

## Article

# Acoustic Granulometry of Granular Avalanches: Laboratory Validation of the Size–Frequency Relationship

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## Abstract

Granular flows generate intense acoustic emissions, yet the quantitative relationship between particle size and sound frequency remains poorly characterized for natural, irregular materials. This study investigates the inverse relationship between mean particle size and the spectral centroid of acoustic emissions under controlled laboratory conditions. We conducted vertical-drop and inclined flume experiments using steel spheres as a control, alongside dacite and pumice sieved into narrow size fractions. Acoustic signals were acquired at a 96 kHz sampling rate and analyzed using the short-time Fourier transform (STFT) to compute spectral centroids. Vertical-drop experiments confirmed a robust inverse size–frequency trend across all materials, with spectral centroids decreasing systematically as particle diameter increased. Flume experiments preserved the general inverse relationship but exhibited greater variability and a systematic shift toward lower frequencies, indicating that boundary interactions and flow kinematics modulate the acoustic signature beyond pure particle size effects. The present work establishes a controlled physical basis for acoustics-based granulometric characterization of granular avalanches, as the first stage of a factor-isolation research program in which the particle size contribution is quantified under dry, single-phase conditions. Operational field deployment lies beyond the scope of this study; the results provide the controlled calibration baselines required before extensions to multiphase, field-scale flows can be meaningfully pursued and highlight the necessity of regime-specific calibration for confined flows.

**Keywords:** granular flows; acoustic emission; spectral centroid; particle size



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## 1. Introduction

Granular flows play a fundamental role in geological processes, representing gravity-driven mass movements of loose granular material. These phenomena occur across vastly different scales, velocities, and temperatures, involving a wide variety of materials (particles and interstitial fluid).

Granular flows encompass processes ranging from large rock avalanches mobilizing millions of cubic meters in mountainous or volcanic terrains, to small sand movements of a few cubic centimeters on dune flanks. These are multiphase (solid, gas, and liquid) phenomena driven by gravity, often at very high speeds. Such flows can be dry or wet, coarse or fine, concentrated or diluted, covering a broad range of compositions and rheological characteristics [1].

In concentrated granular flows, the granulometric distribution plays a critical role, determining particle interactions, energy dissipation, flow rheology, kinematics, runout and topographic control. In such flows, the underlying dense avalanche carries most of the mass, where complex chaotic processes occur, dominated by particle–particle contacts [2].

These phenomena comprise some of the most dangerous geological hazards, including debris avalanches, sturzstroms, pyroclastic density currents and debris flows (lahars when volcanic). They represent a significant threat to infrastructure and communities. In 1902, a pyroclastic density current generated by a dome collapse at Mt Pelée killed the 27,000 inhabitants of St Pierre within minutes [3]. In 1985, a lahar caused by glacial melting at Nevado del Ruiz (Colombia) killed 25,000 people 70 km from the crater [4]. Events of lesser magnitude, but dangerous nonetheless, occur frequently worldwide; in Colima (Mexico), for example, more than 650 people have died during the 20th century as a consequence of debris flows [5].

Studying natural granular flows is, however, difficult. They are highly destructive and difficult to observe remotely because during movement, they may be obscured by dust, ash, spray, or entrained fine material. Nevertheless, these phenomena produce intense ground vibrations and acoustic emissions.

Historically, remote sensing methodologies have primarily relied upon geophysical monitoring [6], i.e., measuring ground vibrations by seismometers [7] or infrasound emissions [8–11]. However, their use has been limited to event recording, flow front localization by triangulation, description of flow-mass distribution or relative magnitude estimation. Despite these advances, the direct quantitative relationship between particle size distribution and the frequency characteristics of acoustic emissions remains poorly characterized for natural granular flows, particularly in the audible and near-ultrasonic range.

Previous studies on acoustic emissions from granular materials provide a foundation for our approach. Laboratory investigations by Leach et al. [12] and Buttle and Scruby [13] demonstrated that rigid particles emit characteristic frequencies upon collision, thereby establishing an inverse relationship between particle size and acoustic frequency. Industrial applications have confirmed this principle: Boschetto and Quadrini [14] successfully measured powder particle sizes using acoustic emission techniques, while Hansuld et al. [15] demonstrated that audible acoustic emissions correlate with particle size in pharmaceutical granulation processes, with larger particles producing lower frequencies. These studies consistently reveal that when particle impacts constitute the primary sound source, larger particles generate lower frequencies, while smaller particles produce higher frequencies.

However, these foundational studies are constrained to simplified systems, either single-particle collisions or industrial processes involving controlled, often spherical, particles under static or low-velocity conditions. Furthermore, systematic experimental validation in geologically representative conditions, particularly for collective granular avalanches with irregular, polydisperse materials remains scarce. Critically, it remains unknown how

irregular particle morphology and heterogeneous density characteristic of natural volcanic and sedimentary materials modulate the spectral signature relative to idealized spherical particles. Consequently, a quantitative framework linking acoustic frequency content to particle size in geologically realistic granular flows remains elusive, limiting the development of acoustics-based remote granulometry for natural hazard assessment.

This study investigates the relationship between the frequency of sound emitted by granular avalanches and particle grain size under controlled laboratory conditions. To provide an idealized reference for particle size and morphology, we employed steel spheres as a control group (monodisperse, isotropic) and compared their results with those from irregular natural materials (dacite clasts and pumice) within specific  $1 - \phi$  intervals. While steel spheres are uniform in both size and morphology, the natural materials comprise irregular particles spanning a controlled  $1 - \phi$  range due to the sieving process [16,17].

We performed two types of experiments. The first involved vertical falls, representing the simplest case where the captured sound is produced primarily by a material colliding against a bed of the same material, establishing the baseline size–frequency relationship under controlled, collision-dominated conditions. A second set of experiments was conducted on an inclined plane (flume) to evaluate the robustness and limitations of the size–frequency relationship under conditions more analogous to natural granular flows. While the vertical falls isolate the primary particle–particle collision mechanism, the dominant acoustic source in concentrated flows, the flume experiments introduce additional complexities inherent to natural flows, including frictional interaction with boundaries, variable flow velocities, and continuous particle rearrangement. Rather than merely corroborating the idealized relationship, these experiments aim to characterize how these secondary physical factors modulate the acoustic signal and to assess the extent to which the fundamental inverse size–frequency trend persists or becomes obscured under more realistic flow conditions.

We hypothesize that an inverse relationship exists between mean particle size and the spectral centroid of acoustic emissions from granular avalanches, applicable to both idealized monodisperse spheres and natural irregular materials within controlled size intervals. This study aims to test this relationship under controlled laboratory conditions, serving as a foundational step to establish acoustics-based cataloging of granular materials. The present study is designed as the first stage of a factor-isolation research program: it deliberately isolates the particle size contribution under controlled, dry, single-phase conditions; flow velocity, boundary and medium interactions, interstitial moisture, and topographic or propagation-path effects are intentionally excluded and will be addressed in the next study. Operational monitoring deployment is therefore beyond the scope of the present work. By comparing vertical-drop experiments which isolate primary particle–particle collisions as the simplest case with inclined flume experiments which introduce frictional and kinematic variables, we evaluate the persistence of the size–frequency trend when additional complexity is incorporated. Ultimately, this work establishes the necessary physical basis for developing future acoustics-based remote sensing methods to characterize granular flow dynamics and granulometry in natural hazard assessment.

## 2. Materials and Methods

### 2.1. Granular Material

The material set was selected to span a wide, controlled gradient in density ( $0.7\text{--}7.87\text{ g/cm}^3$ ), coefficient of restitution ( $0.21\text{--}0.83$ ) [18], and particle morphology, rather than to represent all common geomaterials (Table 1). Carbon steel spheres (AISI 1010 manufactured by GIMEXSA in Mexico City, Mexico) serve as an idealized, monodisperse, elastic control with well-defined diameters and uniform, isotropic contact mechanics. The natural materials were chosen because they represent the dominant constituents of vol-

canic granular flows: dacite clasts represent dense, irregular lithic fragments, and pumice represents low-density, porous juvenile particles, both characteristic components of debris avalanches, pyroclastic density currents, and lahars [1,2]. Other common geomaterials, such as quartz sand or limestone, were not included at this stage, as the experimental design prioritizes endmember contrasts in material properties—combined with controlled  $1 - \phi$  size intervals—to isolate the effect of particle size.

**Table 1.** Experimental materials and granular size fractions.

| Material      | Density (g/cm <sup>3</sup> ) | Coefficient of Restitution | Size ( $\phi$ ) | Diameter Size (mm) |
|---------------|------------------------------|----------------------------|-----------------|--------------------|
| Steel spheres | 7.87                         | 0.83                       | −1              | 2.00               |
|               |                              |                            | −2              | 4.00               |
|               |                              |                            | −3              | 8.00               |
|               |                              |                            | −4              | 16.00              |
|               |                              |                            | −5              | 32.00              |
| Dacite        | 2.6–2.8                      | 0.35                       | −1              | $4 > D > 2$        |
|               |                              |                            | −2              | $8 > D > 4$        |
|               |                              |                            | −3              | $16 > D > 8$       |
|               |                              |                            | −4              | $32 > D > 16$      |
|               |                              |                            | −5              | $64 > D > 32$      |
| Pumice        | 0.7                          | 0.21                       | −1              | $4 > D > 2$        |
|               |                              |                            | −2              | $8 > D > 4$        |
|               |                              |                            | −3              | $16 > D > 8$       |
|               |                              |                            | −4              | $32 > D > 16$      |
|               |                              |                            | −5              | $64 > D > 32$      |

Notes: Natural materials were sieved into  $1 - \phi$  intervals; reported  $\phi$  values indicate the upper sieve limit (material passing mesh  $n$  but retained on mesh  $n + 1$ ), yielding a log-normal size distribution bounded between adjacent mesh sizes. Restitution coefficients were measured against the same material substrate and serve as comparative indices of elastic energy recovery.

Particle morphology was characterized by a two-dimensional image analysis [19] of calibrated digital photographs ( $n = 25, 21$ , and  $9$  particles for pumice, dacite, and steel, respectively). Natural clasts were segmented via Otsu thresholding—which determines the optimal object–background threshold without assuming a predefined shape—and analyzed with the scikit-image regionprops routine [20]; steel spheres were detected with the Hough circle transform [21] ( $\text{minDist} = 300$ ,  $\text{param2} = 50$ ), which is robust to the specular reflections that corrupted intensity-based segmentation of the metallic surfaces. Three scale-independent descriptors were computed per particle: roundness

$$R = \frac{4A}{\pi L_{\text{major}}^2} \quad (1)$$

with  $A$  representing the projected area and  $L_{\text{major}}$  representing the major-axis length—chosen over perimeter-normalized circularity to decouple global form from boundary texture; boundary roughness, the perimeter ratio  $P/P_{\text{hull}}$ ; and convexity, the area ratio  $A/A_{\text{hull}}$ . Absolute dimensions derived from the 2D projections were found to be sensitive to thresholding at particle boundaries and are therefore not reported; the sieve fraction is retained as the operative size classification, consistent with standard granulometric practice. The results are reported in Appendix A (Table A2).

The coefficient of restitution (COR) for each material was experimentally determined by releasing individual particles onto a smooth horizontal impact surface composed of the same material as the particles and recording the resulting collisions with a high-speed camera at 2000 frames per second (fps). Incident and rebound velocities were then quantified



through frame-by-frame kinematic analysis. These values characterize particle–particle contact and serve as a comparative index of elastic energy recovery across materials (Table 1).

## 2.2. Vertical-Drop Experiments

### 2.2.1. Setup and Protocol

The vertical setup consisted of a PVC hopper (10 cm × 10 cm square orifice, 100 cm height) suspended 1.2 m above an impact zone (Figure 1). The hopper featured a dual-gate release mechanism actuated by an electromagnet, with spring-loaded doors ensuring rapid opening (Figure 2). High-speed video verification (400 fps) confirmed that the opening time was sufficiently fast to produce a compact, coherent flow front upon release, preventing segregation during free-fall.

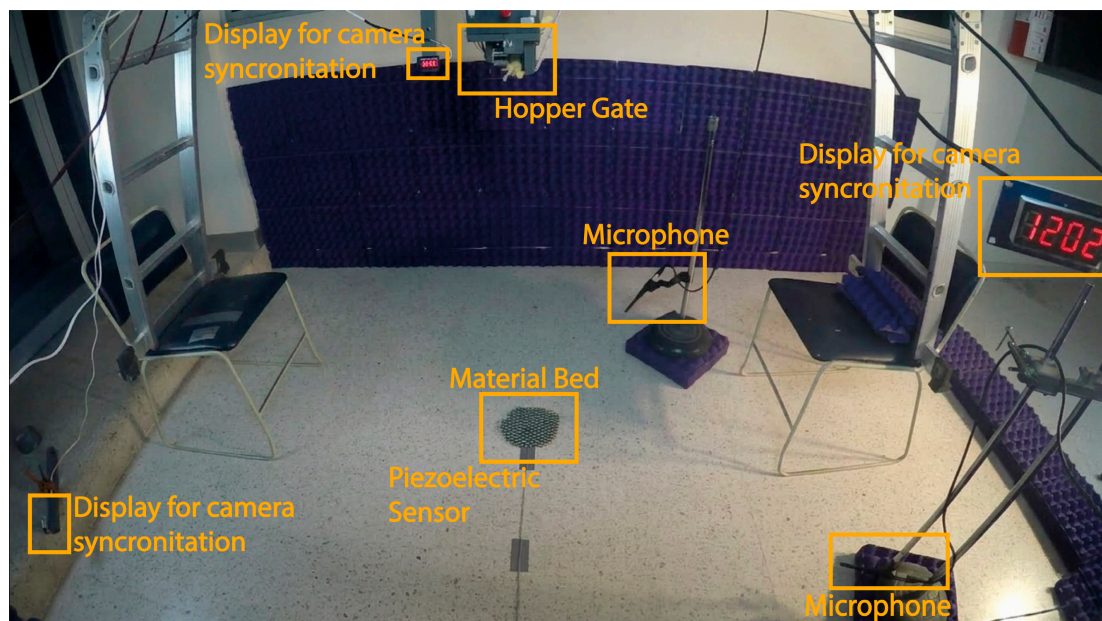


**Figure 1.** Experimental setup for vertical-drop tests of granular materials. Photograph of the complete measurement array showing the hopper gate at the top, the material bed (impact surface) on the floor, two microphones positioned at different angles for acoustic emission recording, and the synchronization displays for camera timing.

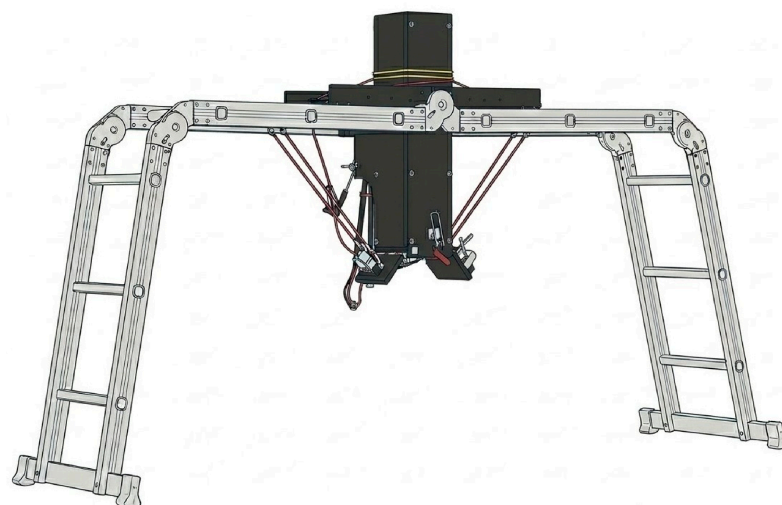


**Figure 2.** Isometric technical drawing of the hopper-ladder support structure, illustrating the support ladders, top beam, suspension cables, hopper, electromagnetic release mechanism, and release gate.

To emphasize primarily particle–particle acoustic interactions, a 4 cm thick bed of the identical test material was prepared on the concrete floor beneath the drop zone. The bed was formed by free pouring to establish the material’s natural angle of repose, without compaction. A fresh bed was prepared for every run: the bed material was removed and a new 4 cm thick bed was formed by free pouring of the same material as the particles to be dropped, following a fixed protocol (same bed mass and pouring procedure, natural angle of repose, no compaction). Bed renewal between runs prevented compaction-history and packing-memory effects.

Three replicate experiments were performed for each of the three materials (steel spheres, dacite, and pumice) at each of the five particle sizes evaluated ( $n = 3$ ). This number of replicates was adopted as a compromise between statistical independence and experimental cost. Each run released on the order of  $10^2$ – $10^6$  particles depending on the size fraction ( $6000 \text{ cm}^3$  hopper charge), so every acoustic record integrated a very large number of collision events. The fixed hopper charge was chosen so that total particle mass and released potential energy remained approximately constant across fractions within each material series, keeping granulometry as the target variable of the comparison. The replicate set was therefore intended to capture run-to-run (ensemble-level) variability rather than single-particle sampling statistics. Fresh material was used for every run to guarantee independence between replicates and to prevent comminution or packing-history effects.

Two electret condenser microphones based on Panasonic WM-61A electret capsules (usable with no degradation up to 48 kHz [22]; omnidirectional polar pattern) were positioned at horizontal distances of 1.0 m and 0.5 m from the impact center, respectively, both at a height of 0.5 m above floor level. Microphones were mounted on tripods with shock-absorbing feet to prevent mechanical vibration transmission.

A piezoelectric impact sensor embedded in the center of the 4 cm bed provided precise timing of initial contact. Three high-speed video cameras (400 fps) recorded the flow kinematics, while a LED chronometer synchronized to the trigger provided millisecond-precision timing visible in the video frames (Figure 3).

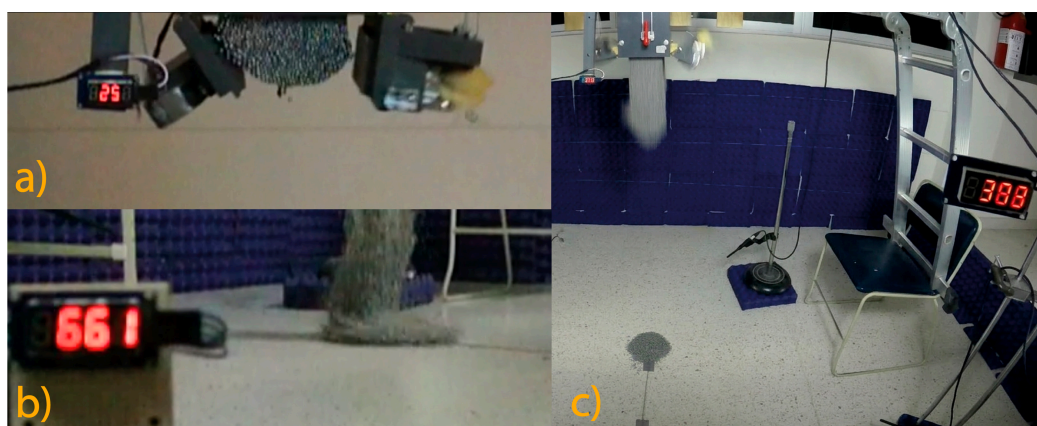


**Figure 3.** Multi-camera views of the vertical-drop experiment. (a) Hopper gate opening. (b) Particle impacts on the material bed. (c) Wide-angle overview of the experimental setup.

All vertical-drop experiments shared identical release conditions (1.2 m drop height, same release procedure for every material and size fraction), ensuring a common nominal impact velocity (4.85 m/s) and full comparability across experiments. Analytical upper bounds on aerodynamic-drag effects (Appendix A, Table A1) show that impact-velocity reductions relative to free fall remain below 1.5%, 4.5%, and 16% for steel, dacite, and pumice, respectively—the largest values occurring in the finest fractions ( $-1\phi$  and  $-2\phi$ ). Impact velocity thus enters this stage as a controlled design variable rather than a mea-

sured one; its explicit measurement and systematic variation define the next stage of this research program.

### 2.2.2. Signal Discrimination

The acoustic record contained multiple phases: (1) gate opening noise, (2) free fall (silent period), (3) initial impact and particle–bed interaction, and (4) secondary scattering (Figure 4). The analysis window was delimited using three independent cues: (a) the electromagnetic trigger signal ( $t = 0$ , gate opening), (b) the piezoelectric sensor signal ( $t = \text{impact}$ ) and (c) high-speed video verification of compact front maintenance.

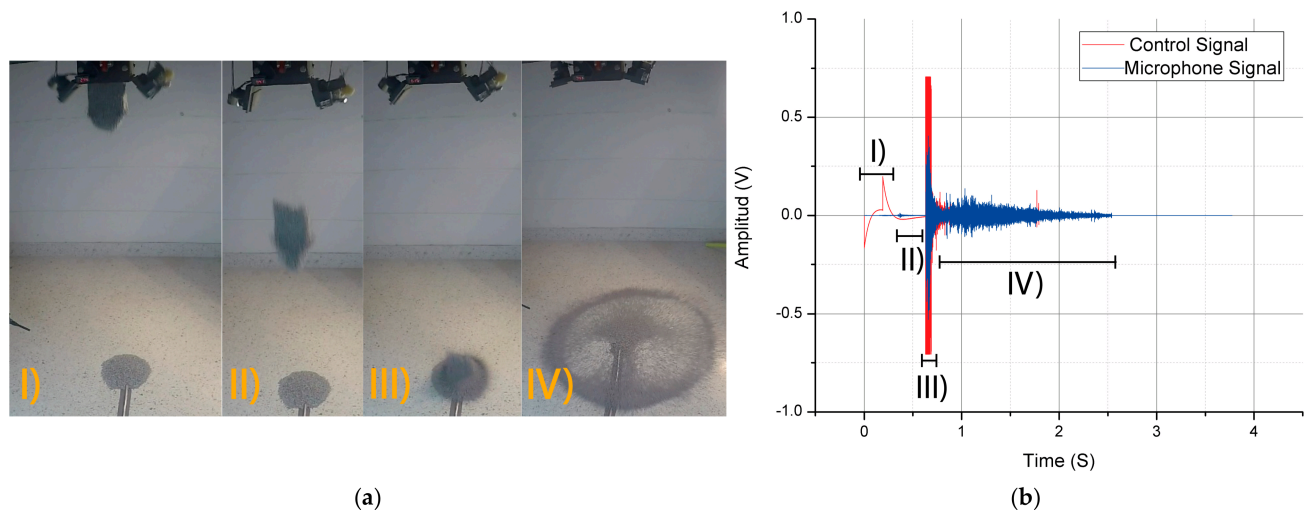


**Figure 4.** Synchronized temporal sequence of a vertical-drop experiment. (a) High-speed camera frames showing the four physical stages of the free-fall process: (I) the hopper gate opens, (II) the material falls in free fall, (III) the material impacts the surface as a compact front, and (IV) the material disperses and expands. (b) Corresponding recorded signals: the control signal (red) comprises the electrical pulse triggering the hopper gate release, followed by the piezoelectric sensor response marking the particle impact; the blue signal corresponds to the acoustic emission recorded by the microphone.

### 2.3. Flume Experiments

#### 2.3.1. Setup and Protocol

A rectangular open-channel flume was constructed from 3 mm acrylic sheet, measuring 1.5 m in length with a cross section of 15 cm width  $\times$  20 cm height (Figure 5).

The flume inclination was fixed at  $36^\circ$  based on static angle-of-repose tests (cylinder lift method) performed on the coarsest fraction ( $-5\phi$ ) of each material. Measured repose angles were  $31^\circ$  for dacite and  $27^\circ$  for pumice; steel spheres did not form a stable deposit cone, consistent with the very low repose angle of smooth, monodisperse spheres. The  $36^\circ$  slope therefore exceeds the repose angle of all tested materials, guaranteeing spontaneous mobilization and a sustained, collision-dominated (inertial) flow regime along the channel rather than intermittent or creeping motion. This slope is not intended to reproduce the geometry of natural flow paths—debris avalanches and pyroclastic density currents can propagate over slopes of only a few degrees—but rather the steep, near-source conditions under which the dense, collisional transport regime investigated in this study develops.

The upper section was fitted with a vertical gate (15  $\times$  15 cm) designed to manually release the material at the time of dam-gate opening. The material was initially loaded behind the gate and allowed to settle under static conditions before the gate was rapidly lifted vertically.



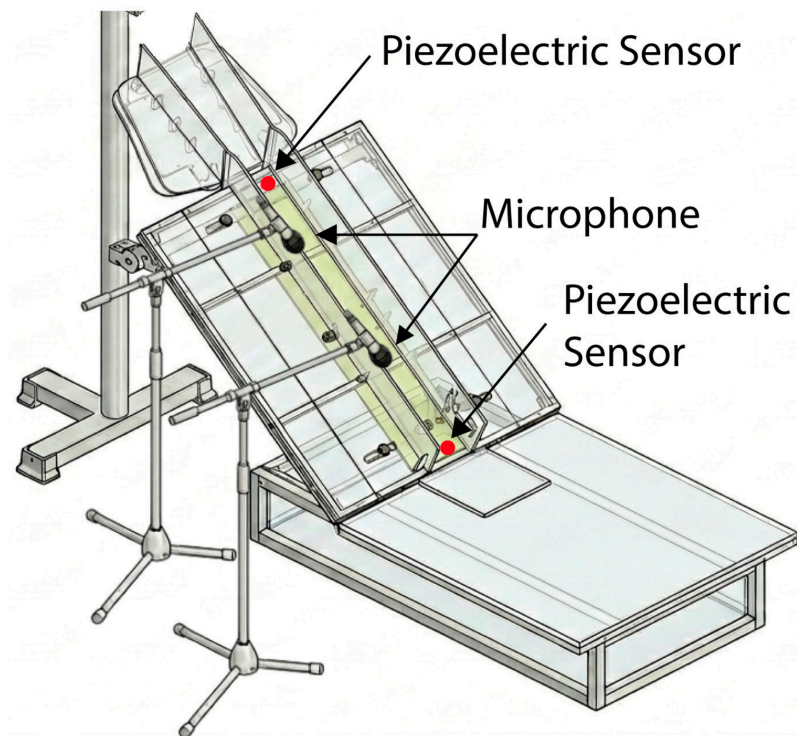


**Figure 5.** Isometric view of the inclined flume setup. The 1.5 m acrylic channel (15 cm × 20 cm) is inclined at 36° with a vertical gate for dam-break release. Two piezoelectric sensors are mounted in the channel floor, and two electret microphones are positioned perpendicular to the slope.

An analogous protocol was followed for the flume experiments (Section 2.2.1). Three replicate experiments were performed for each of the three materials and each particle size ( $n = 3$ ), using a constant released volume of 3 dm<sup>3</sup> per run, so that each acoustic record again integrated many collision events and the replicate set captured ensemble-level, run-to-run variability. As in the vertical-drop tests, fresh material was used for every run to guarantee independence between replicates and to prevent comminution or packing-history effects.

Two piezoelectric sensors were mounted in the channel floor: Sensor 1 at the entry of the measurement section, and Sensor 2 at 1.4 m downstream (defining the analysis length). Two identical electret microphones (identical specifications to Section 2.2.1) were positioned perpendicular to the channel slope: Microphone 1 at 40 cm from the upper end, and Microphone 2 at 40 cm from the lower end, both at 50 cm height relative to the channel floor plane (maintaining the 36° inclination). Microphones were tripod-mounted with vibration isolation.

### 2.3.2. Signal Discrimination

Unlike the vertical drops, the flume experiment required excluding acoustic signals generated outside the target flow regime, specifically gate mechanical noise and final deposition impacts. The two piezoelectric sensors provided temporal markers: Sensor 1 detected when material entered the channelized analysis section, and Sensor 2 detected when material exited this section. The acoustic signal between these two timestamps was extracted for analysis, ensuring that only sound produced by material flowing down the 1.4 m channel section was processed (Figure 6).

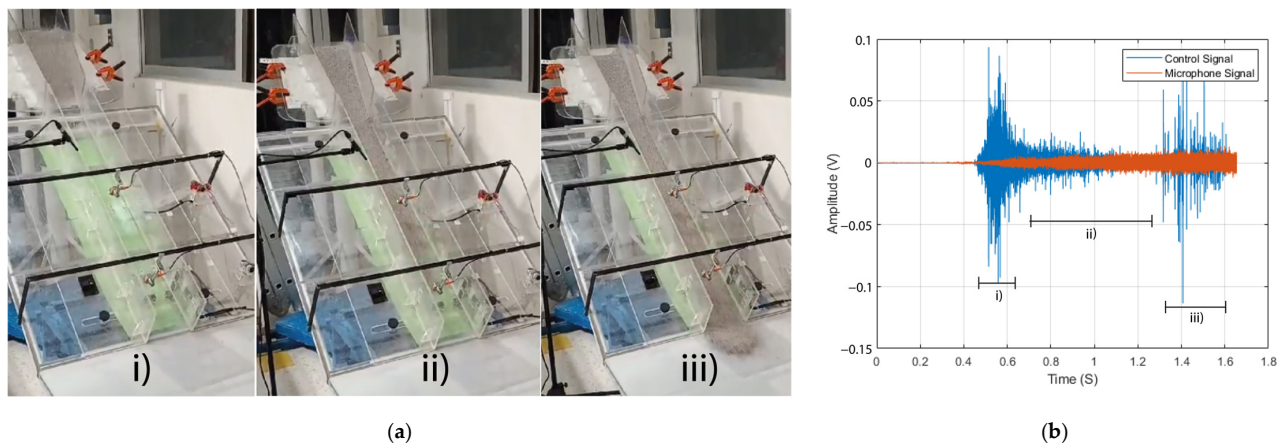


**Figure 6.** Synchronized temporal sequence of the inclined chute experiment. **(a)** Camera frames showing the three physical stages: (i) material release from the reservoir, (ii) flow through the channel, and (iii) exit with deposition. **(b)** Corresponding recorded signals: the control signal (blue) marks the piezoelectric sensor timestamps at the channel entry and exit, while the microphone signal (red) captures the acoustic emission produced during the pure flow regime.

#### 2.4. Data Acquisition

Acoustic and control signals were acquired using a 4-channel analog-to-digital converter with 24 bit resolution at a 96 kHz sampling rate. The 96 kHz rate was selected so that the Nyquist frequency (48 kHz) coincided with the upper limit at which the microphone capsules have been independently characterized with no noticeable degradation [22]; the anti-aliasing stage of the converter prevents energy above this limit from folding into the analyzed band. An extended bandwidth is nonetheless required by the physics of particle impact: the characteristic frequency of Hertzian impact scales inversely with particle size ( $f \propto d^{-1}$  [23]), and acoustic-emission measurements of particles as fine as 50  $\mu\text{m}$  report radiation at 50–200 kHz [12], so the size-dependent content of the present particle range extends beyond the audible band while remaining well below 48 kHz. The analysis bandwidth (80 Hz–48 kHz) was selected to capture the produced acoustic emission spectrum without restricting the analysis to the audible range.

Channel configuration:

- Channels 1–2: dedicated to the two electret condenser microphones, utilizing microphone preamplifiers to ensure high-gain, low-noise capture of the acoustic emissions (22 Hz–48 kHz frequency response).
- Channels 3–4: used for control and synchronization signals (piezoelectric impact sensors, electronic triggers, and gate release signals) via line-level inputs without preamplification, as these signals were already conditioned to line level or provided sufficient voltage output.

This configuration ensured simultaneous, phase-locked acquisition of all acoustic and control channels, critical for precise temporal alignment between the audio signals and the mechanical event markers (piezoelectric triggers). The 24 bit resolution provided sufficient dynamic range to capture both the high-amplitude initial impacts and the lower-amplitude particle–particle interactions without saturation or quantization noise.

#### 2.5. Signal Processing

Acquired signals were analyzed using the short-time Fourier transform (STFT) with a Hanning window and 50% overlap. Because the duration of the target flow phase differs by more than an order of magnitude between configurations ( $\sim 35$ – $100$  ms for vertical-drop impacts versus  $\sim 0.3$ – $0.7$  s for flume flows), the STFT window length was

set adaptively to one-tenth of each analyzed segment, rounded to the next power of two (256–8192 samples, i.e., 2.7–85 ms at the 96 kHz sampling rate). This adaptive scheme addresses the time–frequency resolution trade-off in a regime-independent manner: it yields on the order of 10–20 analysis frames per record in all conditions—sufficient to track transient collision dynamics—while keeping the frequency resolution (12 to 375 Hz) below 7% of even the smallest measured centroid values (6109 Hz for vertical drop, 5210 Hz for flume flows). A fixed window would have either under-sampled the brief vertical-drop impacts (too few frames per record) or over-smoothed the spectral evolution of the longer flume flows. The lower bandwidth bound (80 Hz) excludes Direct Current (DC) offset and low-frequency structural vibration of the support frame, while the upper bound was set at the Nyquist frequency (48 kHz), matching the specified limit of the microphone response. The sensitivity of the computed centroids to these processing choices was verified explicitly (Section Sensitivity Analysis) and the centroid frequencies are consistent with those obtained in previous work using a different analysis [24].

Signals were normalized by their maximum absolute amplitude (peak normalization) prior to spectral analysis to ensure comparability across experiments while preserving the relative dynamic range of impact events.

The spectral centroid ( $f_c$ ) was calculated as the weighted mean frequency of the magnitude spectrum:

$$\frac{\sum_k f_k \cdot |P(f_k)|}{\sum_k |P(f_k)|} \quad (2)$$

where  $f_k$  is the frequency bin and  $|P(f_k)|$  is the magnitude of the short-time Fourier transform at that frequency. The centroid was computed within the analysis bandwidth (80 Hz to 48 kHz, the Nyquist frequency) to exclude DC offset and low-frequency noise while capturing the full audible range of granular collision emissions (Figure 7). The scaling does not affect the spectral centroid value.

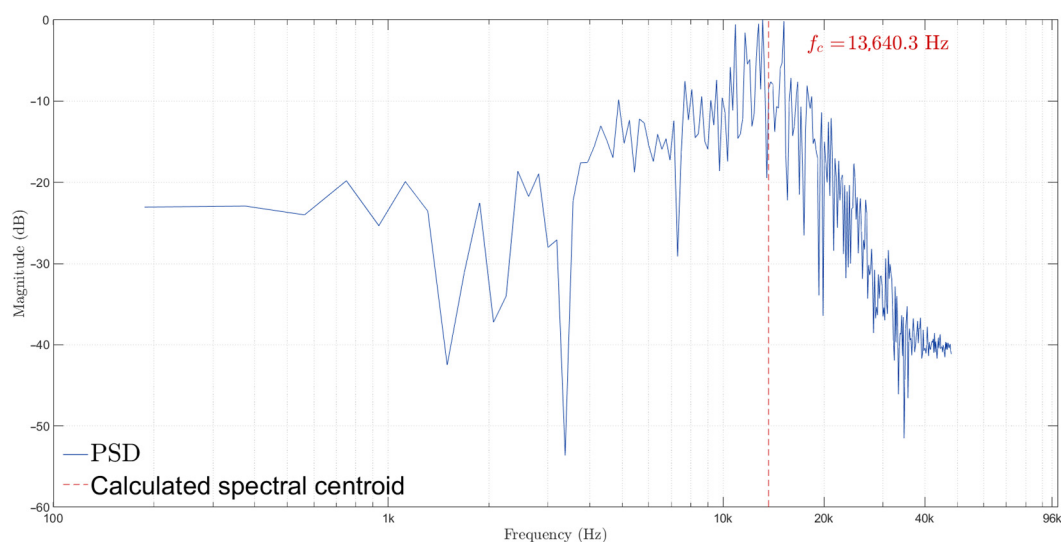


**Figure 7.** Short-time Fourier transform (STFT) spectrogram for dacite with particle size of  $-3 \phi$ , Run 1, free-fall experiment. The dashed vertical line indicates the calculated spectral centroid.

### Sensitivity Analysis

The robustness of the spectral centroid to the processing parameters was quantified on a subset of 30 experimental runs covering all three materials, all five size fractions, and both configurations (one representative run per condition, two microphones per run, 60 signals in total; full results in Table 2).



**Table 2.** Sensitivity of the spectral centroid to STFT window length for the 30 experimental conditions (3 materials  $\times$  2 configurations  $\times$  5 size fractions; one representative run per condition, two microphones per run, 60 signals). Nominal centroid: value used in the original analysis (adaptive window, one-tenth of the segment length rounded to the next power of two; nominal band 80 Hz–48 kHz). For each fixed window length (256–8192 samples), the centroid and the number of analysis frames ( $n$ ) are reported. Max |dev| window = maximum absolute percent deviation across window lengths, computed only over windows yielding  $\geq 5$  analysis frames.

| Material      | Size ( $\varphi$ ) | Vertical Drop Experiments |                         | Inclined Flume Experiments |                         |
|---------------|--------------------|---------------------------|-------------------------|----------------------------|-------------------------|
|               |                    | Nominal Centroid (Hz)     | Window Dev. Min–Max (%) | Nominal Centroid (Hz)      | Window Dev. Min–Max (%) |
| Dacite        | –1                 | 17,541                    | 0.31–0.41               | 9768                       | 0.28–0.44               |
|               | –2                 | 15,828                    | 0.30–0.42               | 8845                       | 0.44–0.62               |
|               | –3                 | 13,244                    | 0.45–0.54               | 7914                       | 0.78–1.10               |
|               | –4                 | 9260                      | 0.64–1.08               | 6114                       | 2.30–3.20               |
|               | –5                 | 6109                      | 1.20–1.49               | 5210                       | 1.69–2.83               |
| Pumice        | –1                 | 16,529                    | 0.03–0.74               | 9134                       | 0.28–0.30               |
|               | –2                 | 14,649                    | 0.34–0.58               | 7980                       | 0.23–0.44               |
|               | –3                 | 13,558                    | 0.31–0.73               | 6370                       | 1.21–1.44               |
|               | –4                 | 11,696                    | 1.79–3.15               | 6037                       | 2.37–5.62               |
|               | –5                 | 10,402                    | 2.48–3.06               | 6319                       | 3.48–3.90               |
| Steel Spheres | –1                 | 21,134                    | 0.05–0.60               | 12,208                     | 1.11–1.16               |
|               | –2                 | 18,294                    | 0.24–0.47               | 14,687                     | 0.62–1.09               |
|               | –3                 | 14,212                    | 0.16–0.60               | 11,447                     | 1.05–1.29               |
|               | –4                 | 8453                      | 0.45–0.77               | 6690                       | 2.63–3.02               |
|               | –5                 | 6811                      | 2.59–3.03               | 6075                       | 4.45–5.98               |

Replacing the adaptive window with fixed window lengths of 256–8192 samples changed the centroid by less than 3% in most conditions and by at most 6.0% (steel spheres,  $-5\varphi$ , flume), for all windows yielding at least five analysis frames; these deviations are several times smaller than the run-to-run variability of the corresponding conditions. The computed centroids are therefore not materially sensitive to reasonable variations in window length bound; larger displacements occur only under aggressive truncation of documented signal content and exhibit gradual, predictable scaling rather than estimator instability.

## 2.6. Statistical Modeling of Size–Frequency Relationships

To characterize the relationship between particle size and acoustic emission frequency across materials and experimental configurations, spectral centroid frequencies were fitted to particle diameter using an empirical power-law relationship of the form:

$$f_c = A \cdot d^m \quad (3)$$

where  $f_c$  is the spectral centroid frequency (Hz),  $d$  is the particle diameter (mm),  $A$  is a material-dependent proportionality coefficient, and  $m$  is the scaling exponent.

The power law was linearized via base-10 logarithms:

$$\log_{10}(f_c) = \log_{10}(A) + m \cdot \log_{10}(d) \quad (4)$$

Ordinary least-squares regression was applied to the transformed data. The proportionality coefficient was recovered as  $A = 10^{(\text{intercept})}$ , and the exponent  $m$  as the regression slope. The coefficient of determination  $R^2$  was computed in logarithmic coordinates to assess goodness of fit. Uncertainty in the fitted exponent is reported as A 95% confidence interval of the regression slope (Section 3.1).

Particle diameter for natural materials: Steel spheres have well-defined diameters (2, 4, 8, 16, 32 mm). For dacite and pumice, particles were sieved through 1-phi interval screens, yielding log-normal size distributions bounded between adjacent mesh sizes. The representative diameter for each fraction was taken as the geometric mean of the sieve bounds:

$$d = \sqrt{d_{min} \cdot d_{max}} = 2^{-\Phi} \quad (5)$$

where  $\Phi$  is the phi-scale midpoint of the fraction (e.g.,  $\Phi = -0.5$  for the 2–4 mm fraction, yielding  $d \approx 2.83$  mm).

The power-law form was selected because (i) it captures the observed inverse size–frequency trend with only two parameters; (ii) it permits direct comparison across materials via the exponent  $m$ ; (iii) it extrapolates physically (positive frequencies for all  $d > 0$ ), unlike polynomial alternatives that predict negative frequencies outside the fitted range.

### 3. Results

The following sections present the spectral analysis of acoustic emissions from vertical-drop and inclined flume experiments. The baseline inverse size–frequency relationship under collision-dominated conditions is established first, followed by an evaluation of its persistence under confined flow. Representative emission spectra and variability metrics are then examined to assess the robustness of the spectral centroid as a granulometric proxy across materials and flow regimes.

#### 3.1. Spectral Centroid as a Function of Particle Size

Spectral centroids for vertical-drop experiments exhibited an inverse relationship between particle size and acoustic frequency for all three materials (Figure 8). Steel spheres showed the highest centroid values, decreasing from 20,949 Hz ( $-1 \phi$ , 2 mm) to 5447 Hz ( $-5 \phi$ , 32 mm), with a power-law fit of  $R^2 = 0.946$ . Dacite ( $R^2 = 0.960$ ) and pumice ( $R^2 = 0.972$ ) showed similar trends.

Flume experiments yielded lower centroid values than vertical-drop experiments for all material–size combinations (Figure 9). Steel spheres decreased from 12,093 Hz ( $-1 \phi$ ) to 5715 Hz ( $-5 \phi$ ), with a power-law fit of  $R^2 = 0.832$ . Dacite showed a comparable trend with  $R^2 = 0.980$ . Pumice exhibited the most pronounced deviation at small particle sizes, with a centroid of 9125 Hz at  $-1 \phi$  dropping to 6224 Hz at  $-5 \phi$  ( $R^2 = 0.752$ ).

All six fitted exponents are negative, and their magnitudes are order identically with material density in both configurations (steel > dacite > pumice); a sign test on the six independent fits yields  $(1/2)^6 \approx 0.016$  under the null hypothesis of no size dependence. The robustness of the size–frequency relationship therefore rests on this cross-material, cross-configuration consistency rather than on any single fit. The single interval that touches zero (pumice, flume configuration) is consistent with the reduced size discriminability of coarse fractions in confined flows, as identified in Section 4.2 (Table 3).

The lower  $R^2$  values for steel spheres and pumice in the flume configuration reflect deviations from monotonic power-law decay, particularly at the smallest particle sizes. The magnitude of the offset between vertical-drop and flume experiments decreased systematically with increasing particle size for steel and dacite. Pumice showed a distinct pattern, with a markedly lower centroid in the flume at  $-1 \phi$  relative to the vertical drop, converging toward similar values at larger sizes.

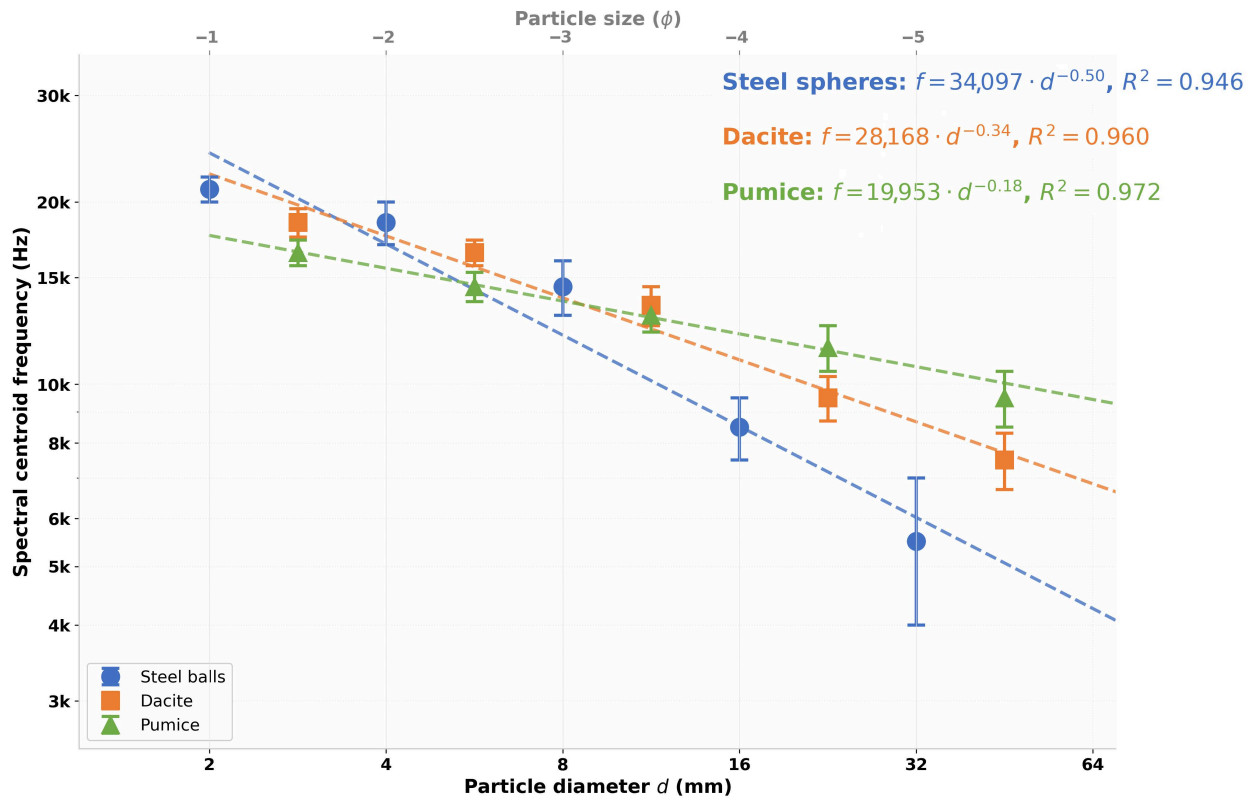


**Figure 8.** Average spectral centroid frequency as a function of particle diameter for vertical-drop experiments. Data points show mean values with error bars for steel spheres (blue circles), dacite (orange squares), and pumice (green triangles). Dashed lines indicate power-law fits.

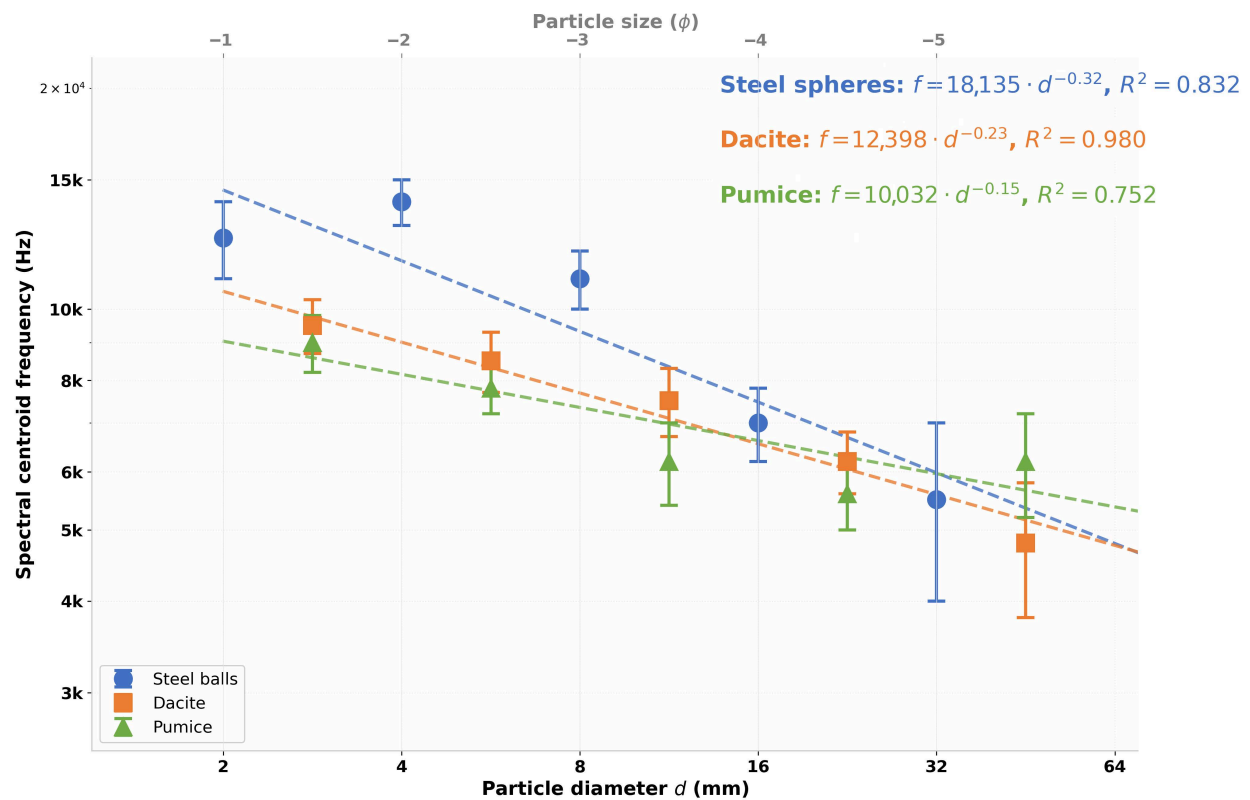


**Figure 9.** Average spectral centroid frequency as a function of particle diameter for inclined flume experiments. The data points show mean values with error bars for steel spheres (blue circles), dacite (orange squares), and pumice (green triangles). The dashed lines indicate power-law fits.

**Table 3.** Fitted power-law parameters (Equation (3)) for the six material–configuration combinations: proportionality coefficient  $A$  (Hz, for  $d$  in mm), exponent  $m$  with its 95% confidence interval (ordinary least squares regression on  $\log_{10}$ -transformed fraction means; five fractions per fit, three residual degrees of freedom), and coefficient of determination  $R^2$  in logarithmic coordinates.

| Configuration  | Material      | $A$ (Hz) | $m$    | 95% CI for $m$   | $R^2$ |
|----------------|---------------|----------|--------|------------------|-------|
| Vertical drop  | Steel spheres | 34,100   | −0.498 | [−0.717, −0.280] | 0.946 |
|                | Dacite        | 28,200   | −0.337 | [−0.464, −0.211] | 0.960 |
|                | Pumice        | 20,000   | −0.181 | [−0.237, −0.124] | 0.972 |
| Inclined flume | Steel spheres | 18,100   | −0.318 | [−0.581, −0.056] | 0.832 |
|                | Dacite        | 12,400   | −0.226 | [−0.284, −0.167] | 0.980 |
|                | Pumice        | 10,000   | −0.155 | [−0.318, +0.008] | 0.752 |

### 3.2. Characteristics of Acoustic Emission Spectra

Mean emission spectra for the smallest particle size ( $-1 \phi$ ), averaged across replicate launches, illustrate the broadband nature of granular collision emissions (Figure 10). In vertical-drop experiments (Figure 10), all three materials exhibited broad energy distributions with significant content extending beyond 20 kHz. Spectral centroids fell within the 16–21 kHz range (upper-audible to near-ultrasonic), positioned in regions of high energy concentration but not necessarily at the peak amplitude.

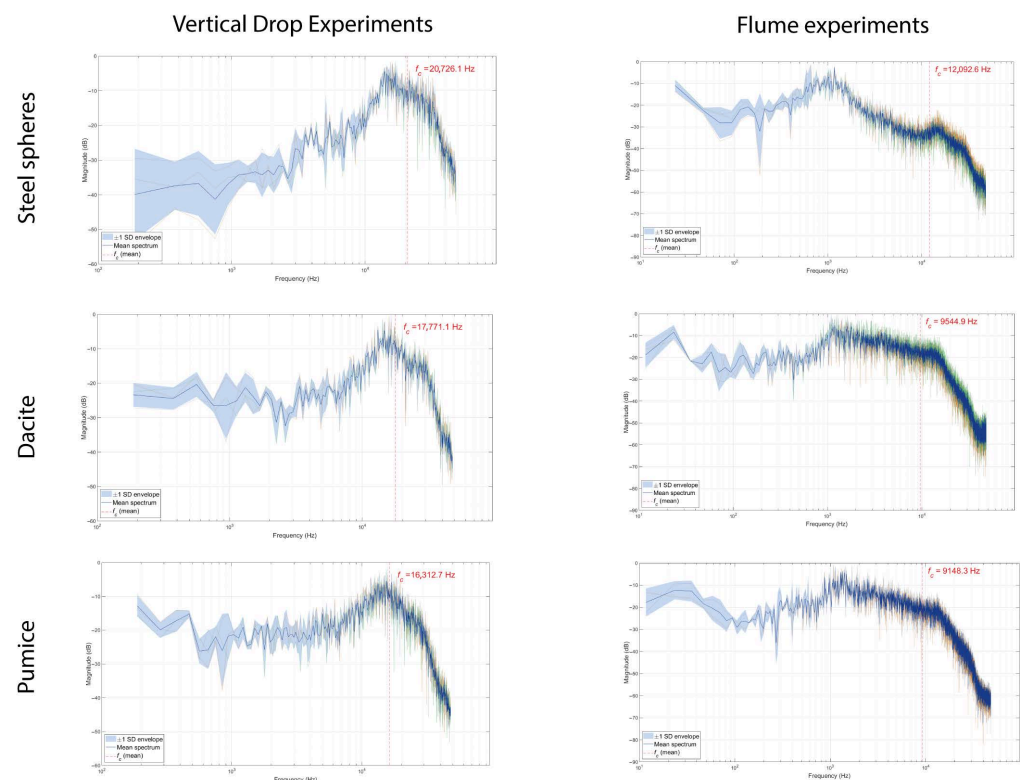


**Figure 10.** Mean acoustic emission spectra for  $-1 \phi$  particles across materials and experimental configurations. Each panel shows the mean spectrum (blue line)  $\pm 1$  standard deviation (shaded band) across replicate launches ( $n = 3$ ), computed from the homogenized two-microphone recording of each run; the red dashed line marks the mean spectral centroid across runs.

Flume experiments (Figure 10) showed comparable spectral shapes with overall lower frequency content across the replicate launches of Figure 10. Steel spheres and dacite maintained broadband characteristics with mean centroids of  $12,093 \pm 351$  Hz and  $9545 \pm 73$  Hz, respectively (mean  $\pm 1$  SD across replicate launches). Pumice in the flume configuration yielded a mean centroid of  $9148 \pm 39$  Hz, consistent with the average trend shown in



Figure 9 and comparable to that of dacite, with energy distributed across a similarly broad frequency range rather than concentrated predominantly below 10 kHz.

The consistent presence of energy above 20 kHz across materials and experimental conditions validates the extended acquisition bandwidth employed in this study. Despite this high-frequency content, calculated spectral centroids remained within the audible range for all experimental conditions.

### 3.3. Variability and Reproducibility

Table 4 reports the mean spectral centroid frequencies, standard deviations (SDs), standard errors of the mean ( $SEM = SD/\sqrt{n}$ ), and coefficients of variation (COV) for three replicate experiments ( $n = 3$ ) across all materials, size fractions, and experimental configurations. These statistics quantify the run-to-run dispersion observed under repeated, nominally identical experimental conditions.

**Table 4.** Mean spectral centroid frequencies, standard deviations (SDs), standard error of the mean (SEM), and coefficients of variation (COV).

| Material      | Size ( $\phi$ ) | Diameter Size (mm) | Spectral Centroid (Hz) | Vertical-Drop Experiments |                                                   |         | Inclined Flume Experiments |                |                                                   |         |
|---------------|-----------------|--------------------|------------------------|---------------------------|---------------------------------------------------|---------|----------------------------|----------------|---------------------------------------------------|---------|
|               |                 |                    |                        | Std. Dev. (HZ)            | Standard Error of the Mean (Hz) ( $SD/\sqrt{3}$ ) | COV (%) | Spectral Centroid (Hz)     | Std. Dev. (HZ) | Standard Error of the Mean (Hz) ( $SD/\sqrt{3}$ ) | COV (%) |
| Steel spheres | −1              | 2.00               | 20,949                 | 466                       | 269                                               | 2.22    | 12,093                     | 1442           | 833                                               | 11.92   |
|               | −2              | 4.00               | 18,338                 | 505                       | 292                                               | 2.75    | 13,917                     | 1121           | 647                                               | 8.05    |
|               | −3              | 8.00               | 14,436                 | 349                       | 201                                               | 2.42    | 10,855                     | 597            | 345                                               | 5.50    |
|               | −4              | 16.00              | 8575                   | 513                       | 296                                               | 5.98    | 6854                       | 316            | 182                                               | 4.61    |
|               | −5              | 32.00              | 5447                   | 2016                      | 1164                                              | 37.01   | 5715                       | 1362           | 786                                               | 23.83   |
| Dacite        | −1              | 4 > D > 2          | 18,262                 | 629                       | 363                                               | 3.44    | 9545                       | 514            | 297                                               | 5.39    |
|               | −2              | 8 > D > 4          | 16,487                 | 503                       | 290                                               | 3.05    | 8423                       | 446            | 257                                               | 5.30    |
|               | −3              | 16 > D > 8         | 13,794                 | 359                       | 207                                               | 2.60    | 7617                       | 468            | 270                                               | 6.14    |
|               | −4              | 32 > D > 16        | 9547                   | 487                       | 281                                               | 5.10    | 6050                       | 416            | 240                                               | 6.88    |
|               | −5              | 64 > D > 32        | 7457                   | 781                       | 451                                               | 10.47   | 5152                       | 1153           | 666                                               | 22.38   |
| Pumice        | −1              | 4 > D > 2          | 16,313                 | 335                       | 193                                               | 2.05    | 9125                       | 823            | 475                                               | 9.02    |
|               | −2              | 8 > D > 4          | 14,435                 | 294                       | 170                                               | 2.04    | 7802                       | 493            | 285                                               | 6.32    |
|               | −3              | 16 > D > 8         | 13,348                 | 278                       | 161                                               | 2.08    | 6102                       | 396            | 229                                               | 6.49    |
|               | −4              | 32 > D > 16        | 11,803                 | 508                       | 293                                               | 4.30    | 5741                       | 504            | 291                                               | 8.78    |
|               | −5              | 64 > D > 32        | 9644                   | 915                       | 528                                               | 9.49    | 6224                       | 915            | 528                                               | 14.70   |

For vertical-drop experiments, standard deviations ranged from 278 Hz (pumice,  $-3\phi$ ) to 2016 Hz (steel spheres,  $-5\phi$ ), with corresponding COV values between 2.0% and 37.0%. The lowest COVs were recorded for pumice at  $-3\phi$  (2.1%) and  $-2\phi$  (2.0%), and for steel spheres at  $-1\phi$  (2.2%). The highest COV in this configuration occurred for steel spheres at  $-5\phi$  (37.0%), followed by dacite at  $-5\phi$  (10.5%).

For inclined flume experiments, standard deviations ranged from 316 Hz (steel spheres,  $-4\phi$ ) to 1442 Hz (steel spheres,  $-1\phi$ ), with COV values between 4.6% and 23.8%. The lowest COVs were observed for steel spheres at  $-4\phi$  (4.6%) and dacite at  $-1\phi$  (5.4%). The highest COVs were recorded for steel spheres at  $-5\phi$  (23.8%) and dacite at  $-5\phi$  (22.4%).

Across both configurations, COV values were generally higher in the flume experiments than in the vertical-drop experiments for equivalent material–size combinations.

Although dispersion increases for the coarsest fractions (COV up to 37% for steel spheres at  $-5\phi$  in vertical drops), the fitted size–frequency trends remain statistically robust under the collision-dominated configuration. The standard error of the mean ( $SEM = SD/\sqrt{n}$ , (Table 4)) remains smaller than the separation between adjacent size

fractions for all vertical-drop combinations; even in the worst case (steel spheres,  $-5\phi$ ), the SEM (1164 Hz) is approximately one-third of the separation from the adjacent fraction (3128 Hz). Aerodynamic drag during the fall represents a systematic, rather than statistical, potential source of bias: it preferentially reduces the impact velocity of the finer, lighter fractions (Appendix A, Table A1). Under the Hertzian impact scaling  $f \propto v^{1/5}$  [23,25], the bounded velocity deviations translate into centroid frequency biases below 0.5%, 1%, and 3.4% for steel, dacite, and pumice, respectively—smaller than the separations between adjacent size fractions (Table 4)—and act in the direction opposite to the observed inverse size–frequency trend. Differential aerodynamic drag therefore cannot account for the reported size–frequency relationship, which is conservative with respect to this effect.

Under flume conditions, the SEM approaches the inter-fraction separation for the coarsest fractions (e.g., pumice,  $-3\phi$  to  $-4\phi$ ). Moreover, the power-law fits are computed on log-transformed mean values, which reduces the influence of run-to-run dispersion on the fitted exponents. Increasing the replicate count would reduce the SEM in proportion to  $1/\sqrt{n}$ —six replicates would narrow confidence intervals by  $\sim 29\%$ , and ten replicates by  $\sim 45\%$ , relative to  $n = 3$ —primarily improving precision for the coarsest fractions, without materially altering the fitted trends, which are anchored by the low-dispersion finer fractions.

## 4. Discussion

### 4.1. Vertical-Drop Experiments: Collision-Dominated Acoustic Emission

The vertical-drop configuration isolates the acoustic signature of particle–bed collisions under conditions of minimal boundary interference. In this regime, the inverse relationship between particle size and spectral centroid ( $R^2 = 0.946\text{--}0.972$ ) is consistent in direction with contact-mechanics models of acoustic emission from impacting particles, in which the characteristic frequency scales inversely with particle diameter [12,13]; the fitted exponents are, however, systematically smaller in magnitude than the ideal theoretical limit, as discussed below.

The fitted size–frequency relationships are empirical. Hertzian contact theory provides the reference framework, predicting a characteristic impact frequency [23,25]

$$f_c \propto d^{-1} \cdot \rho_p^{-2/5} \cdot E_*^{2/5} \cdot v^{1/5} \quad (6)$$

where  $d$  is the particle diameter,  $\rho_p$  the particle density,  $E_*$  the effective elastic modulus of the particle–substrate contact, and  $v$  the impact velocity. At fixed material and velocity, this scaling yields an ideal-limit exponent of  $-1$ , and it has been confirmed experimentally for the radiated energy of single-bead impacts [23]. The exponents fitted here ( $m = -0.18, -0.34, -0.50$  for pumice, dacite, and steel in the drop;  $-0.15, -0.23$ , and  $-0.32$  in the flume) are systematically smaller in magnitude; note that  $|m|$  increases with material density in both configurations and is consistently smaller in the flume. In the drop configuration, this flattening cannot be attributed to residual impact-velocity variations (aerodynamic drag contributes at most  $\approx 0.01$  to the exponent; Appendix A); rather, the centroid is a broadband ensemble metric integrating secondary collisions, inelasticity, substrate roughness—which alone can shift impact frequency by more than a factor of two [25]—and size-dependent radiation efficiency, all acting to flatten the scaling without altering its inverse direction. The steel series, with zero shape variance, reproduces the inverse size–frequency relationship on its own, demonstrating that size ordering alone is sufficient to produce the trend; within each natural material, the measured shape variability likely contributes to the within-fraction spectral scatter (Table 4). The characterization is two-dimensional; three-dimensional shape descriptors and systematic shape-contrast experiments at fixed size

and material are reserved for the next stage (Section 4.4). A physical model reproducing the observed exponents defines one of the objectives of the next stage of this program (Section 4.4).

Beyond size, the framework above identifies particle density and elastic modulus as controls on the contact frequency (the  $\rho_p^{-2/5}$  and  $E_*^{2/5}$  dependences), while internal damping and restitution govern the energy partitioning at impact, and surface roughness modifies the radiated spectrum [23,25]. In the present dataset, density spans nearly an order of magnitude across materials, whereas the two natural materials are nearly indistinguishable in shape (mean roundness 0.694, boundary roughness  $\leq 1.094$ , convexity  $\geq 0.954$ ; Section 2.1, Table A2). Within this stage, the elastic modulus and internal damping enter as fixed properties of the selected endmember materials rather than as controlled variables; their direct characterization is reserved for the single-property designs of the next stage (Section 4.4).

The systematic ordering of spectral centroids—steel spheres > dacite > pumice—at equivalent particle sizes indicates that material properties modulate the acoustic response, yet the dominant control on frequency remains particle diameter. Notably, the vertical offset between material curves aligns with the measured restitution coefficients ( $0.83 > 0.35 > 0.21$ ), suggesting that elastic energy recovery and density may influence the rate at which the spectral centroid decreases with increasing particle size rather than determining the centroid itself. These restitution values characterize particle–surface impacts under controlled binary collisions, whereas the acoustic emissions in vertical drops derive from particle–bed interactions involving identical materials. The qualitative consistency across these different contact configurations supports the inference that material-specific energy dissipation is detectable in collective flows, operating as a secondary modulation superimposed on the primary size–frequency trend.

The COV values (Table 4) quantify run-to-run dispersion across replicate experiments and increase sharply for the coarsest fraction, most notably for steel spheres at  $-5\phi$  (37%) (Figure 11). Three lines of evidence (Table 4) indicate that this scatter is an inherent property of large-particle collision dynamics rather than measurement uncertainty. First, the measurement chain is precise: the two microphones recording the same run agree to within 2% for all fractions finer than  $-4\phi$ , and the centroid estimator is stable within 3% in most conditions under processing-parameter variations (Section Sensitivity Analysis). Second, in the vertical-drop configuration, the COV remains low and approximately constant (2–6%) up to  $-4\phi$  and rises sharply only at  $-5\phi$ , where—because the sample volume is constant—the number of particles per run falls to the order of  $10^2$  and each record integrates only a few hundred collision events. Third, within-run (frame-to-frame) dispersion for steel spheres at  $-5\phi$  (13–17%) is markedly smaller than the run-to-run dispersion (37%), indicating that replicate runs differ systematically: with few particles, the signal is dominated by a small number of high-energy impact and rebound events whose occurrence and geometry vary between realizations. Consistent with this interpretation, natural materials at  $-5\phi$  exhibit lower COV values (9.5–10.5%) than steel spheres, because the 32–64 mm sieve fraction provides intra-fraction size averaging that is absent for the monodisperse 32 mm spheres.

#### 4.2. Flume Experiments: Robustness Testing Under Increased Complexity

The flume experiments constituted the second stage, designed specifically to evaluate whether the size–frequency relationship would persist upon introduction of additional physical complexity—including flow confinement, sustained shear, and potential boundary friction. While the general inverse trend was observable for specific granulometric fractions within each material, the relationship proved less consistent across the full size range

compared to vertical-drop experiments, as evidenced by lower coefficients of determination ( $R^2 = 0.752\text{--}0.832$  for steel and pumice) and non-monotonic deviations.

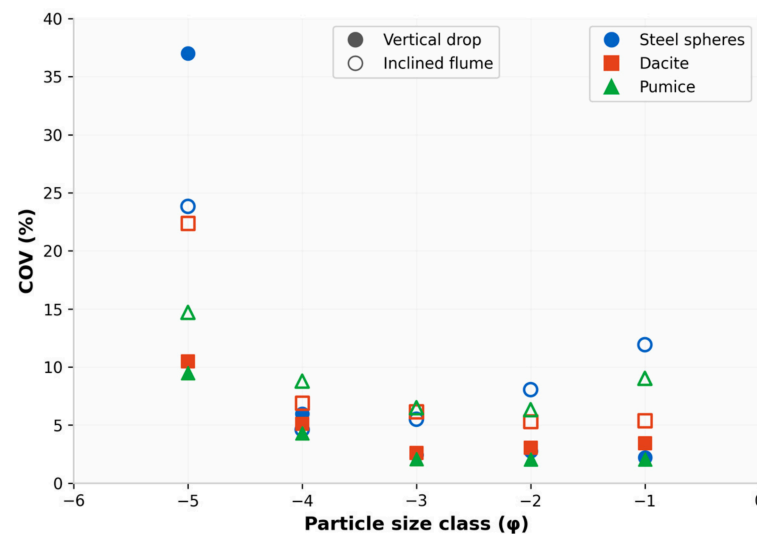


**Figure 11.** Coefficient of variation (COV = SD/mean, %) of the spectral centroid between replicate runs ( $n = 3$ ) as a function of particle size class, for steel spheres (circles), dacite (squares), and pumice (triangles) in the vertical-drop (filled markers) and inclined flume (open markers) configurations. COV remains at or below  $\sim 12\%$  for the four finer fractions ( $-1\phi$  to  $-4\phi$ ) in both configurations and increases sharply at  $-5\phi$  (up to  $37.0\%$  for steel spheres in the vertical-drop configuration), where the fixed sample volume reduces the number of particles—and thus of recorded collision events—per run.

The systematic shift of spectral centroids toward lower frequencies in the flume configuration ( $\Delta f \approx 3000\text{--}9000$  Hz) indicates that the acoustic signature is sensitive to flow geometry. Deviations from the power law, such as the local increase in centroid frequency for steel spheres between  $-1\phi$  and  $-2\phi$  and for pumice between  $-3\phi$  and  $-4\phi$ , are consistent with the expected coupled influence of boundary friction, sustained shear, and variable flow velocity inherent to confined granular flows. These variables were not instrumented in this stage—the flume configuration was designed to test the persistence of the size–frequency relationship, not to quantify individual flow variables—so their influence on the acoustic signal is assessed qualitatively, and their quantification belongs to the instrumented stages of this program (Section 4.4). These deviations are accompanied by a marked increase in run-to-run variability, as quantified by the coefficient of variation (COV) reported in Table 4. Under vertical-drop conditions, COV values remained below  $6\%$  for most material–size combinations, consistent with the kinematic simplicity of isolated particle–bed collisions. In contrast, flume experiments yielded COV values up to  $23.8\%$  for steel spheres ( $-5\phi$ ) and  $22.4\%$  for dacite ( $-5\phi$ ), with even the most reproducible flume runs (e.g., steel spheres at  $-4\phi$ , COV =  $4.6\%$ ) approaching the upper bound of their vertical-drop counterparts. The spectral centroid integrates the net acoustic signature of these concurrent interactions. While this aggregation precludes resolving individual physical mechanisms from the signal alone, it preserves the metric’s discriminative capacity across materials and size fractions under confined conditions, provided that the elevated run-to-run variability is accounted for via regime-specific calibration or ensemble averaging. These experiments were designed to test whether the size–frequency relationship persists under such conditions, not to isolate the specific contribution of each physical factor. Consequently, while the results confirm that particle size remains a detectable control on acoustic frequency in confined flows, they also demonstrate that the spectral centroid captures the net effect of multiple simultaneous interactions rather than a pure size signal.

Overall, these results confirm that a correlation between particle size and acoustic frequency can be detected in confined flow geometries; they also demonstrate that this relationship is not as robust as in collision-dominated vertical drops. The spectral centroid remains a viable metric for granulometric characterization, but its application to natural granular flows, where boundary conditions and kinematics are variable, will require condition-specific calibration.

#### 4.3. Implications for Granular Flow Characterization

Both experimental configurations establish the empirical calibration on which acoustic discrimination of particle size and material type rests; its application to flowing granular material requires that at least these three conditions be met: (i) material-specific calibration curves are established; (ii) the flow regime (unconfined vs. confined) is known or estimated; and (iii) acquisition bandwidth extends sufficiently beyond the audible range to ensure accurate centroid calculation.

The distinctiveness of the acoustic signatures from the vertical-drop experiments—across materials and particle sizes—is further corroborated by the successful application of neural network classifiers to the same dataset, which achieved more than 92% accuracy in material identification and more than 99% of size predictions within 1 $\phi$  [24]. It should be noted that these classifiers were trained and validated exclusively on free-fall data; extension to flume configurations remains to be tested. This convergence between physical characterization and machine-learning performance supports the viability of acoustics-based granulometric monitoring under collision-dominated conditions. However, the spectral centroid metric alone does not capture the multimodal spectral structure that neural networks exploit; future integration of multiple acoustic features will be necessary for robust automated classification across both experimental configurations.

From a broader geological perspective, this study represents, to our knowledge, the first systematic attempt to establish a quantitative, physically grounded relationship between particle size and the frequency content of acoustic emissions in collective granular avalanches, as opposed to single-particle or industrial powder systems [12–15]. Geophysical monitoring of granular hazards has so far relied almost exclusively on seismic and infrasonic techniques, well suited to detect, locate, and track the front of a moving mass [6–11], but not designed to resolve its internal granulometric composition. Acoustic flow monitor (AFM) systems, deployed operationally at several volcanoes since the 1990s for debris-flow and lahar detection [26,27], and more recent infrasound arrays capable of detecting lahars several kilometers away and tens of minutes before their arrival at a downstream monitoring point [28], demonstrate that passive acoustic instrumentation is already an accepted, field-proven tool for real-time hazard detection. The present results suggest that the same class of instrumentation, complemented by the spectral centroid analysis developed here, could in principle be upgraded from a purely detection-and-localization role toward one that also delivers a first-order estimate of the grain-size character of the moving mass—a capability that is not yet routine in any current operational monitoring network.

These results bear directly on the reliability of such first-order field estimates. Because natural flows involve orders of magnitude more particles than our laboratory charges, sustained flows integrate a much larger number of collision events within each analysis window and are therefore expected to fall within the converged, low-scatter regime observed for our finest fractions ( $\text{COV} \approx 2\%$ ). The coarse-fraction scatter documented here is therefore relevant mainly to short-duration pulses or coarse-dominated flows (e.g., fronts, individual block impacts), where few events are integrated per window. For such cases, two mitigation strategies apply: temporal ensemble averaging over longer flow durations, which reduces realization scatter approximately as  $1/\sqrt{N}$ , and spatial averaging with multi-



sensor arrays—inter-microphone differences here reached 13–28% for the coarsest fractions. Until such strategies are routine, coarse-fraction field inversions should be reported with explicit uncertainty intervals.

Room reflections, reverberation, atmospheric attenuation, microphone directionality, environmental noise, and the microphone frequency response were not characterized individually. These factors act as a common, stationary transfer function applied identically to all recordings within each configuration (same room, same microphones, fixed positions; Sections 2.2.1 and 2.3.1); they can bias the absolute centroid level but cannot generate the systematic size ordering observed across materials and configurations. The sub-meter to 1 m microphone distances keep the direct-to-reverberant ratio high and air absorption small; the omnidirectional microphones were used at fixed geometry; environmental noise is stationary and uncorrelated with the high-signal-to-noise ratio (SNR) impact signals. The microphone capsule (Panasonic WM-61A) has been characterized as usable with no degradation up to 48 kHz [22], within the acquisition bandwidth (Nyquist 48 kHz); spectral content beyond 48 kHz carries an unquantified response. The recorded high-frequency content is genuine signal: the signal-to-noise ratio of the active impact segments, estimated against an ambient recording acquired with the same chain in the same room, exceeds 20 dB below 20 kHz and 15 dB in the 20–48 kHz band.

#### 4.4. Limitations and Future Directions

This study is limited to dry materials that were either monodisperse (steel spheres) or narrowly sieved (dacite and pumice) within a restricted size range (2–64 mm) and a modest number of replicates ( $n = 3$ ). Future work must isolate the specific factors introduced in the flume configuration (e.g., via velocity measurements, shear stress estimation, or comparative roughness studies) to disentangle their individual contributions to the observed spectral shifts. Extension to polydisperse mixtures and field-scale validation remain necessary to establish generalizability.

A further limitation concerns impact velocity. The fixed drop height (1.2 m) was chosen to provide a nearly common impact velocity across fractions (Appendix A), so that granulometry was the single varying factor within the configuration. The sensitivity of the size–frequency relationship to impact velocity, impact energy, and drop height therefore falls outside the factor isolated here by design; its systematic study defines the next stage of this research program.

A further limitation concerns the fixed released volume: while this control held total particle mass and released potential energy approximately constant across fractions within each material series, particle count scales with the inverse cube of diameter, so that particle size and impact count covary within each series, and a residual contribution of count to the fitted exponents cannot be excluded at this stage. The spectral centroid is nevertheless an intensive, energy-weighted descriptor: for superposed impacts of similar spectra, the number of impacts modifies amplitude, energy, and duration rather than the normalized spectral shape. Consistently, experimental granular flows on the order of  $10^3$  particles have been shown to emit frequencies similar to those of single-particle impacts of the same material [25]. Systematic volume-variation experiments at fixed granulometry define the next stage of the program, isolating particle size from impact count directly and quantifying any residual contribution of collision rate to the spectral centroid.

Importantly, the dataset reported here has been used for machine learning classification training, demonstrating that algorithms can distinguish between the acoustic signatures of different materials and sizes within this controlled experimental set [24]. However, training was limited to internal validation. The generalization of these classification capabilities

to independent datasets, varying environmental conditions, or field-scale granular flows remains untested and represents a critical next step.

Density, particle morphology, and restitution coefficient covary in the present material set by design (endmember contrast; Section 2.1), so the relative contribution of each factor to the material-specific spectral offset cannot be isolated here (the qualitative parallelism between the measured restitution coefficients and the acoustic hierarchy is discussed in Section 4.1). Future work should address whether restitution alone, or its combination with density and shape, dominates the spectral signature in collective flows, through experimental designs that decouple these variables.

Future work should focus on (i) expanding the feature space beyond spectral centroid to include temporal and spectral shape descriptors; (ii) establishing ensemble averaging and multi-sensor protocols to reduce the elevated variability (COV up to ~29%) observed in confined-flow and coarse-fraction regimes; and (iii) validating machine learning classifiers against independent datasets and field-scale granular flows to establish generalizability; (iv) developing a physical model that reproduces the empirical size–frequency exponents—accounting for collective collisional effects, inelasticity, and radiation efficiency—supported by measurements of the elastic modulus and internal damping of the studied materials and by experimental designs that vary a single material property at fixed granulometry, including three-dimensional shape characterization and shape-contrast series; and (v) expanding replication and size-fraction coverage to tighten the confidence intervals of the fitted calibration parameters toward calibration-grade relationships.

These measurements can draw on complementary technologies: standard optical techniques (high-speed imaging, particle image velocimetry) for flow thickness and surface velocity; instrumented particles with embedded inertial sensors for the direct measurement of collision and entrainment dynamics [29]; and acoustic sensing for the characterization of turbulence-related noise [30].

From an applied perspective, these results constitute a first, laboratory-scale step within a staged program toward real-time acoustic granulometry of geological phenomena; the implications for civil protection practice are therefore long-term and contingent on the extensions outlined below. Grain-size distribution is not a secondary descriptor of a granular hazard but a primary control on its rheology, mobility, and destructive capacity [1,2,31], yet it is presently characterized almost exclusively after the event, through sieving of the deposit. Passive acoustic instrumentation already operating at several volcanoes for flow detection and tracking [26–28] could, in principle, be processed with the spectral analysis demonstrated here; whether the size–frequency relationship survives field propagation, ambient noise, and multiphase flow conditions remains to be established in the next study. This, combined with the use of machine learning techniques that are increasingly entering the day-to-day monitoring routines [32], raises the prospect of upgrading existing detection networks to deliver first-order grain-size information while a flow is still in motion. Such information could support more informed, dynamic decision-making during an unfolding event, for instance, distinguishing a coarse, bouldery flow front of high impact potential from a finer-grained, more mobile one, complementing the warning times of tens of minutes already documented for infrasound-based lahar detection [28]. The explicit recognition that the present dataset is single-phase, and the corresponding research agenda outlined for two, three, and multiphase systems (Section 4.5), should therefore be understood not as a limitation undermining this study’s relevance, but as the deliberate first stage of a factor-isolation program—particle size here; velocity, medium interactions, moisture, and topographic effects in the next study—toward acoustics-based, real-time granulometric monitoring of natural hazards such as debris avalanches, lahars, and pyroclastic density currents.

#### 4.5. From Single-Phase Laboratory Systems to Multiphase Natural Flows

The materials and experimental configurations examined here are deliberately single-phase: a single dry granular phase (steel spheres, dacite, or pumice) moving in air, free of interstitial water and free of mixing with particle populations of contrasting density. This simplification was a necessary methodological choice, allowing the effect of particle diameter on the acoustic spectrum to be isolated from confounding variables such as density, restitution, and particle shape. However, no natural granular hazard is single-phase in this strict sense. Debris avalanches and sturzstroms already constitute at least a two-phase system, combining a granular solid phase with interstitial air (or water) that can become transiently pressurized and modulate internal friction during emplacement [1,33]. Pyroclastic density currents are multiphase and polydisperse, combining juvenile pumice, dense lithic clasts, and crystals of contrasting density suspended in a hot gas phase. They are commonly organized into a concentrated basal current overlain by a dilute turbulent ash cloud, with continuous particle exchange and segregation between the two [2,34]. Lahars are commonly three-phase mixtures of sediment, water, and air. Their rheology evolves continuously along the flow path—transitioning between a debris-flow regime and a hyperconcentrated streamflow regime—as sediment concentration changes through downstream dilution or proximal bulking [31].

Extending acoustic granulometry to these systems will require addressing several physical complications absent from the present dry, single-phase configuration. An interstitial fluid changes the contact mechanics of particle collisions, replacing the largely elastic, dry impacts captured here with lubricated or viscously damped contacts. The spectral signature of these contacts is expected to depend on fluid viscosity and concentration in addition to particle size [33]. When multiple particle populations of contrasting density and size coexist, as in pyroclastic density currents, the resulting acoustic signal becomes a superposition of several concurrent spectral signatures. A single descriptor such as the spectral centroid is therefore unlikely to remain sufficient; spectral unmixing or multi-feature classification strategies will likely be required. In dilute, turbulent regimes, fluid-generated noise may compete with particle-collision noise within the same frequency band, further complicating signal discrimination. Computational frameworks capable of resolving multiphase granular flow–wall interactions [35] may assist in disentangling the relative contributions of boundary friction, particle–particle contacts, and fluid turbulence to the resulting acoustic signature in confined, multiphase flows. Finally, field deployment introduces propagation and site effects—distance-dependent and frequency-selective attenuation, topographically controlled propagation paths with variable source–receiver geometry and line-of-sight obstruction, moving-source effects, and uncontrolled background noise (wind, rainfall, river turbulence)—that have no equivalent in the controlled laboratory geometry used here, reinforcing the need for flow-regime-specific calibration already suggested by the offset observed between the vertical-drop and flume configurations (Section 4.2).

Despite the complexity of natural phenomena, the results obtained for the single-phase materials investigated here should be regarded as a necessary physical foundation for future extensions of this approach, rather than as an alternative research direction. The establishment of calibration curves and material-specific spectral baselines under controlled single-phase conditions is a prerequisite for meaningfully disentangling the overlapping effects of additional phases in more complex systems. Since grain size exerts a first-order control on the mobility, runout, and destructive potential of granular hazards [1,2,31], the capability to infer approximate grain-size information in real time from natural multiphase flows would constitute a significant advance in hazard characterization. This potential benefit justifies the methodological effort required to extend the present framework to two-phase, three-phase, and ultimately multiphase systems.

## 5. Conclusions

This study establishes a robust inverse relationship between mean particle size and the spectral centroid of acoustic emissions from granular avalanches. Under collision-dominated vertical-drop conditions, the relationship holds across three materials spanning a wide range of density, restitution coefficient, and particle morphology ( $R^2 = 0.946\text{--}0.972$ ), confirming particle diameter as the dominant control on centroid frequency, with material properties producing a secondary, systematic offset.

The inverse trend persists in confined flume flows, demonstrating robustness to the introduction of boundary friction, sustained shear, and variable flow kinematics. However, centroids shift systematically toward lower frequencies, the power-law fit degrades for two of the three materials ( $R^2 = 0.832$  for steel and  $0.752$  for pumice, versus  $0.980$  for dacite), and run-to-run variability increases, indicating that under confined conditions the centroid integrates the net effect of concurrent interactions rather than a pure size signal; regime-specific calibration is therefore required.

The elevated dispersion of the coarsest fractions (COV up to 37%) reflects the inherent statistics of few-event collision ensembles rather than measurement uncertainty: the measurement chain is precise (inter-microphone agreement within 2% for fine fractions in the vertical-drop configuration), and dispersion rises sharply only when the particle count per run falls to the order of  $10^2$ . Temporal ensemble averaging and spatial multi-sensor arrays are the natural mitigation strategies for monitoring applications.

Accurate centroid determination requires an acquisition bandwidth extending to 48 kHz even though the final centroid values lie within the audible range, and is robust to reasonable processing-parameter choices (Section Sensitivity Analysis); both constitute concrete design constraints for future monitoring-oriented developments.

Together, these findings constitute the controlled physical foundation of the staged factor-isolation research program outlined in Section 4.4, whose long-term objective is acoustics-based granulometric characterization of natural granular flows.

We stress that the present study validates the size–frequency relationship itself—the calibration underlying acoustic granulometry—and quantifies its uncertainty bounds; a predictive model for the inversion of unknown granular samples, which must incorporate the remaining factors that modulate the signal, is the goal of the subsequent stages of this program.

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## Abbreviations

The following abbreviations are used in this manuscript:

|      |                                   |
|------|-----------------------------------|
| 2D   | Two-dimensional                   |
| AFM  | Acoustic flow monitor             |
| AISI | American Iron and Steel Institute |
| CI   | Confidence interval               |
| COR  | Coefficient of restitution        |
| COV  | Coefficient of variation          |
| DC   | Direct current                    |
| LED  | Light-emitting diode              |
| PSD  | Power spectral density            |
| PVC  | Polyvinyl chloride                |
| SD   | Standard deviation                |
| SEM  | Standard error of the mean        |
| SNR  | Signal-to-noise ratio             |
| STFT | Short-time Fourier transform      |

## Appendix A. Upper-Bound Estimates of Impact Velocity Including Aerodynamic Drag

### Appendix A.1. Governing Equation

A particle released from rest at height  $h = 1.2$  m accelerates under gravity and is decelerated by quadratic aerodynamic drag:

$$m \frac{dv}{dt} = mg - \frac{1}{2} \rho_a C_D A v^2 \quad (\text{A1})$$

which, for a particle falling from rest, admits the exact solution

$$v = v_t \left[ 1 - e^{\frac{-2gh}{v_t^2}} \right]^{\frac{1}{2}} \quad (\text{A2})$$

where  $v_t$  is the terminal velocity at which aerodynamic drag balances the particle weight:

$$v_t = \sqrt{\frac{4\rho_p d g}{3\rho_a C_D}} \quad (\text{A3})$$

and the free-fall (no-drag) reference velocity is

$$v_0 = \sqrt{2gh} = 4.852 \text{ m/s} \quad (\text{A4})$$

### Appendix A.2. Inputs and Parameters

Gravity:  $g = 9.81 \text{ m/s}^2$ . Air properties:  $\rho_a = 1.2 \text{ kg/m}^3$  and  $\mu_a = 1.81 \times 10^{-5} \text{ Pa}\cdot\text{s}$  (standard sea-level values at  $20^\circ\text{C}$ ; at the elevation of the experimental site the air density is lower, which would further reduce drag, the values adopted are therefore conservative). Particle diameters  $d$  were taken from Table 1 of the manuscript: nominal monodisperse values for steel spheres (2–32 mm) and the geometric mean of the sieve bounds for the natural fractions (2.83–45.25 mm). Material densities: 7870 (steel), 2700 (dacite), and



700 kg/m<sup>3</sup> (pumice). Particle mass and cross-sectional area were computed from the equivalent-sphere geometry:

$$m = \frac{\rho_p \pi d^3}{6}, A = \frac{\pi d^2}{4} \quad (\text{A5})$$

### Appendix A.3. Drag Coefficient and Iterative Solution

The drag coefficient depends on the Reynolds number

$$Re = \frac{\rho_a v d}{\mu_a} \quad (\text{A6})$$

which, in turn, depends on the impact velocity. Both were therefore solved simultaneously by fixed-point iteration: starting from  $C_d = 0.47$ , the terminal velocity, Reynolds number, and drag coefficient were recomputed until convergence (~80 iterations). The drag law adopted was a Schiller–Naumann-type correlation for  $Re < 10^3$  and the standard sphere plateau for higher Reynolds numbers

$$C_D = \frac{24}{Re} \left( 1 + 0.15 Re^{0.687} \right) \left( Re < 10^3 \right) \quad (\text{A7})$$

$$C_D = 0.47 \left( Re \geq 10^3 \right) \quad (\text{A8})$$

This class of correlations has been extensively validated against the complete historical sphere-drag dataset [36], whose best-fit expression shares the same high-Reynolds-number plateau ( $C_D = 0.47$ ). To account for the irregular morphology of the natural clasts, a shape factor of 1.5 was applied to  $C_D$  for dacite and pumice, within the range of shape-induced drag corrections reported for non-spherical particles [37]; steel spheres used the unmodified sphere law (shape factor 1.0).

### Appendix A.4. Results and Conversion to Spectral Centroid Bias

The resulting impact velocities and their deviations from the free-fall reference  $v_0 = 4.852 \text{ m/s}$  are listed (Table A1) for all material–size combinations. Under Hertzian contact mechanics, the contact time scales as  $t \propto v^{-\frac{1}{5}}$ , so the characteristic impact-vibration frequency scales  $t_c \propto v^{\frac{1}{5}}$ , a scaling derived analytically for granular impacts [23] and used to relate laboratory impact frequencies to field-scale granular-flow signals [25]. The associated spectral centroid bias is therefore

$$\frac{\Delta f}{f} = 1 - \left( \frac{v}{v_0} \right)^{1/5} \quad (\text{A9})$$

Even the largest estimated velocity deviation (pumice,  $-1\phi$  fraction, 15.6%) thus corresponds to a centroid bias of only 3.3%, and all other material–size combinations remain below 1%.

**Table A1.** Estimated impact velocities, deviations from the free-fall reference (4.852 m/s), and associated spectral centroid biases (Equation (A8), exact evaluation) for all material–size combinations of the vertical-drop experiments.

| Material      | Size ( $\phi$ ) | d (mm) | $\rho$ (kg/m <sup>3</sup> ) | Shape Factor | v Impact (m/s) | Deviation (%) | $\Delta f/f$ (%) |
|---------------|-----------------|--------|-----------------------------|--------------|----------------|---------------|------------------|
| Steel spheres | −1              | 2.00   | 7870                        | 1.0          | 4.780          | 1.49          | 0.30             |
|               | −2              | 4.00   |                             |              | 4.816          | 0.75          | 0.15             |
|               | −3              | 8.00   |                             |              | 4.834          | 0.38          | 0.07             |
|               | −4              | 16.00  |                             |              | 4.843          | 0.19          | 0.04             |

Table A1. Cont.

| Material | Size ( $\varphi$ ) | d (mm) | $\rho$ (kg/m <sup>3</sup> ) | Shape Factor | v Impact (m/s) | Deviation (%) | $\Delta f/f$ (%) |
|----------|--------------------|--------|-----------------------------|--------------|----------------|---------------|------------------|
| Dacite   | −5                 | 32.00  | 2700                        | 1.5          | 4.848          | 0.09          | 0.02             |
|          | −1                 | 2.83   |                             |              | 4.634          | 4.49          | 0.92             |
|          | −2                 | 5.66   |                             |              | 4.741          | 2.29          | 0.46             |
|          | −3                 | 11.31  |                             |              | 4.796          | 1.16          | 0.23             |
|          | −4                 | 22.63  |                             |              | 4.824          | 0.58          | 0.12             |
| Pumice   | −5                 | 45.25  | 700                         | 1.5          | 4.837          | 0.31          | 0.06             |
|          | −1                 | 2.83   |                             |              | 4.097          | 15.57         | 3.33             |
|          | −2                 | 5.66   |                             |              | 4.447          | 8.36          | 1.73             |
|          | −3                 | 11.31  |                             |              | 4.642          | 4.34          | 0.88             |
|          | −4                 | 22.63  |                             |              | 4.745          | 2.21          | 0.45             |
|          | −5                 | 45.25  |                             |              | 4.79           | 1.19          | 0.24             |

#### Appendix A.5. Conservative Character of the Estimates

All values reported (Table A1) are upper bounds, by construction: (i) the estimates assume isolated particles, whereas collective settling of the dense particle cloud entrains the surrounding air, reducing the relative velocity between particles and air and therefore the effective drag; (ii) sea-level air density was used despite the elevation of the experimental site; and (iii) the shape factor of 1.5 for irregular clasts was chosen deliberately high. True impact-velocity deviations are expected to be smaller than the values reported here.

#### Appendix A.6. Quantitative Shape Descriptors per Material

**Table A2.** Quantitative shape descriptors per material (mean  $\pm$  SD). All three descriptors differed significantly across the three materials (Kruskal–Wallis,  $p < 0.001$ , driven by the steel-sphere control); between the two natural materials, roundness did not differ significantly (Mann–Whitney U,  $p = 0.733$ ). No significant correlation was observed between particle size (equivalent diameter from the projected area) and either roundness or roughness within the natural materials.

| Material | n  | Roundness         | Boundary Roughness | Convexity         |
|----------|----|-------------------|--------------------|-------------------|
| Steel    | 9  | 1.000             | 1.000              | 1.000             |
| Dacite   | 21 | 0.694 $\pm$ 0.134 | 1.094 $\pm$ 0.032  | 0.954 $\pm$ 0.016 |
| Pumice   | 25 | 0.694 $\pm$ 0.098 | 1.075 $\pm$ 0.022  | 0.965 $\pm$ 0.025 |

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