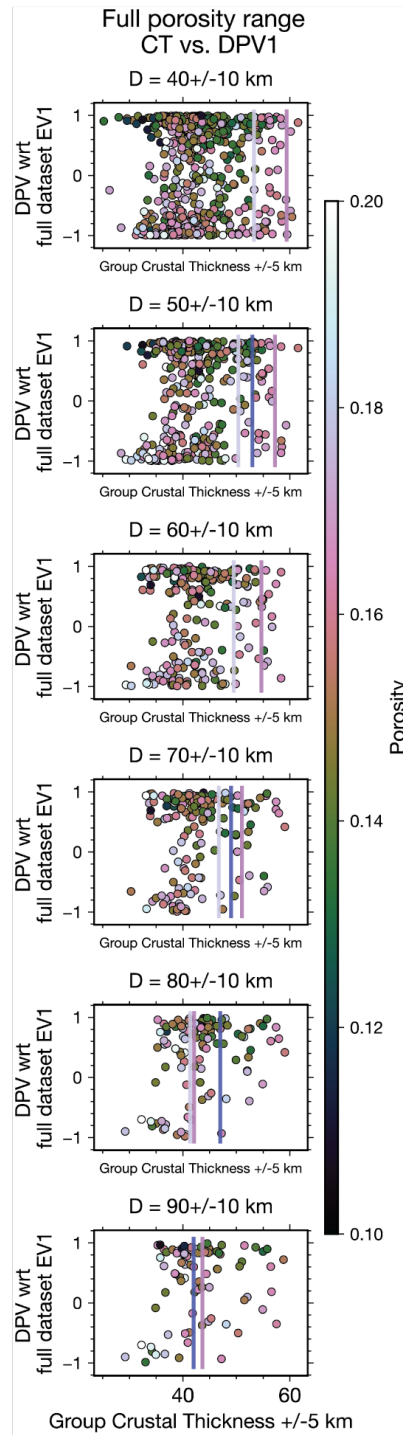


Figure S3-7. DPVs of craters from all porosities (10-20%), color coded for porosity. DPVs are calculated with respect to the first eigenvector of the full Soderblom dataset ($V1_{FD}$, see Figure 4D of the main text).

PCA Results for high porosity
(16-20%) groups of craters

Legend

○ Eigenvalue of a group of craters



Eigenvector of every 4th
group of craters

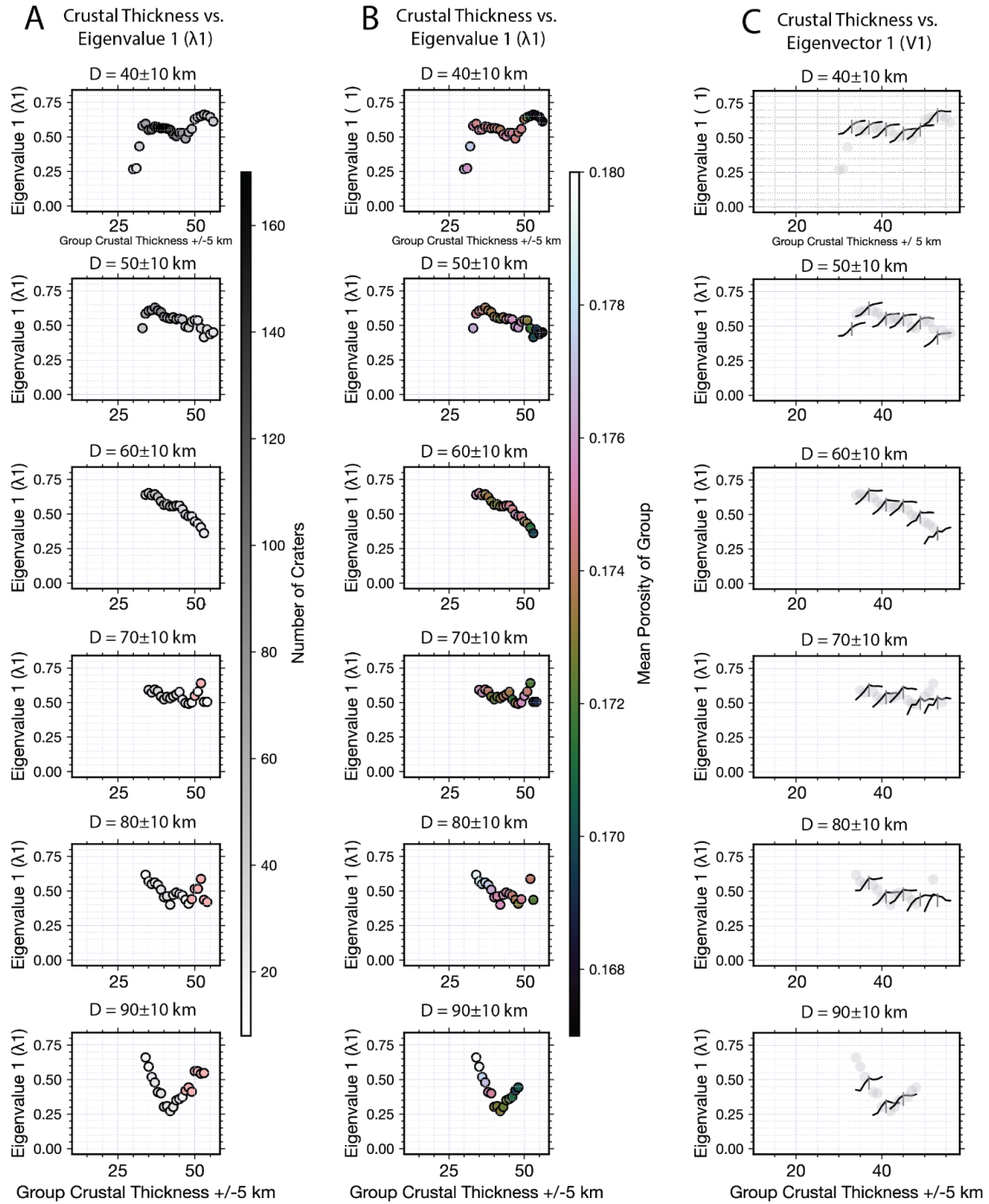


Figure S3-8. PCA Results for high porosity (16-20%) groups of craters.

Crustal Thickness vs. Eigenvalue 1 (λ_1)

14-16.5% Porosity

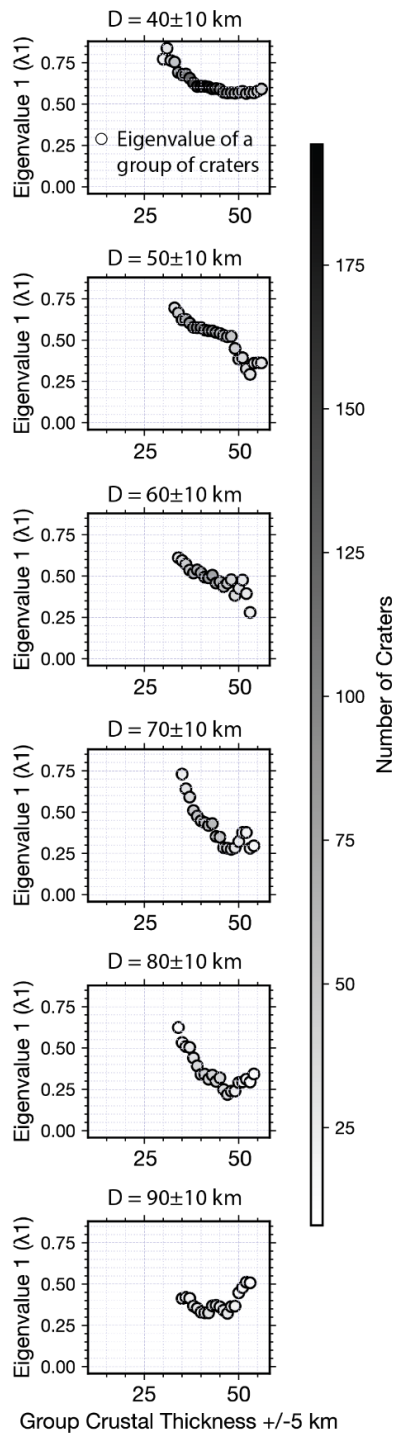


Figure S3-9. Crustal thickness vs. eigenvalue 1s for porosities slightly higher than those shown in Figure 4B of the main text. Trends are less distinct.

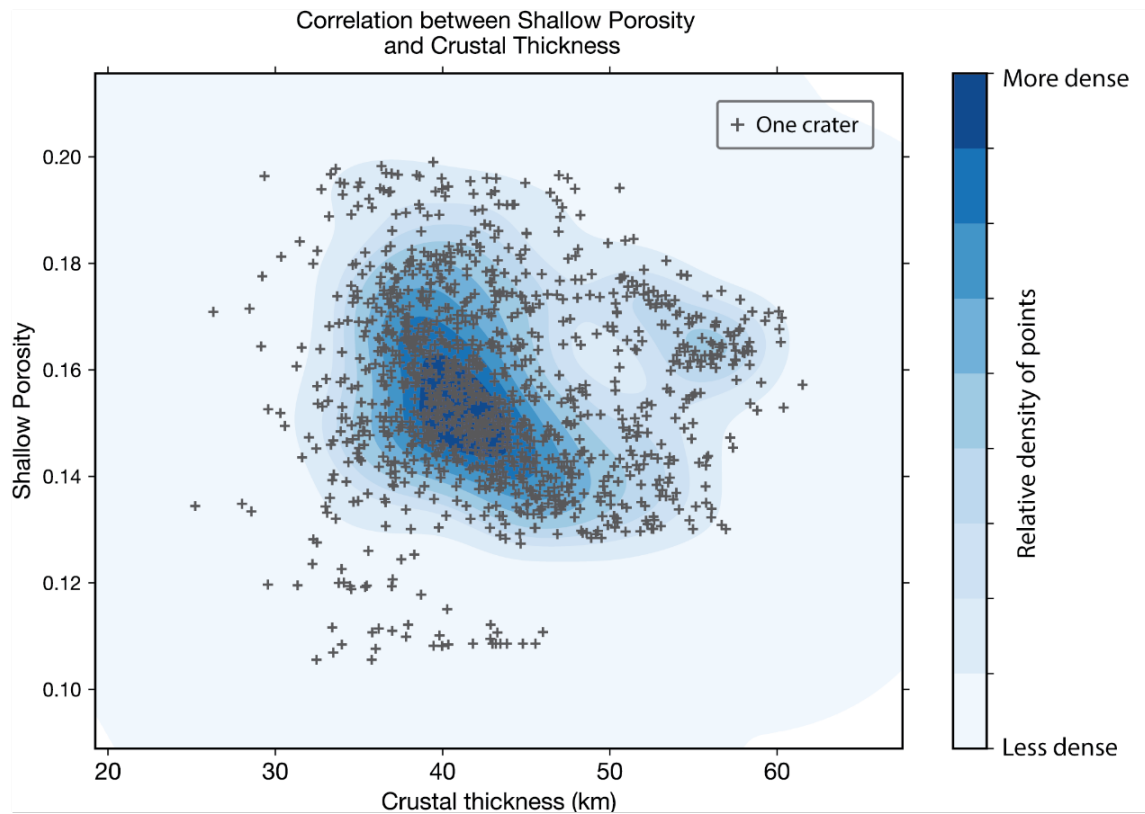


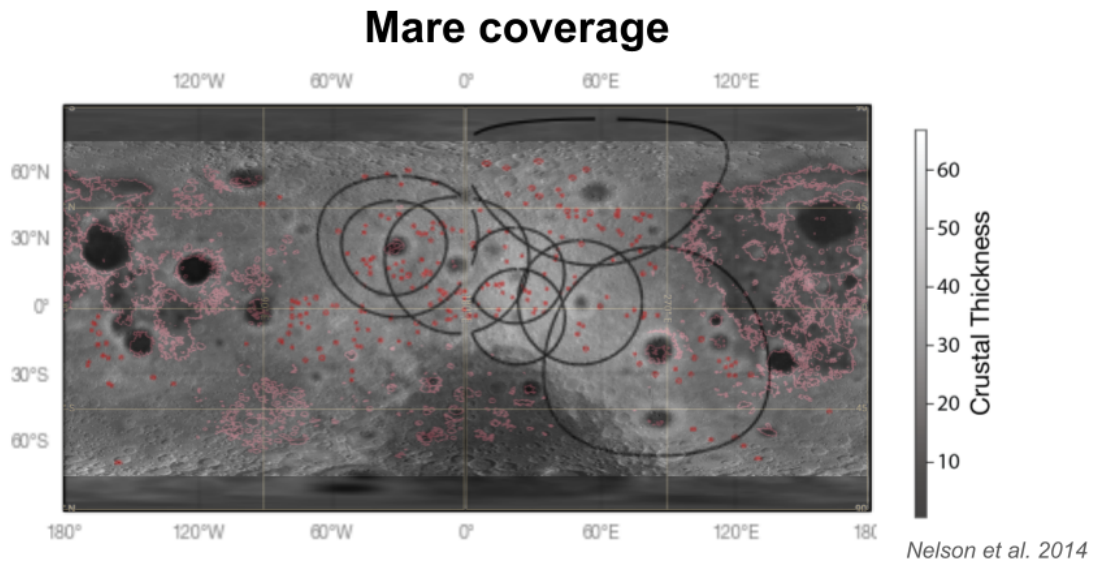
Figure S3-10. Correlation between shallow porosity and crustal thickness for all craters in the Soderblom et al. (2015) database of lunar highland complex craters. Each cross indicates one crater. The depth of blue shows the density of points, highlighting a weak anti-correlation between crustal thickness and regional shallow porosity.

APPENDIX D: Supporting Information for Chapter 4

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*Our **complex craters** do NOT intersect mare
Circles at $3R_{B^*}$, pink lines indicate mare boundaries*

Figure S4-1. Complex crater ($DPV < -0.5$) positions (red circles) with respect to mare outlines (pink) derived from Nelson et al. (2014), overlayed on a basemap of crustal thickness (Wieczorek et al. 2013). Black circles indicate $3R_{\text{Basin}}$ from each basin center.

Cryptomare coverage

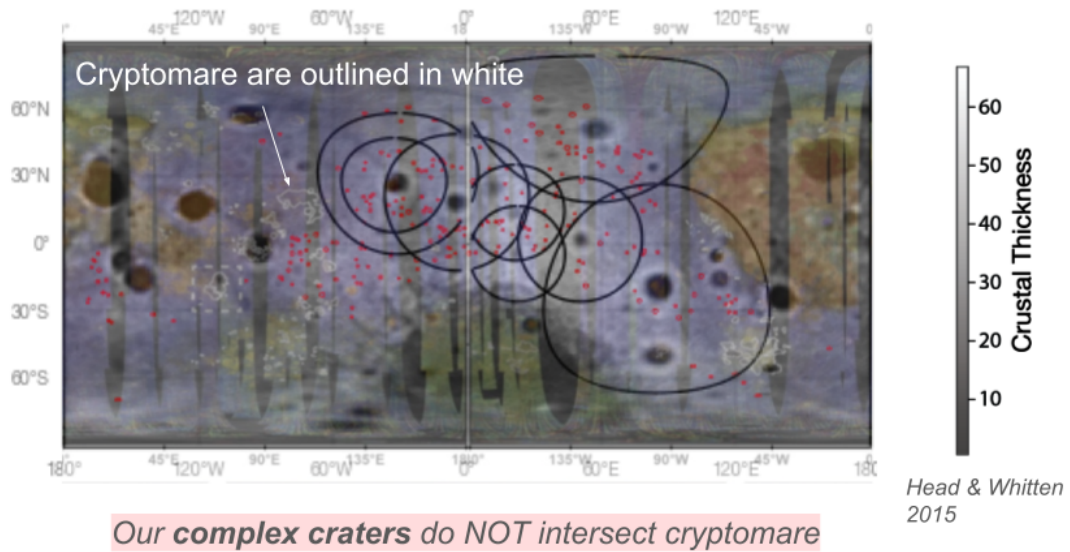


Figure S4-2. Complex crater ($DPV < -0.5$) positions (red circles) with respect to cryptomare outlines (white) derived from Head & Whitten (2015), overlayed on a basemap of crustal thickness (Wieczorek et al. 2013). Black circles indicate $3R_{\text{Basin}}$ from each basin center.

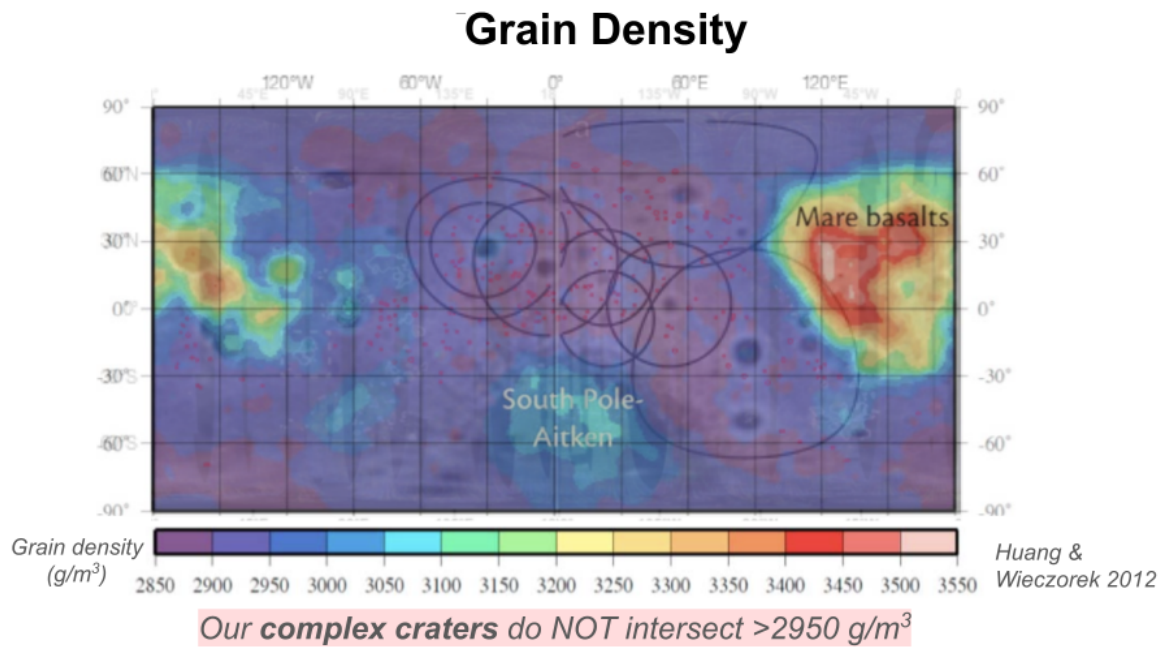


Figure S4-3. Complex crater (DPV < -0.5) positions (red circles) with respect to grain density estimates from Huang & Wieczorek (2012), overlayed on a basemap of crustal thickness (Wieczorek et al. 2013). Black circles indicate $3R_{\text{Basin}}$ from each basin center.