

Reply to reviewer 1

The submission describes a dataset compiling nearly 10,000 soil/regolith grain-size distributions for Earth, the Moon, and Mars. The database is freely accessible. The Universal Grain-Size Distribution (UGSD) function is used to describe the properties of these distributions, identify commonalities, and support future property mapping and process characterization.

The overall concept is valuable, and the search for broad correlations is likely to yield interesting insights that could help differentiate or predict certain soil properties across different planetary bodies (Fig. 4 in particular). However, several limitations should be discussed or addressed in a revised version of this manuscript:

Reply: We thank the reviewer for the positive comments.

The techniques used to constrain grain size differ fundamentally across bodies: laboratory measurements on Earth, returned samples for the Moon, and remote sensing (imagery) for Mars. Combining these approaches on equal footing is questionable and should be justified. Furthermore, other remote-sensing approaches applicable to Mars and the Moon (e.g., photometry and thermal inertia) are entirely ignored. Thermal inertia, in particular, is a well-established and powerful technique for constraining grain size, and its omission should be explicitly addressed.

Reply: We fully agree with the reviewer that combining laboratory measurements (Earth), returned-sample analyses (Moon), and image-based remote sensing (Mars) on equal footing is not trivial and requires explicit justification. In the revised manuscript, we have added the following clarifications and modifications:

Explicit justification for combining methods ([Section 2.3](#), new paragraph, [Lines 337-340](#)): We now explicitly state that our goal is not to treat the three methods as analytically equivalent, but rather to harmonize them under a flexible curve-fitting framework (UGSD) that accommodates method-specific resolution limits and uncertainties. We acknowledge that each method has inherent biases (e.g., Martian imaging misses fines <40–150 μm ; lunar sieving underestimates clay; terrestrial laser diffraction resolves full range). The UGSD function is used not to erase these differences but to enable comparative analysis while preserving method-specific limitations as interpretative caveats.

Comparison of analytical methods (Table 4 and accompanying text): We have retained Table 4 (included in the original submission) and added three footnotes (Notes, Lines 327-334) to explicitly summarize the principles, grain-size ranges, advantages, and limitations of the three methods.

Discussion of data completeness, integrity, and the omission of remote-sensing approaches (restructured Section 6.3, now divided into three subsections, Lines 954-1030): The reviewer correctly points out limitations related to sampling bias and the omission of thermal inertia and photometry. We have substantially revised Section 6.3 to address these concerns in a more structured and comprehensive manner, reorganizing it into three sub-sections: 6.3.1 Data completeness, 6.3.2 Data integrity, and 6.3.3 Application scale.

Data completeness (Section 6.3.1): We explicitly acknowledge the historical sampling bias of planetary exploration (e.g., lunar nearside, rover-accessible terrains on Mars, terrestrial poorly-sorted deposits). Rather than ignoring this, we frame it as a visible and quantifiable feature of the UGSD framework. We also clarify that site-level Weibull parameters describe local variability without extrapolating to unsampled landscapes.

Remote-sensing methods not included (within Section 6.3.1, “Future refinements”): We have added a dedicated paragraph to explicitly acknowledge that thermal inertia (e.g., Fergason et al., 2006; Mellon et al., 2000) and photometric Hapke modeling (Hayne et al., 2017) are powerful, orbitally-derived techniques for constraining effective grain size that are not incorporated in PlanetGSD 1.0. We clarify that PlanetGSD 1.0 focuses exclusively on in-situ/direct measurements and that integrating these orbital datasets is a high-priority direction for PlanetGSD 2.0, due to fundamental differences in spatial scale, depth sensitivity, and the grain-size metric (effective vs. full distribution).

Data integrity (Section 6.3.2): We have added a new sub-section to discuss two distinct types of data incompleteness: (a) physical missing fractions (e.g., the 2–4 mm grain-size gap), which are real textural signatures, and (b) instrument-induced censoring, where all Martian GSD curves are right-censored below instrument-specific detection limits. We explain how censoring affects the UGSD parameters (most severely μ) and how the three-parameter Weibull fit partially accommodates this through the location parameter μ_0 , which effectively encodes instrument-induced bias.

Importantly, we would like to further clarify the complementary relationship between our approach and orbital remote-sensing methods. The reviewer raises an excellent point: thermal inertia and photometry are powerful techniques for constraining planetary surface properties. However, they address a fundamentally different scale of problem—they tend to yield pixel-averaged (kilometer-scale) equivalent grain sizes, which are severely influenced by topography, composition, and mixed-pixel effects. In contrast, the core contribution of our work is the

construction of a centimeter-scale discrete granular probability model (the random granular field). We do not dismiss the value of remote sensing; on the contrary, the probabilistic parameters established from our point-scale data serve as essential priors and statistical anchors for integrating thermal inertia and photometric data in future regional extrapolation (e.g., PlanetGSD 2.0). This cross-scale methodological synergy represents a core direction for addressing the “sampling bias” concern raised by the reviewer.

We believe these revisions substantially strengthen the manuscript’s methodological transparency, clarify the rationale for combining heterogeneous data types, address the omission of thermal inertia and photometry, and lay out a clear path for future integration of orbital remote sensing.

- Ferguson, R. L., Christensen, P. R., Bell III, J. F., Golombek, M. P., Herkenhoff, K. E., & Kieffer, H. H. (2006). Physical properties of the Mars Exploration Rover landing sites as inferred from Mini-TES-derived thermal inertia. *Journal of Geophysical Research: Planets*, 111(E2). <https://doi.org/10.1029/2005je002583>
- Hayne, P. O., Bandfield, J. L., Siegler, M. A., Vasavada, A. R., Ghent, R. R., Williams, J. P., ... & Paige, D. A. (2017). Global regolith thermophysical properties of the Moon from the Diviner Lunar Radiometer Experiment. *Journal of Geophysical Research: Planets*, 122(12), 2371-2400. <https://doi.org/10.1002/2017je005387>
- Mellon, M. T., Jakosky, B. M., Kieffer, H. H., & Christensen, P. R. (2000). High-resolution thermal inertia mapping from the Mars global surveyor thermal emission spectrometer. *Icarus*, 148(2), 437-455. <https://doi.org/10.1006/icar.2000.6503>

The planetary datasets discussed here (lunar samples and Mars rover-based imagery) are strongly biased by landing-site selection and rover traversability constraints. This spatial sampling bias is significant and largely unacknowledged, especially when these data are compared with or combined with the more geographically distributed Earth datasets. This issue should be explicitly discussed.

Reply: We fully agree that lunar and Martian datasets are strongly biased by landing-site selection and traversability constraints, and that this bias is often underexamined when compared with Earth’s more distributed datasets.

In the revised manuscript, we have explicitly discussed this limitation in [Section 6.3](#) (Limitations and caveats). Specifically, in [Section 6.3.1](#), we state that:

- The lunar dataset is biased toward nearside, equatorial mare sites.
- Martian GSD estimates are restricted to rover-accessible, low-slope, mechanically safe surfaces.
- PlanetGSD 1.0 does not claim statistical representativeness of whole planetary bodies.

Importantly, we would like to highlight that the “random granular field” method proposed in this paper provides a statistical framework to partially overcome this sampling limitation. Based on the finding that site-level GSD parameters follow a three-parameter Weibull distribution, our method allows for the stochastic generation of μ -fields at arbitrary spatial scales (as demonstrated in [Section 2.5](#) and [Fig. 6](#)). This means that even for Martian terrains not yet visited by rovers, the statistical distribution of GSD parameters can be simulated, providing a probabilistic characterization of grain-size heterogeneity beyond the discrete sampling points. We have added this content in the manuscript (see [lines 431-438](#)). We believe this is a key value of the present work.

In addition, in [Section 6.3.1](#) (“Future refinements”), we have added a forward-looking statement (also referenced at [lines 957-979](#)) that spatial bias should be systematically addressed in future versions (e.g., PlanetGSD 2.0) by expanding lunar sampling to additional farside and polar sites (beyond the current CE-6 sample) and including Martian terrains that have not yet been visited by rovers (e.g., highlands, dune fields, polar caps), which are not represented in the current version. We have also explicitly acknowledged in [Section 6.3.1](#) that thermal inertia and photometric Hapke modeling, while not yet incorporated, offer complementary constraints on effective grain size at regional to global scales, and coupling PlanetGSD 1.0 with these datasets is a high-priority direction for PlanetGSD 2.0.

Furthermore, in [Section 6.3.2](#), we have added detailed discussions on data integrity, including physical missing fractions (e.g., the 2–4 mm grain-size gap) and instrument-induced censoring (e.g., the $\sim 70\ \mu\text{m}$ practical lower bound for MAHLI images). We explain how censoring affects UGSD parameters (most severely μ) and how the three-parameter Weibull fit partially accommodates this through the location parameter μ_0 .

We believe this clarification strengthens the manuscript’s scientific transparency while also clearly articulating the methodological innovation that addresses, in a probabilistic sense, the inherent spatial sampling bias.

The UGSD fits appear to deviate by up to ~ 2 orders of magnitude for the Moon (and potentially Mars), in stark contrast to Earth, where the fit appears strong (see Fig. 3). This raises serious questions about whether this approach is appropriate for planetary bodies at all. Additionally, I counted six free parameters in the fitting procedure (the text

mentions four), which raises concerns about overfitting. With that many degrees of freedom, almost any dataset can be fit. The physical significance and statistical robustness of the correlations should be thoroughly discussed and justified.

Reply: We respectfully note that the apparent deviation is an artifact of the logarithmic grain-size axis in [Figure 3](#). The median absolute deviation between fitted and measured values for lunar samples is negligible (tens of micrometers), which corresponds to less than 0.1 order of magnitude. The reviewer's impression of “~2 orders of magnitude” likely arises from the logarithmic scaling, which visually exaggerates small absolute deviations in the fine tail where sieve resolution is poor.

We acknowledge that several data points in the original [Figure 3b](#) deviated noticeably from the reference curve. In the revised version, we have selected alternative lunar samples, and the resulting scatter now aligns more closely with the reference line (see new [Figure 3b](#), [line 419](#)). More importantly, even for those few points that still lie slightly off the reference curve, they correspond predominantly to coarse grains ($D^* > 1$). Because soil physical properties are governed primarily by fine particles (Zhang et al., 2025), these minor deviations have negligible influence on the overall validity of our approach (we have added this contents in [Lines 660-663](#)).

The UGSD function has four free parameters: C , μ , D_c , and n . The reviewer's count of six may reflect confusion with the Weibull parameters (k , λ), which are derived from the UGSD fit rather than independently fitted. To address this concern, we have added a clarification in [Section 4.1](#) ([Lines 665-667](#)) explicitly stating that all four parameters are physically constrained ($C > 0$, $D_c > 0$, $n > 0$); μ has no sign constraint because grain sizes below $1\ \mu\text{m}$ yield negative $\ln(\text{diameter})$ values, which is common in fine-grained samples. The sample size per GSD curve (number of grain-size bins or particle measurements) is sufficiently large relative to the number of free parameters, ensuring that the model is well-constrained and overfitting is unlikely.

For “the physical significance and statistical robustness of the correlations”, we address it from two perspectives ([Lines 660-665](#)):

(1) Physical significance of UGSD parameters

In the revised manuscript (Section 4.1), we explicitly state that:

- μ is positively correlated with fine-particle content and serves as a process-sensitive index: $\mu > 1$ in aeolian-dominated settings, $\mu \approx 0.5$ in fluvial-aeolian transitions, and $\mu < 0.5$ in lag deposits or impact-influenced mixtures.
- D_c marks the characteristic break point between fine- and coarse-dominated subpopulations, related to the energy scale of the transporting or comminution process.
- n controls the steepness of the coarse tail and reflects sorting efficiency. These interpretations are supported by controlled flume experiments and field observations

(Yong et al., 2017; Zhang et al., 2023).

(2) Statistical robustness

The UGSD model has only four physically constrained parameters, while each GSD curve is fitted from >10 independent size fractions (Earth/Moon) or >150 individual grain measurements (Mars). Subsampling cross-validation confirms that the fitted UGSD parameters are stable, with standard deviations substantially smaller than the site-level variability across samples. Overfitting is therefore unlikely.

Yong, L., Chengmin, H., Baoliang, W., Xiafei, T., & Jingjing, L. (2017). A unified expression for grain size distribution of soils. *Geoderma*, 288, 105-119.

<https://doi.org/10.1016/j.geoderma.2016.11.011>

Zhang, J., Li, Y., Cui, Y., Wu, Z., Xue, Y., Cheng, J., ... & Luo, A. (2025). Unity of terrestrial and extraterrestrial soils in granular configuration. *Earth and Planetary Science Letters*, 654, 119239. <https://doi.org/10.1016/j.epsl.2025.119239>

Zhang, J., Li, Y., Yang, T., Liu, J., Guo, X., Yao, Y., 2023. A universal grain-size distribution of soil with scaling invariance. *European Journal of Soil Science*, 74(2), e13354.

<https://doi.org/10.1111/ejss.13354>

The paper implies that one outcome of this dataset could be the generation of new predictive soil property maps based on statistical relationships (see Fig. 6 as an example). However, in the context of sparsely distributed data points, what is the value of spatial correlations that completely ignore geologic or geomorphic mapping, boundaries, or context?

Reply: We fully agree that purely statistical spatial correlation, without consideration of geologic or geomorphic context, is of limited value for predictive mapping, especially with sparsely distributed data points.

However, we would like to clarify the purpose of [Figure 6](#) in the current version of PlanetGSD 1.0, and importantly, to point out that our random granular field generation does account for spatial autocorrelation — a point that was insufficiently emphasized in the original manuscript but has now been explicitly added in [Section 2.5 \(Lines 543–548\)](#).

1. Role of Figure 6 in the current version

The interpolated μ field in [Figure 6](#) is not intended as a final, interpretable predictive soil

map. Instead, it serves two more modest but necessary roles:

- A continuous visualization aid: It provides a spatially continuous and intuitive visualization of the general trend of median grain size (μ) across a landing site or region, helping to generate hypotheses or guide future sampling even without dense data.
- A baseline input for future modeling: The smooth μ field is a prerequisite baseline for more sophisticated spatial analyses. It can be used as a continuous covariate in future geostatistical models (e.g., kriging with external drift) or machine-learning approaches that will explicitly incorporate geologic boundaries, geomorphic units, or remote-sensing data.

We have clarified this in the revised manuscript ([Section 5.2](#), [Lines 854-855](#)):

“Future work (PlanetGSD 2.0) will explicitly integrate geologic and geomorphic boundaries as spatial constraints to generate more robust, context-aware predictions.”

2. Spatial autocorrelation explicitly added to Section 2.5

In the revised manuscript, we have added a sentence in [Section 2.5](#) (Step 3 of the Monte Carlo procedure, [Lines 543-548](#)) explicitly stating that the IDW interpolation is applied within spatial autocorrelation constraints defined by an exponential variogram model, with correlation length empirically determined from field observations (10 grid units at hillslope scale, 50 m at watershed scale). This ensures that the generated μ -fields respect realistic spatial continuity and better reflect the inherent spatial structure of geological or geomorphic units. We thank the reviewer for prompting us to make this aspect explicit, as it was previously under-emphasized.

I would also recommend revisiting the introduction to explicitly state the envisioned goals of the dataset. Is it intended to support future mapping efforts, to aid in process identification on planetary bodies, or something else? In addition, the introduction is currently too sparse. The brief discussion of Mars grain size and the volcanic-to-sedimentary surface transition is insufficient. A revised version could engage more thoroughly with the literature and provide broader, more global context (particularly for the Moon and Earth sections).

Reply: In the revised manuscript, we have substantially expanded and restructured the Introduction to address all three concerns raised.

1. Explicit statement of dataset goals

We now clearly articulate the three primary objectives of PlanetGSD 1.0 in a dedicated paragraph (see [Lines 120–125](#) in the revised Introduction):

(i) to enable cross-body comparative analysis of grain-size distributions under a unified parametric framework;

(ii) to support planetary mapping and process identification by linking site-level GSD parameters to geologic units, depositional environments (aeolian, fluvial, impact, volcanic), and surface processes; and

(iii) to provide a quantitative benchmark for regolith simulant development for future lunar and Martian missions.

These goals are now stated explicitly at the end of the Introduction, following the presentation of the dataset and its key advances.

2. Broader global context and deeper literature engagement

We have added broader context for both the Moon and Earth sections:

For the Moon: We now cite recent findings from the Chang’e-6 mission, which reveal that farside regolith is finer-grained, more poorly sorted, and more cohesive than nearside samples (Qi et al., [2025](#)), highlighting the need for a systematic cross-mission GSD database (see [Lines 127–131](#)).

For Earth: We now reference the global SoilGrids product and the Webb et al. ([2000](#)) soil texture database as complementary large-scale resources (see [Lines 51–56](#)).

3. Expanded discussion of Mars grain size and volcanic-to-sedimentary transition

We agree that the original Introduction treated the Martian context too briefly. In the revised version, we have added a dedicated discussion of explosive volcanism on Mars ([Lines 59–65](#)), including:

- The formation of widespread tephra and accretionary lapilli deposits (Wilson & Head, [2007](#));
- The contrast between poorly sorted, unimodal/bimodal primary volcanic deposits and better-sorted aeolian or fluvial deposits with distinct Weibull shape parameters;
- The Medusae Fossae Formation as a key example of the volcanic-to-sedimentary transition, interpreted as a pyroclastic deposit subsequently shaped by aeolian erosion into yardangs and other wind-carved landforms (Ojha & Lewis, [2018](#)).

4. Structural improvement

As a result of these revisions, the Introduction has been reorganized from seven to six paragraphs, with a clearer logical flow: (i) importance of GSD; (ii) data fragmentation and methodological limitations; (iii) presentation of PlanetGSD 1.0 and its advances; (iv) method-specific biases and harmonization strategy; (v) explicit statement of three objectives; (vi) paper organization. We believe this revised structure is more reader-friendly and better aligns with ESSD’s standards for data papers.

- Ojha, L., Lewis, K., Karunatilake, S., & Schmidt, M. (2018). The Medusae Fossae Formation as the single largest source of dust on Mars. *Nature Communications*, 9(1), 2867. [https://doi.org/ 10.1038/s41467-018-05291-5](https://doi.org/10.1038/s41467-018-05291-5)
- Qi, S., Li, L., Hou, X., Qiao, S., Ma, X., Lu, X., ... & Wu, F. Y. (2026). Strongly cohesive lunar soil identified at the Chang'e-6 landing site. *Nature Astronomy*, 10(2), 214-223. <https://doi.org/10.1038/s41550-025-02715-3>
- Webb, R., Rosenzweig, C. E., & Levine, E. R. (2000). Global soil texture and derived water-holding capacities (Webb et al.). ORNL Distributed Active Archive Center (DAAC) dataset 10.3334/ORNLDAAC/548 (2000, 548. <https://doi.org/10.3334/ORNLDAAC/548>
- Wilson, L., & Head, J. W. (2007). Explosive volcanic eruptions on Mars: Tephra and accretionary lapilli formation, dispersal and recognition in the geologic record. *Journal of volcanology and geothermal research*, 163(1-4), 83-97. <https://doi.org/10.1016/j.jvolgeores.2007.03.007>

Finally, the figures would benefit from additional polishing. In Figure 6, panels have inconsistent sizes and scales; some labels in Figure 5 are too small to read; the yellow text in Figure 4 is difficult to see; in Figure 2, it may be worth considering whether the x-axis could be standardized (not certain); and in Figure 1, at least the projection style should be made consistent.

Reply: We have systematically revised all figures as detailed below.

For [Figure 6](#), we have resized all three subfigures to be smaller and consistent. The three panels in the upper row have been adjusted to the same scale, with the x-axis representing 60 cm (20 cm per unit) and the y-axis representing 80 cm (20 cm per unit) ([Line 774](#)).

For [Figure 5](#), we have enlarged all font sizes in the figure ([Line 566](#)).

For [Figure 4](#), we have changed the color from yellow to purple to improve readability ([Line 504](#)).

For [Figure 2](#), in the revised version, we have set the x-axis of all six subfigures to the same range (0.001–1000 mm) ([Line 391](#)). As shown in the new [Figure 2](#), the grain-size distributions of soils from the three planetary bodies are now more directly comparable. We have revised the corresponding text in the manuscript (see [Lines 357–372](#)).

For [Figure 1](#), we have replaced the old Earth map. The new Earth map uses the same

projection style as those of the Moon and Mars ([Line 177](#)).

Reply to reviewer 2

The manuscript describes a method of assessing grain size distribution and parameterizing this characteristic, and presents a database of terrestrial, lunar and Martian regolith/soil samples using this method. The database itself is a unique and useful collation of potentially cross-referenceable data, and the method itself is well-described and has the potential to provide information that could be used to better understand regolith characteristics. I suggest the following to improve the usefulness of the work to the planetary community in assessing and comparing regolith across regions and bodies. Note that my expertise is in assessing grain sizes using images, so I have left a review of the mathematical aspects of this manuscript to others more capable of discussing them.

Reply: Thank you for your positive evaluation.

General

- **Define specialized terms being used earlier in the manuscript:**
- **Line 46-47, 54: Specify what curves are being referred to; specify what is meant by “30 m”.**

Reply: In the revised manuscript, we have explicitly defined that the “**curves**” (original Line 54) mentioned in the text refer specifically to grain size frequency distribution curves (showing the relative abundance of each particle size fraction). This definition has been added at the first occurrence of the term ([Lines 55-56](#) in the revised manuscript), where we now write: “complete GSD curves (hereafter GSD ‘curves’ showing the relative abundance of each particle size fraction).”

Regarding “30 m” (original [Lines 46-47](#)): We have removed this sentence from the revised manuscript, as the spatial resolution of the POLARIS dataset is not essential to our argument. The key point—that terrestrial compilations report only texture classes rather than complete GSD curves—remains unchanged.

- **Lines 80-83: Lots of jargon here without definition. To make the manuscript more accessible across disciplines, consider defining these terms or at least pointing to a later Section and defining them there.**

Reply: We agree that terms such as “cumulative curves”, “Weibull statistics”, “stochastic field generation”, and “unified parameterization” may be unclear to readers unfamiliar with soil mechanics or geostatistics.

In the revised manuscript, we have made the following changes:

At the first occurrence of these terms ([Lines 108-111](#)), we have added brief clarifications and explicitly pointed readers to the later sections where these concepts are defined in detail. Specifically:

“complete raw cumulative curves” → revised to “complete raw cumulative GSD curves (mass percentage passing)” ([Line 108](#) in the revised manuscript)

“Weibull statistics” → revised to “Weibull distribution statistics (see [Section 2.4](#) for full definition, formula, and application to grain size analysis)” ([Lines 109-111](#) in the revised manuscript)

“stochastic field generation” → revised to “stochastic field generation (see [Section 2.5](#) for detailed methodology)” ([Lines 110](#) in the revised manuscript)

- **More details are needed regarding what and why specific assumptions were made in assessing actual geologic materials. For example, I see a “spherical grain” is assumed by the program. What is the logic behind this assumption other than it simplifies things for the program? If that’s the logic, provide the rationale as to why this is a reasonable assumption to make for this work. The limitations listed are not complete (e.g., as on the Moon, clay fractions aren’t resolved by any martian imager at this time, but this is not noted); nor do they appear to be the most salient limitations to “harmonization” (e.g., if clay fractions aren’t resolvable then why not just cut off the grain size distribution there?).**

Reply: We thank the reviewer for raising these important methodological points.

Regarding the spherical grain assumption: We agree that the original statement “it simplifies things for the program” is insufficient justification. In fact, the spherical grain approximation is a standard practice in 2D image-based granulometry, supported by extensive literature. For instance, Pizzati et al. ([2023](#)) demonstrated that approximating particles as perfect spheres with a shape correction factor yields 2D-to-3D conversions that match laser diffraction measurements. This assumption has also been adopted in previous Martian grain-size studies (e.g., Lapotre et al., [2017](#)). In the revised manuscript, we have added these citations (see [Line 327-334](#) in [Table 4](#)) to justify the

assumption. We also clarify that we apply the equivalent circular diameter (ECD) method, which is standard for sand-sized and coarser grains where shape deviation does not substantially bias the distribution statistics.

Regarding the unresolved fine fractions: The reviewer correctly points out that Martian imagers cannot resolve clay-sized particles ($<2\ \mu\text{m}$) or even silt-sized grains in some cases. Following the reviewer's suggestion, we have revised our approach (see [Lines 253-261](#)) to explicitly truncate the grain-size distributions at the instrument-specific detection limits ([Table 3](#)). For each Martian sample, only grains larger than the minimum detectable size ($\sim 3\times$ pixel scale, i.e., 0.04–0.15 mm depending on the instrument) are retained for UGSD fitting. The truncated portion is not extrapolated or artificially filled; instead, we treat the cumulative percentages at the smallest size bin as lower bounds. This truncation is now clearly noted in [Section 2.3.2](#) and the limitations section ([Section 6.3](#)). We agree that this is a more conservative and transparent approach than fitting across unresolved size ranges.

Regarding completeness of limitations: We have expanded [Section 6.3](#) ([Lines 954-1030](#) in the revised manuscript) to explicitly list the unresolved clay/silt fractions as a key limitation for Martian data. Specifically, item (1) notes that clay fractions are unresolved for the Moon, and item (2) explains that Martian GSD curves are right-censored below detection limits, with fine-tail cumulative percentages representing lower bounds.

Pizzati, M., Mantovani, L., Lisotti, A., Storti, F., & Balsamo, F. (2023). Particle size distributions in Earth Sciences: a review of techniques and a new procedure to match 2D and 3D analyses. *EGUsphere*, 2023, 1-71. <https://doi.org/10.5194/egusphere-2023-2636>, 2023.

Lapotre, M. G., Ehlmann, B. L., & Minson, S. E. (2017). A probabilistic approach to remote compositional analysis of planetary surfaces. *Journal of Geophysical Research: Planets*, 122(5), 983-1009. <https://doi.org/10.1002/2016JE005248>.

- **There is insufficient detail on the methodology for assessing grain size. What does semi-autonomous mean? What parameters were used to determine grain size? How were grains discriminated from composite grains (i.e. grains-within-grains)? How did the authors adjust methodology among the different types of images from Mars,**

particularly RMI (a fisheye-lens imager that on MSL is greyscale) and MAHLI/WATSON? MAHLI/WATSON in particular acquire a range of resolutions; which were used? How was assessment of two-dimensional images regularized with lunar dry sieving, and with the large number of laboratory techniques that may be brought to bear for Earth-based samples? Real-world limitations of the data with respect to resolution also should be discussed in more depth. MAHLI and WATSON have acquired images <1 cm from the surface, yielding better than 20 $\mu\text{m}/\text{pixel}$. However, a reasonable estimate of resolution is typically at least across 3 pixels (as noted in Table 3), meaning no better than $\sim 60 \mu\text{m}/\text{pixel}$. This assumes a nearly pristine target; with even a small covering of ubiquitous martian dust, that resolution degrades. The manuscript acknowledges the problem without discussing how it was addressed.

Reply: We thank the reviewer for these important technical questions.

Regarding “semi-automated”: Our analysis workflow follows established photoanalytical methods (Shi et al., 2024; Zhao et al., 2023). “Semi-automated” means that while grain boundary detection and size/shape calculations are performed algorithmically (implemented in Mathematica/Python), several steps require manual intervention: (1) image quality filtering (blurred or out-of-focus regions are masked); (2) parameter tuning for foreground-background separation (thresholds adjusted per image due to variable illumination); (3) manual correction of erroneous grain merging. This hybrid approach balances reproducibility with the flexibility needed for heterogeneous Mars images. Detailed operator decisions are documented in [Supplementary Text S3 \(Lines 2070-2080\)](#).

Regarding parameters used to determine grain size: we fit each sample to the UGSD function, which characterizes the full GSD using three interpretable parameters: μ (power exponent correlated with fine-particle content), D_c (characteristic grain size, in mm), and n (shape exponent controlling coarse-tail steepness). These three parameters collectively capture the entire grain-size distribution curve in a compact form, enabling quantitative comparison across samples and planetary bodies. The UGSD function and parameter definitions are provided in [Section 2.3.2 \(Lines 405-408\)](#) and summarized in [Table 5 \(Line 444\)](#).

Regarding discrimination of composite grains (grains-within-grains): We have already

considered this issue in our image analysis workflow. Specifically, our two-step protocol addresses composite grains as follows. First, the watershed segmentation algorithm separates touching grains based on local intensity minima. Second, each segmented image undergoes manual inspection. According to our established criteria: (1) small grains sitting on larger grains are counted separately if $\geq 50\%$ of their boundary is visible; (2) surface textures, cements, or alteration rinds are not counted as separate grains; (3) images with foreground coverage $> 5\%$ (e.g., granules overlying fine matrix) are excluded following Shi et al. (2024). In the revised manuscript, we have elaborated this protocol in [Section 2.2.5 \(Lines 306-311\)](#) and [Supplementary Text S3 \(Lines 1350-1363\)](#) to provide a more complete and transparent methodological description.

Regarding instrument-specific adjustments: MAHLI/WATSON (color, arm-mounted, 14-77 $\mu\text{m}/\text{pixel}$) and RMI (grayscale, mast-mounted, $\approx 40 \mu\text{m}/\text{pixel}$ at 2 m, with fisheye distortion) require different processing. For MAHLI/WATSON, we use the highest resolution (14-21 $\mu\text{m}/\text{pixel}$), manually mask out-of-focus areas, and apply edge detection with adaptive thresholds. For RMI, we analyze only the central 40 % of the field of view to minimize distortion ($< 2\%$) and apply histogram equalization for contrast enhancement. Cross-instrument validation on 30 co-located targets shows D_{50} agreement within $\pm 12\%$ ([Supplementary Material Text S5.2, Lines 2081-2093](#)). These instrument specifications have been added to [Table 3 \(Line 268-269\)](#).

Regarding resolution selection: We exclusively use the highest-resolution images available for each target. For MAHLI, this means working distances of 2-10 cm, yielding pixel scales of 14-32 $\mu\text{m}/\text{pixel}$. The specific focus motor count (which inversely correlates with working distance) is recorded for each image to enable scale calculation ($p = 6.9 + 3.52 \times w$, where $p = \mu\text{m}/\text{pixel}$, $w =$ working distance in cm; Edgett et al., 2012; Minitti et al., 2013). For WATSON and MI, fixed scales (14 $\mu\text{m}/\text{pixel}$ and 31 $\mu\text{m}/\text{pixel}$, respectively) are used when available. The pixel scale of each image is reported in [Table 3](#).

Regarding 2D-to-3D harmonization: The fundamental incompatibility between 2D image analysis and 3D mass-based methods (dry sieving, laser diffraction) is acknowledged. Our approach is comparative rather than absolute: (1) Martian GSDs are processed exclusively through the same image-based method, enabling internal comparisons; (2) Lunar and terrestrial data are mass-based; (3) Cross-method comparisons are performed only at the parameter level (UGSD μ , D_c , n) rather than raw percentages. We also apply stereological conversion where appropriate (Pizzati et al.,

2023): ECD-based distributions are multiplied by a shape factor of 1.3-1.5 when directly compared to sieve data. These stereological conversions are detailed in [Supplementary Information Text S5.5 \(Lines 2109-2116\)](#).

Regarding resolution limits and dust effects: The reviewer raises a critical point. MAHLI achieves 14 $\mu\text{m}/\text{pixel}$ at minimum working distance (~ 2.1 cm), theoretically resolving ~ 40 μm grains at the 3-pixel threshold ([Table 3](#)). However, three factors degrade effective resolution: (1) The point spread function (PSF) of the optics requires ≥ 3 pixels for reliable grain boundary detection (Eibl et al., [2016](#)); (2) Foreground-background contrast is reduced by ubiquitous Martian dust (Chen-Chen et al., [2023](#)); (3) Dust aggregates (< 100 μm) are often indistinguishable from true grains (Friday et al., [2013](#)).

Following the methodology of Karunatilake et al. ([2014](#)) and Shi et al. ([2024](#)), we adopt a conservative minimum detectable grain size of 5-7 pixels (not 3 pixels) for Martian images. This corresponds to ~ 70 -100 μm for MAHLI at 14 $\mu\text{m}/\text{pixel}$. For the VFS class (< 125 μm), individual grains are often not resolvable; such samples are classified based on their homogeneous appearance and dust-like chemistry rather than explicit grain counts (Shi et al., [2024](#)). To address dust contamination: (1) We preferentially select images acquired after dust removal tool (DRT) brushing when available; (2) For unbrushed targets, we manually mask regions with obvious dust aggregates; (3) The fine tail ($<$ min detectable size) is truncated, not extrapolated. These resolution and dust mitigation protocols are detailed in [Supplementary Information Sections 5.3 and 5.4 \(Lines 2094-2108\)](#).

We have revised [Table 3](#) accordingly.

- Chen-Chen, H., Pérez-Hoyos, S., Sánchez-Lavega, A., & Peralta, J. (2023). Characterisation of deposited dust particles on Mars insight lander Instrument Context Camera (ICC) lens. *Icarus*, 392, 115393. <https://doi.org/10.1016/j.icarus.2022.115393>.
- Edgett, K. S., Yingst, R. A., Ravine, M. A., Caplinger, M. A., Maki, J. N., Ghaemi, F. T., Goetz, W. (2012). Curiosity's Mars hand lens imager (MAHLI) investigation. *Space science reviews*, 170, 259-317. <https://doi.org/10.1007/s11214-012-9910-4>.
- Eibl, M. A., & Fedo, C. M. (2016, March). A Mars Analog Study of 2D Textural Image Analysis: Effects of Shadows, Image Resolution, and Comparisons to Actual Sediment Textures from

- Aeolian Dune Sand, Moses Lake, WA. In 47th Annual Lunar and Planetary Science Conference (No. 1903, p. 2321).
- Friday, M. E., Fedo, C. M., McGlynn, I. O., & McSween, H. Y. (2013, March). The accuracy of 2D assessment of sediment textures, and application to Mars. In 44th Annual Lunar and Planetary Science Conference (No. 1719, p. 2361).
- Karunatillake, S., Wray, J. J., Gasnault, O., McLennan, S. M., Rogers, A. D., Squyres, S. W., ... & Olsen, N. (2014). Sulfates hydrating bulk soil in the Martian low and middle latitudes. *Geophysical Research Letters*, 41(22), 7987-7996. <https://doi.org/10.1002/2014GL061136>.
- Minitti, M. E., Kah, L. C., Yingst, R. A., Edgett, K. S., Anderson, R. C., Beegle, L. W., ... & Van Beek, T. (2013). MAHLI at the Rocknest sand shadow: Science and science-enabling activities. *Journal of Geophysical Research: Planets*, 118(11), 2338-2360. <https://doi.org/10.1002/2013JE004426>.
- Pizzati, M., Mantovani, L., Lisotti, A., Storti, F., & Balsamo, F. (2023). Particle size distributions in Earth Sciences: a review of techniques and a new procedure to match 2D and 3D analyses. *EGUsphere*, 2023, 1-71. <https://doi.org/10.5194/egusphere-2023-2636>, 2023.
- Shi, Y., Zhao, S., Karunatillake, S., Cousin, A., Zhao, J., & Xiao, L. (2024). Sorting and eathering trends of soil at Gale Crater, Mars: Implications for regional pedological processes. *Journal of Geophysical Research: Planets*, 129(12), e2024JE008598. <https://doi.org/10.1029/2024JE008598>.
- Zhao, S., Karunatillake, S., & Shi, Y. (2023). Semi-automated granulometry software for Martian soil analysis (beta). Zenodo. <https://doi.org/10.5281/zenodo.7998487>.

- **Grain size distribution is a fundamental characteristic of rocks and fines, and can in some cases be a discriminator of geologic history or provenance. However, the geologic variations in each site are not clearly explained, nor more importantly, how these differences may influence resulting grain size distribution. In general, the manuscript makes a good case that the UGSD equation can mathematically separate out generalized soil/regolith populations (Earth, Moon, Mars), thus allowing comparison. However, without a deeper understanding of the geologic provenance and history of the samples shown in Figure 4 (a key figure), their predictive use is unclear. For**

example, it is to be expected that impact gardening would strongly influence the grain size distribution of any lunar sample, so that these samples should be tightly clustered. But why should this tight cluster then plot so firmly in the “multi-process terrestrial” region? There are terrestrial squares that land right in this lunar oval (I’m not clear on the acronyms used for each site); why is this? Without being able to at least hypothesize about the results in Figure 4, the predictive use of the method remains theoretical rather than practical. I agree with the authors’ assessment in lines 559-561; process attribution is currently not reliable with this method, lessening its value.

Reply: Thanks for the comments and they offer an opportunity to explain our ideas of the UGSD paradigm. The revised Figure 4 now includes two subplots, presenting the variability of UGSD parameters from two complementary perspectives.

Figure 4a (μ vs. D_c) shows the raw parameter space for all 42 sites. The three planetary bodies exhibit distinct and interpretable distribution patterns:

- Lunar samples are the most tightly clustered, with both μ and D_c at low values. This reflects the dominance of impact comminution as the primary soil-forming process on the Moon, producing a narrow range of fine-grained, well-sorted regolith.
- Terrestrial samples show an extremely wide range in D_c but a relatively concentrated μ range (approximately -0.3 to 1.3). This reflects the diversity of Earth’s surface environments—from fine-grained loess to coarse glacial till and alluvial fan gravels—while the fine-particle content (μ) varies within comparatively limited bounds.
- Martian samples exhibit the widest μ range (approximately -1.6 to 1.3) but the narrowest D_c range. This distinctive combination likely reflects the peculiarities of Martian aeolian processes: wind sorting restricts the characteristic grain size (D_c) to a relatively narrow range of fine to medium sand, while the fine-particle fraction (captured by μ) varies widely due to local source differences, dust cover, or variable pedogenic modification.

Figure 4b exhibits the Weibull-distribution parameters (k, λ) of the UGSD exponent μ (Eq.4 in the text), which is used to illustrate the variability of the UGSD in Earth, Moon and Mars; and actually the clusters fall into three areas, although with overlaps. In particular, the two points highlighted in the comment are worth noting: **Why do lunar samples plot within the terrestrial field?** and **Why do terrestrial squares plot inside the lunar oval?** The lunar samples are tightly

clustered because soils on the Moon are relatively generated in simple ways, e.g., dominated by impact comminution and alteration by physical and mechanical surface processes. These produce a narrow range of GSD characteristics. Consequently, the (k, λ) cluster falls within the range of terrestrial soils. On the other hand, the overlap points of terrestrial soils are those from mass movements (e.g., landslides and debris-flows), periglacial colluvium (Kunlun Mountains), and glacial till—are dominated by physical fragmentation with minimal chemical weathering. These processes are quantitatively similar to the surface processes on the Moon and produce similar GSD characteristics. The overlap therefore does not indicate identical processes, but rather demonstrates that the k - λ space captures textural similarity across different genetic environments.

For clarity we have now revised [Figure 4](#) caption ([Lines 505-515](#)) and added a complete acronym table ([Table 6](#)) to aid interpretation.

What is the predictive value if process attribution is not reliable? First, we agree with the reviewer that the UGSD is insufficient for making predictions of mechanical processes and identifying geological environments. Limited by the scope of this data-focused journal, we do not specifically address the issues related to prediction and general application. In fact, the primary intention of proposing the dataset holds twofold significance, one is soil-data parameterization — compressing high-dimensional textural data into interpretable, comparable low-dimensional UGSD parameters, as discussed in the present article; and the other is the data base for dynamical analysis of surface processes, which we have discussed elsewhere. For example, while the (k, λ) -plot distinguish soils in different planets on large scale and in total statistic sense, the UGSD parameters (μ, D_c) -plot, distinguishes soils from different sites related to local processes. As shown in the following [Figure A](#) ([Figure A](#) is for illustrative purposes only and is not included in the manuscript), the (μ, D_c) -clusters in the four study areas in Mars exhibit great variety in soil types and are indicative for surface processes. Moreover, from the (μ, D_c) -fields one may derive random fields of mechanical and physical parameters of soils (e.g., the cohesion, friction angle, porosity, and hydraulic conductivity), which are the fundamental inputs for dynamical analysis.

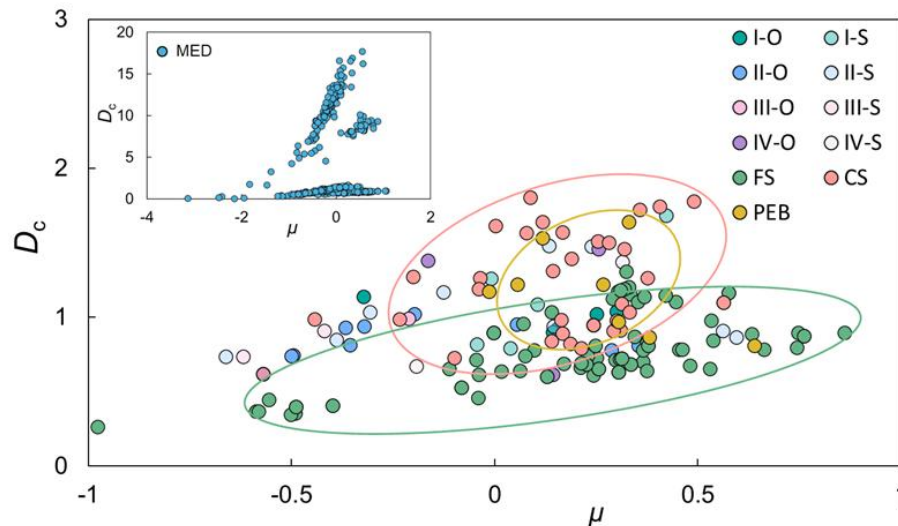


Figure A. (μ, D_c) -clusters for soil types in Mars, indicating local conditions of soil genesis and surface processes

Revisions made:

Expanded Figure 4 caption to explain the terrestrial-lunar overlap (Lines 505-515)

Added acronym definitions and geological descriptions (Table S5 in <https://doi.org/10.6084/m9.figshare.32362083>)

Expanded Section 6.3 to clarify the limitations of process attribution (Lines 954-1030)

Zhang, Jun (2026). Dataset for "PlanetGSD 1.0: a cross-planetary grain-size distribution dataset from Earth, the Moon, and Mars". figshare. Dataset. <https://doi.org/10.6084/m9.figshare.32362083>

Specific

- Lines 34-35: Probably appropriate to reference Carrier's works here, too.

Reply: We have added this citation.

- Lines 35-36: This is probably too broad – grain size distribution is one factor in assessing both volcanic and sedimentary regoliths, but I think the second clause (past hydrological activity) is fully accurate.

Reply: We agree that the original phrasing “records the transition” may be overly broad. We

have revised the sentence to: “On Mars, GSD records the transition from volcanic to sedimentary surface processes and provides constraints on past hydrological activity (Grotzinger et al., 2015; Rivera-Hernández et al., 2020).” (Lines 37-39) This wording acknowledges that GSD is one factor among several (e.g., sedimentary structures, mineralogy, geochemistry) used to interpret Martian surface processes, while still highlighting its value for constraining hydrological activity.

Grotzinger, J. P., Gupta, S., Malin, M. C., Rubin, D. M., Schieber, J., Siebach, K., ... & Wilson, S. A. (2015). Deposition, exhumation, and paleoclimate of an ancient lake deposit, Gale crater, Mars. *Science*, 350(6257), aac7575. <https://doi.org/10.1126/science.aac7575>

Rivera-Hernández, F., Sumner, D. Y., Mangold, N., Banham, S. G., Edgett, K. S., Fedo, C. M., ... & Wiens, R. C. (2020). Grain size variations in the Murray formation: Stratigraphic evidence for changing depositional environments in Gale crater, Mars. *Journal of Geophysical Research: Planets*, 125(2), e2019JE006230. <https://doi.org/10.1029/2019JE006230>

- **Line 85: Not sure what you mean by data-driven. As opposed to what?**

Reply: By “data-driven” we simply mean an approach based directly on measured data rather than on a pre-defined theoretical model.

- **Line 95: Please define the UGSD earlier than Line 255.**

Reply: Thank you for the comment. We have checked Line 65 (in the revised manuscript) and confirm that UGSD is already defined at its first appearance as “Universal Grain-Size Distribution (UGSD).” To avoid any confusion and redundancy, we have now removed the redundant definition at Line 402 and replaced it with: “The UGSD function, developed and...” We believe this addresses the reviewer’s concern.

- **Line 181: What process was used to digitize lunar data?**

Reply: We digitized the lunar data from Graf (1993) by taking screenshots of each PDF page, using GPT to convert the screenshots into editable text, pasting the extracted text into Excel, and then manually verifying all data against the original tables.

- **Lines 206-211: I'm not familiar with this software, but some treatment of its ability to identify grains using known analog targets would be very helpful.**

Reply: The software is a Mathematica-based semi-automated segmentation tool (Zhao et al., 2021) developed from the algorithm of Karunatillake et al. (2013, 2014). Its ability to identify grains has been validated in three ways:

(1) Comparison with manual segmentation: Using 57 MAHLI and MI images, the software was qualitatively compared against BASEGRAIN, ImageJ Trainable WEKA Segmentation, and ENVI classification tools, showing superior speed and accuracy.

(2) Known analog targets: Karunatillake et al. (2014, Icarus, Part 2, Section 3.4) tested the algorithm on terrestrial basaltic sand from Costa Rica (0.1–1.0 mm) with manually placed foreground pebbles (5–10 mm). The algorithm successfully segmented the foreground pebbles while correctly excluding background sand grains, demonstrating its ability to handle grain size contrasts in a known analog setting.

(3) Internal consistency: The same study (Part 2, Fig. 3) demonstrated that manual segmentation has substantial internal inconsistency (areal mismatch of 35–50 %), whereas the algorithm provides consistent results across repeated runs.

We have added a brief summary of these validation approaches in the revised manuscript at Lines 253-261, citing Karunatillake et al. (2014) and Zhao et al. (2021). The terrestrial analog test is now explicitly referenced.

Karunatillake, S., McLennan, S. M., Herkenhoff, K. E., Husch, J. M., Hardgrove, C., & Skok, J. R. (2014). A martian case study of segmenting images automatically for granulometry and sedimentology, part 1: algorithm. Icarus, 229, 400-407.
<https://doi.org/10.1016/j.icarus.2013.10.001>

Zhao, S., Shi, Y., Karunatillake, S., & Xiao, L. (2021, March). Computational photoanalysis software for Martian soil Granulometry. In 52nd Lunar and Planetary Science Conference (No. 2548, p. 1959).

- **Figure 2: Please define the y-axis for both columns. Also, the sweeping comment of Lines 231-232 is not supported sufficiently.**

Reply: We have revised the caption of [Figure 2](#) to clearly define the Y-axes for both columns. The left column Y-axis is now labeled as “percentage of grain mass per size class (%)” and the right column as “cumulative percentage passing (%)”. ([Lines 393-394](#) in the revised manuscript)

We agree that the original statement requires appropriate literature support. We have revised the text (originally [Lines 231-232](#), now [Lines 366-372](#) in the revised manuscript) to include specific citations. The revised sentence now reads:

“Martian samples thus exhibit intermediate characteristics: some sites (e.g., Meridiani Planum) show well-sorted distributions indicative of aeolian sorting (Kozakiewicz et al., [2025](#)), while others (e.g., Gale Crater) preserve multi-modal or poorly sorted signatures reflecting primary sedimentary textures (Milliken et al., [2014](#); Kapui et al., [2018](#)).”

The supporting evidence is as follows:

Aeolian sorting: Kozakiewicz et al. ([2025](#)) documented active aeolian processes and well-sorted sand grains in Meridiani Planum.

Preserved primary textures: Milliken et al. ([2014](#)) described preserved dune bedforms in Gale Crater; Kapui et al. ([2018](#)) demonstrated using Earth analogs that mature basaltic sands can retain original grain-size signatures distinguishing fluvial from aeolian transport.

Kapui, Z., Kereszturi, A., Kiss, K., Szalai, Z., Újvári, G., Hickman-Lewis, K., ... & Westall, F. (2018).

Fluvial or aeolian grains? Separation of transport agents on Mars using earth analogue observations. Planetary and Space Science, 163, 56-76.
<https://doi.org/10.1016/j.pss.2018.06.007>

Kozakiewicz, J., Maj, D., Mol, S., Sobucki, M., Michaels, T., & Frodyma, N. (2025). Seasonality of aeolian landforms on Meridiani Planum, Mars. Icarus, 425, 116325.
<https://doi.org/10.1016/j.icarus.2024.116325>

McSween, H. Y., McGlynn, I., & Fedo, C. (2010, December). Soils in Gusev Crater, Mars: What We Can And Cannot Learn From Surface Sediments. In AGU Fall Meeting Abstracts (Vol. 2010, pp. P52B-02).

Milliken, R. E., Ewing, R. C., Fischer, W. W., & Hurowitz, J. (2014). Wind-blown sandstones cemented by sulfate and clay minerals in Gale Crater, Mars. Geophysical Research Letters, 41(4), 1149-1154. <https://doi.org/10.1002/2013GL059097>

- **Lines 494-498: The fact that the authors see less error across martian sites may be due to a number of reasons other than “geological signal”, including the fact that nearly every image captures some fraction of the global fines mobilized by storms. Other possibilities should be discussed.**

Reply: Thank you for this insightful comment. Indeed, attributing the observed inter-site variability solely to “geological signal” is an oversimplification. Two factors should be considered:

(1) Resolution limits of image-based measurements. As shown in [Table 3](#), all Martian GSD curves are right-censored below ~0.04–0.15 mm (depending on the instrument). This truncation of the fine tail reduces the number of constraining size fractions available for curve fitting, which may artificially reduce apparent inter-site variability in UGSD parameters. In other words, some of the observed similarity across sites could be an artifact of what the instruments cannot see, rather than a true geological signal.

(2) Limited geographic and environmental coverage. The four landing sites (Gale, Jezero, Gusev, Meridiani) are all located in low-latitude regions with broadly similar aeolian regimes. This sampling does not capture the full range of Martian surface textural diversity (e.g., high-latitude mantling terrains, dust-dominated regions, or polar layered deposits).

We note that while dust storms are known to mobilize and transport fine particles globally (Kahre et al., [2017](#); Senel et al., [2021](#)), the grain-size fractions most affected by this process (silt and clay, <62 μm) are below the detection limit of the rover imagers used in this study ([Table 3](#)). Therefore, the potential homogenizing effect of dust storms cannot be directly evaluated with our data and is not invoked as an explanation for the observed inter-site variability.

We have revised the discussion in the manuscript accordingly ([Lines 730-747](#)).

Kahre, M. A., Murphy, J. R., Newman, C. E., Wilson, R. J., Cantor, B. A., Lemmon, M. T., & Wolff, M. J. (2017). The Mars dust cycle. *The atmosphere and climate of Mars*, 18, 295.

Senel, C. B., Temel, O., Lee, C., Newman, C. E., Mischna, M. A., Muñoz-Esparza, D., ... & Karatekin, Ö. (2021). Interannual, seasonal and regional variations in the Martian convective boundary layer derived from GCM simulations with a semi-interactive dust transport model. *Journal of Geophysical Research: Planets*, 126(10), e2021JE006965.

- **Figure 6: This figure is not effectively demonstrating the statements made in lines 517-525. How does the top row relate to the bottom row? How do either of these rows relate to actual geologic maps as suggested in the text? I can't discern how the martian region shows "strongly graded" grain size distribution, for instance. It looks homogeneous to me – in fact they all do.**

Reply: We agree that direct comparison with actual geologic maps would strengthen the interpretation. However, for the Apollo 17 and Gale Crater sites, in-situ grain-size transects at the scale of our simulations (kilometers) are not available. For Laowa Gully, we do not possess detailed geologic maps or measured grain-size spatial transects for validation.

Therefore, we have revised the text to present these simulations as demonstrations of methodological capability rather than validated predictions (Lines 781-723). Specifically:

1. We no longer claim that the patterns "reflect" or "are consistent with" actual geologic processes; instead, we state they "represent" or "emulate" the expected patterns based on first principles.
2. We explicitly acknowledge the lack of validation data for planetary sites and frame the simulations as generating testable hypotheses.
3. We clarify that the terrestrial case (Laowa Gully) serves as a baseline (homogeneous) simulation, with field validation deferred to future work.

We have revised Figure 6 with improved color scaling, making the Martian μ -field gradient visually apparent (Line 774). The quantitative statistics (range = 1.612, Moran's I = 0.76) are reported in the text. The bottom row (d–f) provides enlarged views of the corresponding areas (a–c) at higher spatial resolution to better visualize local heterogeneity patterns.

- **Lines 550-554: Gaps in geographic coverage likely have less meaning with respect to the predictive power of this method than gaps in representation of geologic provenance/environment. Asia has little scientific value as a discriminator, for example, while "playa lake" has far more.**

Reply: We fully agree that gaps in geologic provenance/environment representation are more

consequential for the predictive power of our method than geographic coverage per se. "Asia" is indeed a poor discriminator, whereas "playa lake," "debris-flow fan," or "aeolian dune" carry direct process-based meaning.

We have revised the text (Lines 843-855) to reframe the discussion from geographic to geologic/environmental terminology. Specifically, we now discuss underrepresented geomorphic settings (e.g., playa lakes, aeolian dune fields, glacial outwash plains, coastal sediments, tropical weathering profiles, and cold-desert soils) rather than geographic regions (e.g., South America). We have also explicitly noted that the current terrestrial dataset is dominated by gravity-driven and fluvial deposits (debris flows, landslides, alluvial fans), while other process regimes remain underrepresented. This revision directly addresses the reviewer's concern that environmental context is more scientifically meaningful than geographic labels.

The revised text is provided below and highlighted in the revised manuscript. Thank you for guiding us toward a more process-based framing.

“(1) Gaps in geologic and environmental representation. The terrestrial component is dominated by gravity-driven and fluvial deposits (debris flows, landslides, alluvial fans), while other geomorphic settings remain underrepresented. These include playa lakes, aeolian dune fields, glacial outwash plains, coastal sediments, tropical weathering profiles, and cold-desert soils (e.g., Antarctic dry valleys). The current geographic bias toward Asia (73% of samples) is less critical than the underrepresentation of these process-based endmembers. Lunar samples are predominantly from nearside mare regions, with highland, farside, and polar materials. Martian samples are limited to four low-latitude landing sites, lacking high-latitude and dust-dominated terrains. Priority targets for future data collection include underrepresented geomorphic settings on Earth (as listed above), lunar farside and polar regions, and new Martian landing sites (e.g., Zhurong at Utopia Planitia, and high-latitudes sites such as Arcadia Planitia).”

- **Lines 582-585: Being able to demonstrate grain size distribution of a site would provide important ancillary data, but note that there are other, more well-tested ways of determining geological context for landing site assessment, such as geologic maps.**

Reply: We agree that geologic maps remain the most well-tested and authoritative means of determining geological context for landing site assessment. We did not intend to suggest that GSD

estimates could replace established methods such as geologic mapping, spectroscopic analysis, or thermal inertia measurements.

We have revised the text to clarify that pre-landing GSD estimates derived from PlanetGSD serve as ancillary data that complement, rather than substitute for, traditional approaches. The revised text now reads ([Lines 915-921](#)):

“(3) Landing site assessment. While geologic mapping and remote sensing analyses (e.g., spectroscopy, thermal inertia) remain the primary methods for determining geological context, pre-landing GSD estimates can be generated as ancillary data by identifying PlanetGSD entries with geological context similar to candidate landing sites. Such estimates provide additional constraints on surface mechanical properties (e.g., trafficability, drilling resistance) that are not directly accessible from orbital data alone. [Table 11](#) provides example analog matches to illustrate this complementary approach.”

This revision positions GSD-based estimation as a supplementary tool that adds value to existing well-established methods, rather than as a standalone alternative. We thank the reviewer for guiding us toward a more accurate framing.