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Key Points:
- We mapped 28,101 granular flow features between 60°N and S using a neural network
- Dense flow feature hotspots are predominantly located in (a) craters, (b) on the lunar nearside, (c) in the lunar maria
- Flow feature occurrence is mainly controlled by impacts, where the target rock properties and terrane age appear to play an important role

Supporting Information:
Supporting Information may be found in the online version of this article.

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A Global Perspective on Lunar Granular Flows
V. T. Bickel, S. Loew, J. Aaron, and N. Goedhart

Abstract
Dry granular flows are ubiquitous, yet poorly understood mass wasting features on the Moon. Above all, their global distribution, relation to the physical environment, and drivers are poorly understood. Here, we build and deploy a convolutional neural network and map 28,101 flow features between 60°N and S by scanning through ~150,000 Lunar Reconnaissance Orbiter images. We observe that flows are heterogeneously distributed over the Moon, where all major hotspots are located in craters and almost all hotspots are located in the nearside maria. We further observe that younger surfaces feature higher flow feature densities, while pre-Nectarian terranes can still host flows, remaining subject to active erosion billions of years after their formation. Our observations suggest that impacts at various scales have been—and likely still are—acting as the main, global-scale, long- and short-term driver of flow occurrence, strongly influenced by the properties of the target rock material.

Plain Language Summary
Lunar granular flows are dry mass movements that have been identified in a few regions of the Moon. As of today little is known about these features: How many are there? Where are the majority of these features located? What is driving their occurrence? Here, we build and use a convolutional neural network to automatically and rapidly process a stack of ~150,000 lunar satellite images. Our network is able to identify 28,101 flow features, which appear to be predominantly located in craters and nearside maria, as well as in very young and very old surfaces. Our observations indicate that impacts have been—and likely still are—the main driver of granular flow feature occurrence, in connection with the properties of the target material.

1. Introduction
The surface of the Moon has been subject to weathering and erosion for billions of years—and still is today. One of the most common modes of erosion is geological mass wasting, that is, the release and detachment as well as lateral and/or downslope displacement of rock and/or granular material driven by gravity and other long- and short-term drivers (Arvidson, Drozd, et al., 1975; Hovland & Mitchell, 1973; Kokelaar et al., 2017). The suite of known lunar mass wasting types includes slumps, slides, flows, rockfalls, and slope creep (Bickel, Aaron, et al., 2020; Hovland & Mitchell, 1973; Kokelaar et al., 2017; Xiao et al., 2013). Flows, also called dry granular flows, flow-like features, and granular avalanches, are characterized by the flow-like movement of fine to coarse granular material over hundreds of meters (Figure 1), controlled primarily by the flow volume and grain size distribution (Kokelaar et al., 2017). The analysis of lunar flows has the potential to reveal important insights into the mechanisms governing dry granular flows, both on the Moon and on Earth, differences in regolith properties across the lunar surface as well as the long- and short-term drivers of lunar landscape evolution. However, this requires an understanding of the global distribution of lunar flows, which has previously been lacking.

Lunar flow characteristics have been studied in a small number of craters. Kokelaar et al. (2017) proposed three geomorphically distinct classes of lunar flows; Multiple Channel and Lobe Type (MCL), Single-Surge Polylolobate Type (SSP), and Multiple-Ribbon Type (MR). MCL type flows involve small volume piecemeal failures of well graded debris, which can self channelize due to the formation of coarse grained levees. SSP flows involve large volume collapses of extensive source regions, and feature more uniform grading. MR, the rarest type encountered by Kokelaar et al. (2017), involve small volume collapses of material on erodible substrates, and form narrow, long ribbons. Kokelaar et al. (2017) do not consider granular flows directly ejected by impact events that typically form on the shallow, outward facing walls of primary craters (Bandfield et al., 2014), but this type of granular flow is specifically included in this work (see Figure S1 in Supporting Information S1). The deposits of lunar flows usually form fans, fingers, rays, and/or lobes and represent distinct features that can be
recognized from orbit, both morphologically and radiometrically, despite their small size (Kokelaar et al., 2017; Xiao et al., 2013).

Earlier studies hypothesized that granular flows most often occur in craters of specific ages (Xiao et al., 2013). It is thought that flow occurrence requires the presence of certain substrate material, such as impact melt or basaltic lava flows, overlying a more competent layer (Kokelaar et al., 2017; Kumar et al., 2013; Xiao et al., 2013), although sound statistical evidence is missing. Past work also highlighted that the distribution and characteristics of mass wasting features provide information about their drivers and, thus, the endo- and exogenic activity of their planetary host body, making their study and analysis highly relevant for planetary science and exploration. Proposed drivers of flow occurrence are impacts, moonquakes, tides, and thermal fatigue (Fassett & Thomson, 2014; Hovland & Mitchell, 1973; Kokelaar et al., 2017; Watters et al., 2019; Xiao et al., 2013).

Unfortunately, the manual, human-driven identification and mapping of granular flows in satellite images is a time-consuming task, while suffering from a substantial amount of (technical and human) limitations and biases. This contributes to the lack of knowledge about the spatial distribution and density of flow features, leaving the majority of above mentioned causal hypotheses untested or without compelling statistical evidence (Kokelaar et al., 2017; Kumar et al., 2013; Xiao et al., 2013). In this work we use a machine learning-driven approach to solve this major limitation, opening—for the first time—the door to a statistically sound, global-scale analysis of the spatial distribution, density, and drivers of granular flows, while providing the foundation for future studies on the full range of spatial scales. We complement this automated analysis with a human-led large-scale mapping campaign to further enrich this data with information about the relative abundances of flow features classes.

2. Materials, Methods, and Data

We have trained a convolutional neural network (CNN) to detect flows in images taken by Lunar Reconnaissance Orbiter’s Narrow Angle Camera (LRO’s NAC) instrument. We employed an off-the-shelf object detector architecture (RetinaNet, Lin et al., 2017) that was successfully deployed in a number of earlier studies (e.g., Bickel, Aaron et al., 2020; Bickel et al., 2018). Training this CNN required the creation of a large database of labeled flows, which was assembled during an extensive mapping campaign. During this campaign, a human operator sampled the lunar surface uniformly yet coarsely (see Figure S2 in Supporting Information S1), and identified a total of 6,248 flow toes following the procedure established by Bickel et al. (2018), Bickel, Conway et al. (2020), and Bickel, Mandrake et al. (2021). This campaign further assigned classes to each identified flow using the classification system proposed by Kokelaar et al. (2017) and described in the introduction (see Figure S3 in Supporting Information S1). As the human mapping campaign was following Kokelaar et al. (2017)’s classification system, impact-ejected flows (not included by Kokelaar et al., 2017) were not specifically labeled. This training data set was further enriched with 1,200 negative samples.

We limit our (human and CNN) mapping to between ~60°N and S and images with solar incidence angles below 60° to avoid false negatives (FN) due to shadowing, that is, slopes <~30° - representing the overwhelming majority of the lunar surface—should always be sunlit. This means that our catalog does not provide information about the distribution of flows in the lunar polar regions.

A training label consists of a rectangular box placed around the feature of interest, here the toe (downslope terminus) of a flow. In preparation for this study we performed a tradeoff analysis and found that flow toes are the geomorphic feature that best allows the CNN distinguish the feature of interest from the background, which can include for example, small craters and impact melt “flows.” Thus, training a CNN to detect flow toes (vs., e.g., the entire flow body or the flow source region) helped to maximize true positives (TP, correct detections) and minimize FN (missed detections) and false positives (FP, false detections). We note that flow toe density might be biased, as some flows tend to feature a multitude of toes or rays (fingers), while others only feature one (Figure 1). The trained CNN achieved a mean recall of 0.61, a mean precision of 0.78, and a mean average precision of 0.55 at CT 0.5 (confidence threshold). The performance is visualized in Figure S4 of Supporting Information S1.

We deployed the validated CNN in an existing processing pipeline consisting of an image selection algorithm, the CNN, and a number of post-processing routines (Bickel, Aaron et al., 2020). This image selection algorithm has worked well in previous studies, however it can exclude some parts of the lunar surface and occasionally results in flows being detected in more than one image due to spatial over- or underlap of selected images. The
CNN returns the locations of all detections per image (Figure 1) and in real world coordinates (Bickel, Aaron et al., 2020). More details about the methodology, including training, testing, deployment, and data, are available in Supporting Information S1.

We then compared the mapped flow distribution to auxiliary datasets that include information about the age and geology of the lunar surface, the locations of key geomorphic features (such as craters), as well as the global scale distribution of lunar rockfall. The main auxiliary datasets used for the analysis of the data are the Digital Unified Global Geologic Map of the Moon (Fortezzo et al., 2020), the global catalogs for craters with diameters of 5–20 km (Povilaitis et al., 2017) and >20 km (Kadish et al., 2011), and a global catalog of lunar rockfalls (Bickel, Aaron et al., 2020).

Previous research has suggested that tectonic activity may be an important driver of erosive processes on the Moon. To investigate this, we compared the spatial distribution of 3,543 lobate scarp centers (54,780 segments, cropped to 44,810 segments between 60°N and S, Watters et al., 2019), Apollo-era quakes (Nakamura et al., 1979), and all CNN-mapped flows, as well as 3,543 and 50,000 randomly placed locations on the surface in six radial distance bins (1°, 2°, 3°, 4°, 5°, 10°). The calculated quantities include the number of features, their distance, standard deviation, and variance.

We analyzed our database of lunar flow features to assess whether different pre-conditioning factors, such as those in the mare versus highland, tend to favor different flow classes. Our detector struggled to distinguish the three different flow classes as proposed by Kokelaar et al. (2017) likely due to the fact that differences in illumination and viewing geometry have a larger impact on the visual appearance of flows than the flow type, particularly when focusing on flow feature toes (Figure S5 in Supporting Information S1). To account for this, we used the information collected during the human-led mapping campaign to estimate the relative abundances of the different flow types that were manually mapped and classified (excluding impact-ejected flows).
3. Global Distribution and Characteristics of Lunar Granular Flows

We observe that the distribution of flow features is distinctively heterogeneous, with clear “hotspots” across the Moon (Figure 2). Here, the term hotspot is used to describe locations with particularly high concentrations of flow features. The CNN identified a total of 44,785 flow candidates, storing a visual representation (NAC crop) of each candidate. The identified candidates were reduced to a catalog of 28,101 flow features following removal of obvious FP by a human operator analyzing these visual representations, and we therefore expect that our final catalog only contains a small number of FP. We note that this catalog might overestimate the total number of individual flows present on the lunar surface given that some flows exhibit multiple toes.

We find that 26.4% of flows are located in mare regions, while 73.6% of flows are located in highland regions. We note that a large number of flows are hosted by craters that are located within mare regions, which are not labeled as part of the mare. When including flows within “intra-mare” impact craters (Figure S6 in Supporting Information S1), we find that 46.7% of flows are located in mare regions. Remarkably, we note that the density of flows is one order of magnitude higher in mare regions than in the highlands, when normalizing by area. We measure a spatial density of $1.2\times10^{-3}$ features/km$^2$ in mare regions ($2.1\times10^{-3}$ features/km$^2$ when including flows in intra-mare craters) and $2.6\times10^{-4}$ features/km$^2$ in highlands ($1.9\times10^{-4}$ features/km$^2$).

The distribution of flows over the northern (48.1%) and southern hemisphere (51.9%) is well balanced. Interestingly, there are significantly more flows on the lunar nearside (75.4%) than on the farside (24.6%). There are 16 flow feature hotspots with densities above 125 flows/2° by 2° quadrangle; 15 of those hotspots are located on the nearside; 10 of those are located in a mare region and/or in an intra-mare impact crater (Figures 2 and 3). Terranes of Copernican age host 18% of flows, Eratosthenian 23%, Imbrian 42%, Nectarian 13%, and pre-Nectarian 4%. When normalized over their area, we find that younger terranes feature higher spatial densities of flows (Figure 3). The observed relation between density ($\delta$, in features/km$^2$) and age ($t$, in Ma) can be described with a logarithmic fit (Figure 3):

$$\delta = -0.003 \ln(t) + 0.0274$$

We observe locations where flows run over and cover tracks carved by rockfalls, further highlighting that flow features are recent features with geologic formation times of less than $\sim1.55$ to $\sim35$ Ma, that is, the estimated upper bound of rockfall track survival time (Arvidson, Drozd, et al., 1975; Hurwitz & Kring, 2016). It is unclear what the survival time of flows is, but it is likely longer than rockfall tracks, assuming that it takes longer to erode a granular volume (topographically positive) than to fill up a shallow and narrow topographic depression (i.e., a track, see, e.g., Arvidson, Crozaz, et al., 1975). We further observe that 79.5% of all flows are located in

Figure 2. Global spatial density of flow features (number of flows per 2° by 2° quadrangle) between 60°N and S. All major hotspots are located in impact craters. The locations of hotspots are circled and their host crater name, density, and age (per Fortezzo et al., 2020) are shown (Copernican, Eratosthenian, Imbrian, Nectarian). Equirectangular projection, Lunar Reconnaissance Orbiter Wide Angle Camera mosaic in the background (Wagner et al., 2015).
craters, although this number appears to be much larger in reality: we observe numerous flow features in very small craters (<5 km), which have not been accurately mapped on a global scale, however, impeding any reliable counts. We specifically note that we identified a small number of granular flows outside of impact craters, including grabens (e.g., Rima Hyginus) and rilles (e.g., Vallis Schröteri, Rima Marius).

Table S1 in Supporting Information S1 complements these observations with the overall distribution and percentage of flows in the different geologic units on the Moon as identified by Fortezzo et al. (2020) and Meyer et al. (2019). We observe that the geologic units with the highest number of features are the Crater Unit (1.5E−03 features/km²), the Crater Undivided Unit (5.0E−03 features/km²), the Mare Dome Unit (5.1E−03 features/km²), and the Plateau Unit (8.7E−03 features/km²). The mean (baseline) density across all units is 7.4E−04 features/km². Light plains as mapped by Meyer et al. (2019) host ∼6.4% of all flow features (n = 1791). We note that we consider the high spatial density in the Crater Unit the most significant one as it contains the largest portion of flows of all units (41.1%). We additionally point out that the seemingly low density values in the Mare Unit, Upper Mare Unit, and Lower Mare Unit are caused by the same intra-mare crater labeling issue mentioned above. Interestingly, the highest density of features was observed in the Terra Dome Unit (1.2E−02 features/km²), but the significance of this observation is probably low, as this unit only contains 0.8% of all mapped flow features (n = 215).

We do not observe any global, obvious relation between the spatial distribution of flows and visible tectonic features, including lobate scarps, graben, and impact basins >200 km, and Apollo-era seismicity (Nakamura et al., 1979; Watters et al., 2019). Our statistical experiment, described in the methodology and with results given in Tables S2–S4 in Supporting Information S1, shows a weak correlation between the distribution of lobate
scars and flows, where the number of flows is, on average, 16% larger around lobate scarps than around the randomly placed locations. Particularly noteworthy are apparent clusters of flow features around lobate scarp segments (derived for the 4° and 10° bins) across the Dorsa Aldrovandi—Taurus Littrow, NE Mare Nubium, Fra Mauro, Lacus Excellentiae (SE) SE, and Oersted/Atlas regions (all on the nearside). However, many of the respective flow clusters could also be explained by recent, small-scale impact events. Further, the mean distance, variance, and standard deviation are nearly identical for all distance bins, which makes a causal relation less likely (Tables S2–S4 in Supporting Information S1). Notably, the Laue crater region that hosted the strongest recorded Apollo-era moonquake (magnitude 3.2 in 1975) does not feature an increased abundance of flows, as does the Orientale region (magnitude 1.2 in 1972).

As a large number of flow hotspots are located in nearside maria, we further investigated a potential correlation with wrinkle ridges (Nypaver et al., 2022a, 2022b; Valantinas & Schultz, 2020), which almost exclusively occur in maria. Despite their abundance in maria, we do not recognize a general significant qualitative relation between the two; on the one hand, some of the potentially (present-day) active wrinkle ridges (with high rock abundance values and/or high densities of tectonically-deformed craters, per Valantinas & Schultz, 2020 and Nypaver et al., 2022a, 2022b) appear to be co-located with flow hotspots (e.g., Reiner, Marius, and Marius A), on the other hand many other high rock abundance/deformed crater density ridge features are not associated with any flow feature hotspot, despite the abundance of potential, local host impact craters, for example, in the Flamsteed and eastern Mare Serenitatis regions (Figure 2). Our observations are consistent with recent findings by Nypaver et al. (2022a) who compared the distribution of boulder-rich features such as rocky craters with (presumably) recently active wrinkle ridges, but did not identify any clear relation either.

The direct comparison of the global rockfall (Bickel, Aaron et al., 2020) and granular flow feature maps provided a number of interesting insights. We find that the overall distribution of rockfall and flow hotspots are significantly different; common hotspots are, for example, Reiner, Marius, and Godin crater, but many major rockfall hotspots, such as in Mare Frigoris, Tsiolkovsky crater, and Mare Orientale, do not feature any significant flow hotspots. Further, rockfall hotspots predominantly occur in the lunar highlands, whereas flow hotspots predominantly occur in the lunar mare regions. Both rockfall and flow hotspots are well correlated with overall rock abundance (Bandfield et al., 2014), but we note differences in the relation between spatial density and host surface age (Figure 3), with younger terranes hosting more flows than rockfalls, relatively. Finally, the relation between feature spatial density and host surface age follows a power law relation for rockfalls, but a logarithmic relation for flow features (Figure 3).

One remarkable feature of our data set is a distinct and globally unique “cloud” (vs. hotspot) of flows in the Marius Hills region. This “cloud” features a large number of flows that are not concentrated in one crater but in many, very small craters (<<5 km) distributed over a wider area (Figure S7 in Supporting Information S1). This area of central Oceanus Procellarum is believed to be one of the youngest volcanic regions on the Moon (e.g., Spudis et al., 2013), potentially as young as ~0.7–~1.5 Ga (Huang et al., 2011). Two major global-scale flow hotspots are also co-located with large volcanic complexes—Gardner and Kepler (Figure 2)—, but the abundance of flows is limited to the impact craters themselves, that is, not as diffusively scattered over an entire region as in the Marius Hills. We do not observe any flow “clouds” in other volcanic complexes, such as Rümker, Prinz, and Aristarchus, but note that those complexes are potentially significantly older than the Marius Hills complex (e.g., Huang et al., 2011; Spudis et al., 2013). We further note that flow “clouds” are absent in other very young (~1.2–~1.7 Ga) volcanic regions, such as in northern and southern Oceanus Procellarum, including one of the presumably youngest volcanic region P60, south of the Aristarchus plateau (~1.2 Ga, Hiesinger et al., 2011).

The human-led mapping campaign (the CNN training data set) identified a total of 460 craters and/or features that host granular flows (Figure S3 in Supporting Information S1). Of these, 296 locations (65%) feature MCL type flows, 140 SSP (31%), and 9 MR (2%). The features present in eight locations (2%) did not unambiguously match the criteria proposed by Kokelaar et al. (2017) and were recorded as “unclassified.” The campaign identified seven craters with more than one flow type present. Of all locations with flows mapped in the mare regions, 42% feature SSP (vs. 26% in highlands). MR flows were the least common flow type, as also found in Kokelaar et al. (2017), and none were identified in mare regions. Impact-ejected flows were excluded from this particular analysis.
4. Discussion

The occurrence of granular flow features appears to be predominantly controlled by impact processes at various scales, underlying their role as long-term drivers (pre-conditioning factor) of flows—the number of flows observed in non-crater terranes and units is exceedingly small, yet existent. We were able to identify a number of locations where small-scale impacts appear to have directly triggered and/or induced flows, outward-facing flows (impact-ejected) as well as inward facing flows (e.g., MCL, SSP, and MR), highlighting how impacts also act as short-term drivers (triggers), both through direct ejection of material and impact-generated seismicity (Figure S8 in Supporting Information S1). Our data does not provide any insights in whether and how the composition, velocity, and angle of an impactor influence the occurrence and type of flows, however.

Earlier studies investigated whether the physical properties and composition of the target material has an influence on the mechanisms and morphology of granular flows (Kokelaar et al., 2017; Xiao et al., 2013), but were not able to identify a significant difference between mare and highland flow feature characteristics. Our observations show that the physical properties of the impacted material have a major effect on the distribution and spatial density of flows. The basaltic material found in the maria—or its interface to underlying strata—seems to be highly susceptible to flow formation, as particularly apparent in the Marius Hills volcanic complex (Figure S7 in Supporting Information S1). Interestingly, we do not observe a relation between flow distribution and light plains, which are believed to be ballistically sedimented ejecta deposits that formed during basin formation (e.g., Orientale and Imbrium, see, e.g., Meyer et al., 2019).

The material properties also have an effect on the flow mechanism, as SSP-type flows—characterized by large-volume collapses of extensive source regions (Kokelaar et al., 2017)—appear to disproportionately occur in the mare regions. The existence of the Marius Hills flow “cloud” further suggests that the age of the material might influence the occurrence of flows as well, although it seems like there is no general relation as flow “clouds” are absent in similarly young or younger volcanic regions and complexes.

The importance of the physical properties of the impacted material is further highlighted by the differences between the flow and rockfall catalogs, noted above. We interpret these to reflect differences in the short- and long-term drivers required for the different landslide types. Rockfall occurrence requires the release of boulders on topographic highs (typically from weathered cliffs, outcrops, or boulder fields, e.g., Bickel, Aaron et al., 2021), whereas flow occurrence requires that the regolith or a (largely) cohesionless mass is susceptible to failure. Our results indicate that these two factors rarely coincide on the lunar surface, at least on a global scale. Both the rockfall and granular flow catalogs show that feature density declines with age, likely due to topographic smoothing through time due to erosion.

We do not find any compelling, global-scale evidence that volcanic and tectonic activity act as major short-term drivers (Tables S2–S4 in Supporting Information S1), but do note some exceptions. These include a weak spatial correlation between flow feature hotspots and lobate scarps, one potentially young volcanic complex (Marius Hills), and a number of presumably recently active (geologically and/or present-day) wrinkle ridges. A recently published global rockfall distribution map (Bickel, Aaron et al., 2020) does not feature any rockfall hotspot in the wider Marius Hills region (except the Marius and Reiner craters), suggesting that the abundance of flows in that region might not be controlled by geologically recent seismicity, however.

Our CNN was able to map flow features in pre-Imbrian terranes that are not directly connected to fresh impacts (i.e., impact-ejected), providing additional evidence that mass wasting of surfaces on airless planetary bodies can continue over billions of years and that even very old (pre-Nectarian) surfaces are not necessarily in their final evolutionary stage (Xiao et al., 2013), as recently observed by Bickel, Aaron et al. (2020) using rockfalls. Our neural network additionally found flows in non-crater environments such as volcanic rilles, highlighting that lunar granular flows can form without the influence of impacts, further amending previously established hypotheses (Xiao et al., 2013).

We note that the used CNN has a non-perfect recall of about 0.61, meaning that there is a potentially substantial portion of flow features that were not detected and mapped. As the detector was trained using labels from all over the Moon (Figure S2 in Supporting Information S1) we do not expect there to be any geographic, geomorphic, or terrane-related bias, that is, we expect the recall to be more or less consistent in all regions of the Moon. We point out that the distribution and characteristics of SSP, MR, MCL, and impact-ejected type flows was not completely disentangled in this study. In particular, impact-ejected flows may disproportionately occur near recent impact...
craters, leading to elevated flow density in younger terrains. Examining this potential in the future could provide insights into the formation mechanisms of the different flow types. We also note that some of the auxiliary data used for the analysis, such as the geologic map and other feature catalogs (e.g., craters >5 km), are subject to individual limitations that might influence the results of this study. Future work should look at the global distribution, types, and characteristics of flows, including runout, slope angle, material properties, and morphology to explore whether more detailed relations between flow feature occurrence, their environment, their drivers, and the endo- and exogenic dynamics of the Moon can be found.

5. Conclusions

We use a CNN to map lunar granular flows between 60°N and S, identifying a total of 28,101 features. All major flow feature hotspots are located in craters and most hotspots are located in nearside maria. Younger terranes feature higher spatial flow feature densities than older surfaces, but very old terranes (pre-Nectarian) still host flows, indicating that they might not represent the final evolutionary stage of planetary surface evolution. A complementary manual mapping campaign suggests that MCL and SSP-type flows are the most common on the Moon, while SSP-type flows appear to disproportionally occur in mare regions. Our observations suggest that impacts at various scales act as the major long- and short-term drivers of granular flows, while the physical properties of the target material appear to exert significant influence on flow feature distribution, density, and type, where volcanic material appears to be predominantly susceptible to relatively large granular flows. We do not observe compelling, global evidence for any other short-term driver, such as volcanic and tectonic activity, but note that volcanic eruptions appear to be an important long-term driver. The global distribution of granular flows and other mass wasting features, such as rockfalls, expresses a number of similarities and differences, indicating that those processes might be controlled by somewhat different endo- and exogenic processes and dynamics, while both are likely actively occurring to this day.

Data Availability Statement

The workflow is entirely based on open source software and tools. RetinaNet is available here: https://github.com/fizyr/keras-retinanet (Lin et al., 2017). The Lunar Reconnaissance Orbiter NAC image data used for this study is freely available on the PDS, for example, here: https://wms.lroc.asu.edu/lroc/search. The datasets used for the analysis, such as the geologic map (Fortezzo et al., 2020), the global mare boundaries (Nelson et al., 2014), light plain map (Meyer et al., 2019), and global crater catalog 5–20 km (Povilaitis et al., 2017; here only the link to the catalog for 0°E–90°E is shown) are freely available here, respectively: https://astrogeology.usgs.gov/search/map/Moon/Geology/Unified_Geologic_Map_of_the_Moon_GIS_v2, https://wms.lroc.asu.edu/lroc/view_rdr/SHAPEFILE_LROC_GLOBAL_MARE, https://repository.hou.usra.edu/handle/20.500.11753/1362, and https://wms.lroc.asu.edu/lroc/view_rdr/SHAPEFILE_LROC_5TO20KM_CRATERS_0TO90E. The catalog of lobate scarp centers was provided by Tom Watters, but an older version (Watters et al., 2019) is available online here: https://wms.lroc.asu.edu/lroc/view_rdr/SHAPEFILELOBATESCRAPS. We do not expect that the utilization of the older lobate scarp catalog provides significantly different results. The produced and reviewed catalog of lunar granular flow features is freely available here: https://doi.org/10.3929/ethz-b-000550395.

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