

Article

Comparative Analysis of Large-Scale Testing and Three-Dimensional Rockfall Modeling in Assessment of Tabulated Coefficients of Restitution

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Featured Application

Predicting the trajectory of falling rocks is essential for safe infrastructure design in mountainous regions. The coefficient of restitution is the keystone to accurate modeling.

Abstract

Rockfall hazard assessment and mitigation design relies heavily on three-dimensional trajectory modeling, in which the coefficient of restitution (COR) is a governing parameter controlling rebound, energy dissipation, and runout distance. In practice, COR values are commonly selected from generalized tables based on slope material type, introducing significant epistemic uncertainty and limiting predictive accuracy. This study presents a comparative evaluation of large-scale field rockfall experiments and 3-D numerical simulations conducted at a former aggregate quarry in Boise, Idaho, to assess the performance of tabulated restitution coefficients. Concrete blocks of controlled shape (spheres, cubes, and rectangular prisms) and mass (17–68 kg) were instrumented with inertial sensors and released from two slope configurations. High-resolution UAV-based LiDAR was used to reconstruct slope geometry, while dynamic cone penetrometer and friction tests were performed to characterize spatial variability in slope material stiffness. These data were incorporated into RocFall3 to simulate block trajectories using spatially varying COR values. Initial models assuming zero rotational velocity and tabulated COR ranges failed to reproduce observed runout distances, dispersion patterns, and modes of motion, particularly for non-spherical blocks. Incorporating field-measured initial rotational velocities significantly improved agreement between modeled and observed trajectories, by correcting the unrealistic sliding mode of motion previously observed. However, quantitative discrepancies in deposition and dispersion persisted, highlighting limitations associated with simplified slope geometry and the loss of small-scale surface features during LiDAR surface reconstruction. The results demonstrate that restitution behavior is strongly shape-dependent and that realistic initial conditions are essential for physically meaningful simulations. The findings underscore the need for site-specific, material-informed approaches to COR estimation and for improved integration of high-fidelity field data into physics-based rockfall models.



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1. Introduction

Rockfall is a pervasive natural hazard in mountainous terrain and poses a persistent threat to transportation corridors, lifelines, and nearby communities. As development expands into steep and geologically complex environments, the need for reliable tools to predict rockfall trajectories, impact energies, and runout distances has become increasingly critical. Three-dimensional rockfall modeling has become a core component of modern hazard assessment and mitigation design; it has been used to assess rockfall trajectories [1–4] and to support the placement and sizing of protective measures such as catchment ditches and barriers [5–7].

Among the parameters required by physics-based simulation software, the coefficient of restitution (COR) is frequently among the most influential, as it directly controls rebound, energy dissipation, and therefore runout distance and dispersion. In practice, COR is often represented as normal and tangential components and used as a simplified proxy for complex impact physics. Many models are highly sensitive to these values, and selecting them from generalized tables can introduce substantial epistemic uncertainty. Bourrier et al. [8] explicitly note the sensitivity of rockfall models to restitution coefficients and the practical difficulty of estimating them in the field, motivating more objective or site-calibrated approaches.

The impact process and resulting motion of a block moving downslope are more complex than the straight-line translational motion of its center of mass, which is the velocity quantity implicitly assumed in most coefficient of restitution formulations, as rotational and tangential energy components can be redistributed into the normal rebound direction during impact. Rotational energy, impact angle, surface roughness, and local geometry can strongly affect rebound. The importance of these controls is reflected in early experimental work on restitution and rotation in rockfall impacts [9] and in later studies that emphasize the role of impact angle and rotational energy transfer in controlling normal and tangential COR [10–13]. Because of these complexities, “single-value” restitution assumptions can be misleading, especially when surface roughness and micro-topography strongly influence contact conditions.

Despite this, engineering workflows commonly rely on tabulated restitution values for broad slope material categories (e.g., bedrock, talus, soil), including those embedded in commercial software guidance and training materials. For instance, widely circulated rock engineering guidance notes that hard, clean rock surfaces generally exhibit higher restitution than soil/gravel surfaces, reflecting the intuitive relationship between substrate compliance and energy loss. However, such qualitative categories frequently mask large within-category variability (due to weathering, moisture, vegetation, cobbles, and stiffness contrasts), which can translate into large differences in modeled runout and impact energies.

This uncertainty has direct implications for hazard mitigation design. Overestimation of COR leads to inflated runout distances and energy envelopes, often resulting in unnecessarily conservative and costly mitigation systems, whereas underestimation may compromise public safety. Although prior work has explored restitution behavior using laboratory-scale tests or limited in situ experiments [9,14,15], there remains a lack of large-scale, instrumented fieldwork that explicitly links measurable elastic slope properties to restitution behavior of slope materials.

This study addresses these needs by comparing large-scale field rockfall experiments with 3-D numerical simulations at a former aggregate quarry in Boise, Idaho. Concrete blocks of controlled shape and mass were instrumented with inertial sensors and released on two slopes with differing inclinations and stiffness profiles. High-resolution UAV-based LiDAR was used to reconstruct slope geometry, while dynamic cone penetrometer and friction tests provided spatially distributed measurements of slope material properties.

These data were incorporated into RocFall3 to evaluate the performance of tabulated restitution coefficients and to investigate whether material-informed COR values and measured initial conditions can produce more accurate predictions of runout, dispersion, and modes of motion.

2. Coefficient of Restitution

The coefficient of restitution (COR) is the keystone of rockfall modeling. It is the numerical quantification of the elasticity of a collision between two objects. An extreme value of 0 indicates a perfectly inelastic collision, in which the falling object does not rebound. In the case of a rockfall event, this means the rock would impact the slope and come to a complete stop. The other extreme case is a value of 1, which describes a perfectly elastic collision where no energy is lost during the impact. Real-world collisions have a COR somewhere between these extreme values.

The rockfall COR can be calculated by investigating the rock motion immediately before and after impact. This is frequently performed with respect to both velocity and translational kinetic energy, as described below in Equations (1) and (2). Once the energy-based COR equation is simplified, it is just the squared version of the velocity-based COR equation.

$$\text{Velocity COR} = \frac{v_{out}}{v_{in}} \quad (1)$$

$$\text{Energy COR} = \frac{KE_{t, out}}{KE_{t, in}} \equiv \frac{\frac{1}{2}mv_{out}^2}{\frac{1}{2}mv_{in}^2} \equiv \frac{v_{out}^2}{v_{in}^2} \quad (2)$$

Strictly viewing rockfall impacts through a translational framework is an oversimplification of the complex energy storage and shedding mechanisms at play. As the rock moves downslope, the potential energy it once had due to its relative elevation at the summit is transformed into kinetic energy (Equation (3)). It has components of velocity in both translation and rotation, which together comprise its total kinetic energy. With each impact, a portion of this energy is transferred to the soil, as described by the COR, or is dissipated through friction between the slope and the bouncing, rolling, or sliding rock. Once the entirety of the rock's kinetic energy has been transferred and transformed into other forms, it comes to rest.

$$\begin{aligned} E_{total} &= KE_{translational} + KE_{rotational} + PE_{gravitational} \\ E_{total} &= \frac{1}{2}mv^2 + \frac{1}{2}I\omega^2 + mgh \end{aligned} \quad (3)$$

Early rockfall modeling used a lumped-mass computational approach, in which blocks are simulated without shape or size, but with an associated mass and designated both normal and tangential coefficients of restitution. The normal COR only considers the portion of the rock's motion normal to the slope (indicated by the dotted red line in Figure 1), while the tangential COR is the portion tangent to the slope. Splitting the COR into its constituent parts allowed the effect of the rock shape to be accounted for to some extent while maintaining ease of computation.

Previous research [11,15–18] has experimentally determined that the normal COR is greater than 1 for certain impacts. This is because the normal velocity accounts for only a portion of the system's total energy. The incoming rock may have had substantial tangential or rotational velocity, which was converted into normal velocity during the impact due to the rock's geometry and the slope. This does not mean the rock gained energy during impact; it just transformed the energy it had into another form. It is crucial that rockfall impact mechanics and modeling are anchored in physics-based principles and abide by the law of conservation of energy. For this reason, it is critical to approach rockfall

impact mechanics through the lens of total energy. If we are to use a COR value, it should include both translational and rotational components. The potential energy of the rock can be ignored for a single impact since the elevation immediately before and after impact is identical.

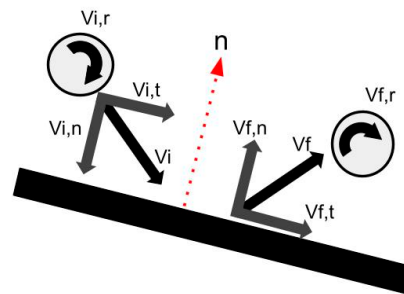


Figure 1. Coefficient of Restitution Diagram. Initial rotational velocity ($V_{i,r}$), initial normal velocity ($V_{i,n}$), initial tangential velocity ($V_{i,t}$), initial resultant velocity (V_i), final rotational velocity ($V_{f,r}$), final normal velocity ($V_{f,n}$), final tangential velocity ($V_{f,t}$), final resultant velocity (V_f), vector normal to impact surface (n).

In the case of a perfectly spherical rock, the impact will be unaffected by which portion of the rock impacts the slope. However, any other shape, as seen in real-world scenarios, presents the necessary complication of substantial differences in rebound depending on which portion of the block impacts the slope.

As rockfall modeling became more sophisticated, the effect of shape could be accounted for directly using the rigid-body calculation approach. This requires a mass for the falling rock, a single COR value, and an input shape. This shape component makes it much more realistic by modeling the impacts of face, edge, and corner differently within the model.

The goal of the COR is to capture the elastic response of a slope material during impact, with a single value. Previous research has found that COR is highly dependent on many factors related to both the rock and the slope, as described in Figure 2. In 2002, Chau et al. [9] used spherical rocks on artificial laboratory slopes, finding that normal COR increases with slope angle, whereas tangential COR showed no clear trend. They also found rotational kinetic energy increases with slope angle, peaking at 40 degrees, then declines. In 2008, Imre et al. [14] used steel and granite spheres to explore restitution patterns on rock surfaces. Findings indicate that COR varies with drop height, with higher impact forces resulting in greater energy dissipation. In 2011, Buzzi et al. [17] conducted controlled laboratory experiments finding that square and pentagonal blocks show increased normal COR due to multiple contact points and flipping motions. They also found that the introduction of surface roughness dissipated energy and significantly modified rockfall behavior. In 2015, Giokari et al. [19] investigated slope surface weathering, finding that more weathered surfaces decreased COR values. In 2013, Ferrari et al. [16] conducted in situ rockfall tests in Northern Italy, finding that steeper slopes, more elongated blocks, and lower impact velocities yielded higher normal COR values. In 2016, Li et al. [20] conducted laboratory experiments using plate- and strip-shaped blocks, finding higher COR values associated with increased slope angle, lower impact angles, and strip blocks than plate blocks. In 2019, Asteriou [11] used spherical blocks of different materials (concrete, marble, sandstone) to test different impact angles and incident velocities, finding that lower impact angles increase normal COR but not tangential COR. He determined normal COR is the most reliable metric for predicting rebound behavior, noting that energy COR (which accounts for rotational effects) has minor implications for spherical objects. In 2019, Ji et al. [10] expanded on this by considering 10 different shapes, finding that rotational speed has

minimal effect on normal COR for round blocks but significantly modifies the trajectories of non-spherical blocks.

Many other researchers have also explored the complex influence of rotation on rockfall [12,21–23]. In 2025, Li et al. [24] simulated multi-block rockfall dynamics, finding that higher block sphericity leads to greater bouncing and rolling, yielding longer runout distances. They also found that vegetation significantly dissipates energy and decreases runout. Vegetation was also explored by Dorren et al. in 2006 [25]. In conducting over 218 full-scale rockfall experiments in the French Alps, damping coefficients were created for highly vegetated (forested) slopes. In 2013, Asteriou et al. [26] proposed a momentum-based scaling factor for COR after finding that higher impact velocities result in greater plastic deformation and, therefore, greater energy shedding.

Each of these studies supports the framework that COR is both complex and nuanced. Together, they contribute to a gallery of tabulated COR values based on the slope material. In practice, an engineer will typically determine which tabulated soil type most closely correlates to their slope, and select a COR or range of COR values to model their situation. Typical values for varying soil and rock slope types are presented below in Table 1.

Table 1. Normal and Tangential Restitution Coefficients for Varying Soil and Rock Types.

Soil Type	R _n	R _t	Source
Talus cover	0.28–0.36	0.76–0.84	Rocfall3 by Rocscience
Asphalt	0.36–0.44	0.87–0.93	
Concrete	0.29–0.67	0.35–0.70	
Soil	0.393	0.567	
Talus cover	0.28–0.36	0.76–0.84	[27]
Asphalt	0.36–0.44	0.87–0.93	
Concrete	0.44–0.52	0.50–0.56	
Soil	0.12–0.16	0.46–0.54	
Sandstone face	0.37–0.69	0.63–0.69	[28]
Vegetated soil slope	0.20–0.37	0.55–0.81	
Soft soil, some vegetation	0.21–0.39	0.56–0.83	
Limestone face	0.22–0.40	0.50–0.74	
Talus cover with vegetation	0.22–0.42	0.56–0.83	[29]
Bedrock	0.25–0.75	0.88–0.98	
Intensely weathered bedrock	0.15–0.37	0.75–0.95	
Fragmented rock layer	0.15–0.37	0.75–0.95	
Dense gravel layer, hard soil slopes, shrub-based vegetation	0.12–0.33	0.30–0.95	[30]
Dense gravel layer, hard soil layer, no vegetation	0.12–0.32	0.65–0.95	
Loose rock layer, soft soil layer, and shrub-dominated vegetation	0.10–0.25	0.30–0.80	
Loose soil layer, no vegetation	0.10–0.30	0.50–0.80	
Medium to thick bedded cretaceous limestones	0.46–0.52	0.85–0.92	[30]
Semi—cemented scree	0.29–0.35	0.79–0.85	
Semi—cemented scree with sparse vegetation	0.26–0.33	0.77–0.83	
Limestone with dense low vegetation	0.28–0.34	0.67–0.74	
Thick bedded fractured Triassic limestones with low vegetation	0.27–0.37	0.70–0.80	[30]
Thin bedded fractured Jurassic limestones with dense low vegetation	0.25–0.35	0.65–0.75	

Variation of material behavior, even within the same soil type, leads to wide ranges of values for both normal and tangential restitution coefficients. This study supports ongoing research to develop and implement efficient testing methods for assessing the dynamic properties of slope materials for more accurate rockfall modeling.

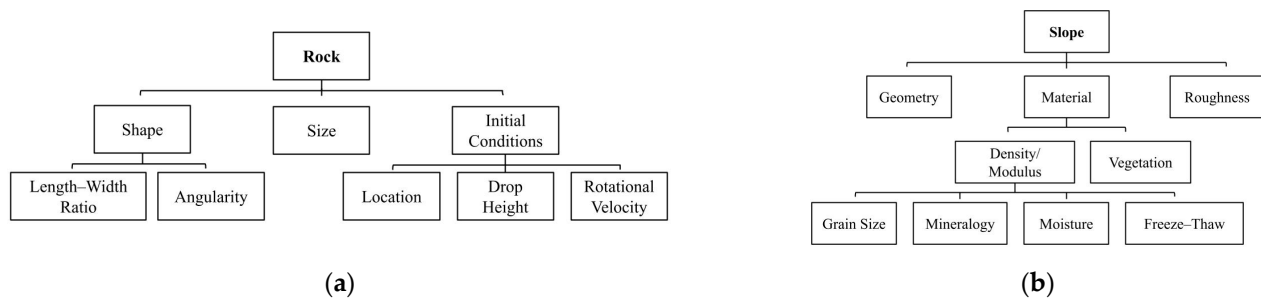


Figure 2. Factors Influencing Coefficient of Restitution and Rockfall Trajectory: (a) Rock; (b) Slope.

3. Materials and Methods

3.1. Study Site (Slopes) and Lidar Scan

Drop tests were conducted on two slopes of varying inclination in what previously served as an aggregate quarry in Boise, Idaho, USA. An initial LiDAR scan of the site was performed using a DJI Matrice 350 RTK (SZ DJI Technology Co., Shenzhen, China) unmanned aerial vehicle with a RESEPI Hesai XT-32 (Inertial Labs, Paeonian Springs, VA, USA) LiDAR unit. At the time of the survey, UAV-based LiDAR was selected because it provided a rapid and reliable means of capturing high-density three-dimensional surface geometry across the quarry slope, with minimal sensitivity to lighting conditions, surface texture, or shadowing that can complicate photogrammetric reconstructions. The intent was to generate the highest-fidelity terrain representation possible for import into the rockfall modeling software, particularly in areas of steep relief, sharp break-in-slope features, and rough surface micro-topography. In practice, however, subsequent down-sampling and surface smoothing required by the modeling software limited the extent to which the native LiDAR resolution could be fully exploited. As a result, a photogrammetrically derived digital surface model would likely have produced a similar large-scale slope geometry for this specific site. A preliminary model of the site is shown in Figure 3 with the drop or seeder locations indicated.

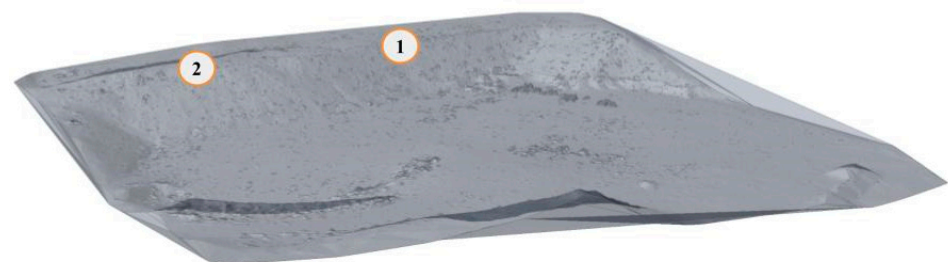


Figure 3. Aggregate Quarry Model with Drop/Seeder Locations Indicated.

The first drop location will be referred to as Seeder 1 and sits at the crest of a slope with an average inclination of 31.2 degrees. The material comprising the slope is a sandy gravel with intermittent cobbles and minor sagebrush vegetation. The slope cross-sectional profile is shown below in Figure 4a. The second drop location will be referred to as Seeder 2, and has an average inclination of 26.2 degrees. The material comprising the slope is sandy gravel with minor sagebrush vegetation. The slope cross-sectional profile is shown below in Figure 4b.

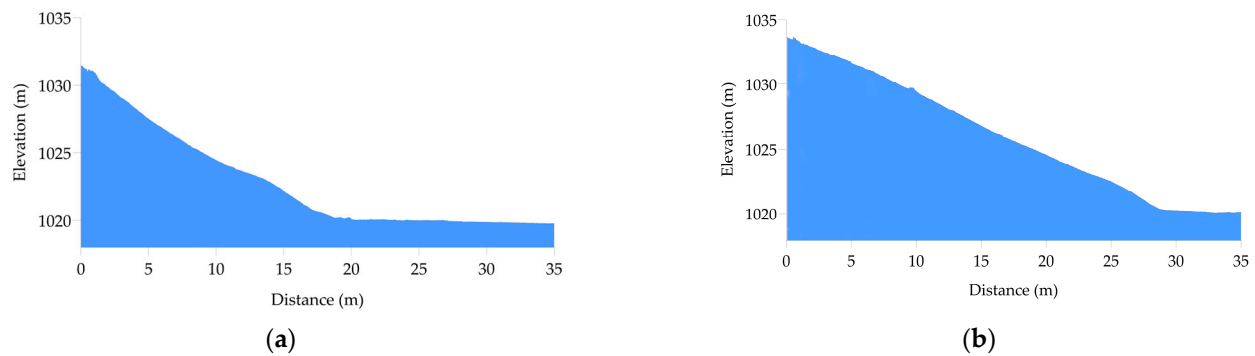


Figure 4. Slope Profile: (a) Seeder 1; (b) Seeder 2.

3.2. Concrete Blocks

The shapes of the concrete blocks (Figure 5a) used for testing were spheres, cubes, and rectangular prisms (length-to-width ratio of 2:1). These shapes were chosen for ease of construction, similarity to idealized rock shapes in the real world, and comparability. The effect of rock angularity can be assessed by comparing sphere and cube results, while the effect of elongation can be assessed by comparing cubes and rectangular prisms. Each shape was made of Portland cement concrete, and fabricated in three sizes: 17, 34, and 68 kg. Each block was constructed with an internal threaded PVC sleeve terminating just past the center of the block, allowing an inertial sensor (enDAQ sensor model S4-R2000D40, Woburn, Massachusetts, USA) to be placed at the centroid. This sensor internally logs rotational velocity and acceleration to analyze the initial conditions of the blocks as they leave the ramp (Figure 5b). The sensor is locked into place with a threaded end cap. At Seeder 1, 34 and 68 kg blocks were dropped for each shape. The cubes and rectangular prisms were dropped six times, and the spheres were dropped seven times. At Seeder 2, 17, 34, and 68 kg spheres and cubes were dropped and only the 17 and 34 kg rectangular prisms were dropped. Each block size was dropped 10 times.



Figure 5. (a) Artificial Concrete Rocks and (b) Drop Ramp.

The ramp shown in Figure 5b was set up at an angle of approximately 27 degrees and placed at the crest of both slopes. All blocks were set at the top of the ramp and then released. The ramp was fabricated with cylindrical rollers, allowing cubes and rectangular prisms to slide down the ramp, while the spheres were rolled on two lumber guides. It is worth noting that although all shapes exited the ramp with translational kinetic energy, only the spheres had a component of rotational kinetic energy. Cameras were placed around the ramp to record the motion of the blocks during the test.

To record the initial and final location of each block, an Emlid Reach RS+ Base and Rover RTK system (Emlid, Budapest, Hungary) was used. The Base remained stationary for the entirety of the drops while the Rover and the Emlid Flow app (software v14.5) were used to record locations of the drops in the WGS 84/UTM Zone 11N coordinate system. The Emlid Flow 360 website and Emlid studio software (v1.9) was later used to extract the recorded points, which were used to analyze the dispersion and deposition of the blocks released from the two seeder locations.

3.3. Material Testing and Results

At the site, soil tests were conducted along the slope and on the ground near both slopes. At Seeder 1, six dynamic cone penetrometer (DCP) tests were performed; two on the slope and four on the flat area near the toe of the slope. At Seeder 2, ten DCP tests were performed along the slope, and five were performed on the flat runout zone near the toe of the slope. Friction tests were also performed at the site to determine the dynamic friction coefficient of the soil. This was achieved using a simple pull scale set up attached to a cube block. The horizontal tension force applied to the block increased until the block began moving. Then, the block was pulled at a constant velocity, with the average force applied during this time being recorded. Tests were performed under dry surface conditions, with ambient temperatures of approximately 12 °C and low relative humidity. A total of five replicate tests were completed at multiple locations, yielding a mean dynamic friction coefficient of 0.4, which was therefore adopted for numerical modeling.

Dynamic soil tests conducted at the site were used to evaluate soil stiffness on the ground and along the slope. The tests showed that the soil was much stiffer at the base of the slope than on the slope. The soil stiffness varied significantly along the slope. The slope material was found to be stiffer towards the crest and toe and least stiff in the middle. These changes along the slope are shown below in Figure 6a with lighter blue shades indicating fewer blows needed to penetrate the cone one centimeter, meaning the soil is less stiff. Stiffer soils, requiring more blows per centimeter of penetration, are shown in dark blue. Using data from the site, it was evident that the slope's COR needed to be modeled as a range of COR values. Due to the computational demands of 11 material zones, the slope was idealized with five zones in Rocfall3 (by Rocscience, software version 1.017) as shown in Figure 6b. Each of these zones could then be assigned its own COR value.

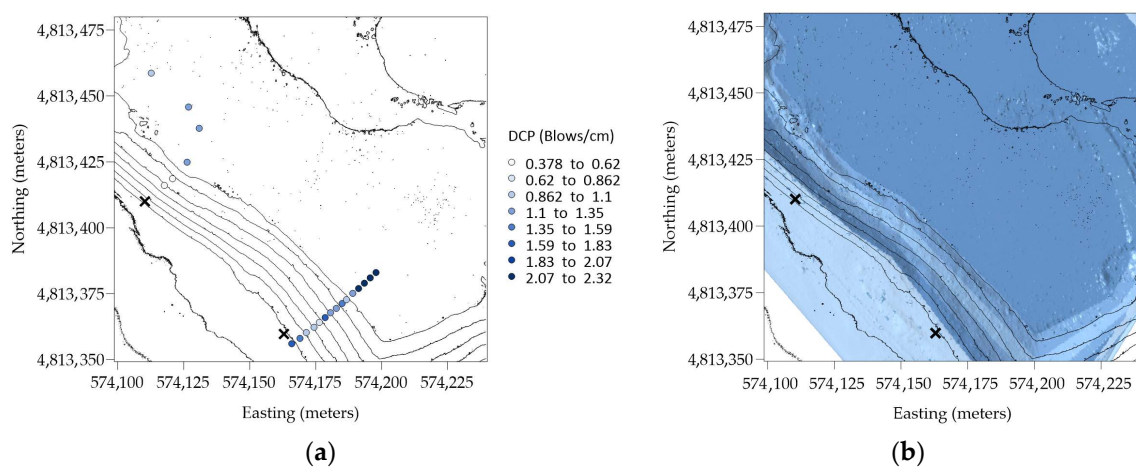


Figure 6. Dynamic Material Properties (a) DCP Test Points Shaded by Stiffness (b) RocFall3 Material Regions Identified.

3.4. Modeling

The LiDAR scan and seeder locations for each slope were imported into RocFall3 (by Rocscience) to recreate and analyze the drops. The reconstructed slope surface appears smoother than the in situ slope because small-scale roughness elements were necessarily reduced during point-cloud processing and surface generation for numerical modeling. The raw UAV–LiDAR survey produced on the order of 120 million points over the quarry. To retain high resolution in the areas relevant to block motion, the dataset was first spatially cropped to the immediate drop and runout zones, reducing the cloud to approximately 80 million points. Even at this reduced extent, the point density exceeded what could be reliably triangulated within the rockfall modeling software, and required additional down-sampling to approximately 5 million points prior to mesh generation. Following down-sampling, the triangulated surface also underwent smoothing and localized repair to remove spurious depressions and artifacts produced during meshing. While these steps were necessary for numerical stability, they inevitably suppressed micro-scale surface asperities that were observed in the field. In RocFall3, 30 simulations were performed for each block size and shape at both seeder locations. When using a sphere in RocFall3, the minimal contact surface area led to almost no energy loss from friction and a greatly exaggerated runout distance. These rocks would continue moving until the maximum computational step limit of the model was reached, which was not coincident with field results. Therefore, a 79-faced icosphere (Rocscience quasi-spherical shape) was used to more accurately represent the runout distances of the spheres recorded in the field. When inputting the dynamic friction coefficient in RocFall3, a value of 0.4 was used on the slope and ground based on the results obtained from the friction tests performed at the site. COR values used along the slope varied by material region to more accurately reflect the data from the soil tests. The model was split into five material regions: four along the slope and one on the ground at the bottom of the slope, as shown in Figure 6b.

4. Results and Discussion

4.1. Field Results

Field results are presented in terms of block movement down slope and final block locations. Blocks move with different modes of motion in accordance with their associated energies. Free fall and bouncing are associated with high-energy movement, while rolling and sliding are most likely to occur at the end of a rockfall event, when kinetic energy is lower. Modeling rockfall behavior accurately depends on achieving the correct mode of motion throughout the event. The final location of the blocks is also important. Runout distance measures the average distance from the seeder to the resting location of simulated blocks. Deposition area measures the minimum area required to encapsulate the final resting locations of all blocks in a grouping. The dispersion area is similar but includes the seeder as a point in the area calculation.

4.1.1. Seeder 1 Field Results

At Seeder 1, both sphere sizes had similar deposition areas, yet the 34 kg blocks had a shorter runout distance, as shown in Figure 7. The cubes and rectangular prisms yielded smaller deposition areas than spheres, with the rectangular prisms coming to rest closest to the toe of the slope. Due to the steeper angle of the slope below Seeder 1, all blocks traveled all the way down the slope, landing in the runout zone, with none coming to rest on the slope.

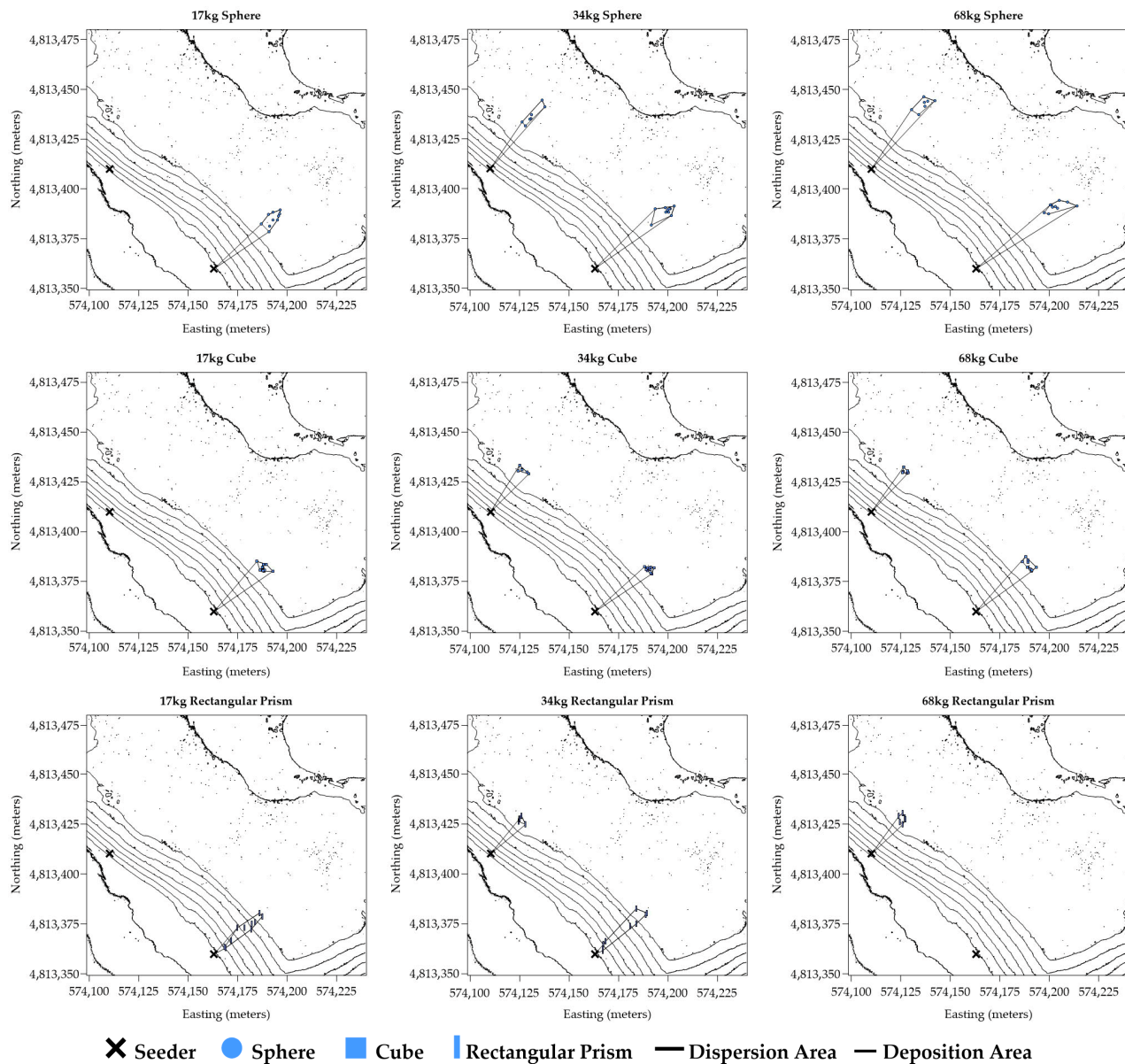


Figure 7. Field Results.

During field testing, video analysis showed that all shapes experienced a large bounce on their first impact near the crest of the slope, and then continued to progress downslope with more bouncing as they came closer to the bottom. Neither cubes nor rectangular prisms experienced sliding along the slope. At the location of first impact on the slope, a scar (Figure 8) began to form from the blocks, specifically from the angular geometry of the cubes and rectangular prisms. The scar had little to no effect on the spheres and only caused the cubes and rectangular prisms to lose some momentum after their first impact. As the scar continued to grow through each set of drops, its effects on the blocks also slightly increased, but not enough to inhibit the blocks' motion completely.



Figure 8. Scar on Slope from Block Impacts. Red arrow indicating the location of impact scar on the soil slope.

4.1.2. Seeder 2 Field Results

Of the blocks dropped at Seeder 2, the spheres exhibited the most consistent patterns with the runout distances increasing as the size of the block increased (Figure 7). Cube runout distances also slightly increased as the size of the cube increased. Both sizes of the rectangular prisms yielded similar deposition areas with many of the blocks coming to rest on the slope. This was expected as the slope below Seeder 2 had a lower inclination angle than Seeder 1, where blocks barely made it to the toe of the slope.

While traveling down the slope, the spheres rolled and bounced with larger bounces occurring from contact with large cobbles, and no spheres came to rest on the slope. All cube sizes exhibited primarily the rolling mode of motion with occasional bounces occurring towards the bottom of the slope, when the blocks contacted large cobbles. The cubes did not exhibit sliding after leaving the ramp and began rolling at initial contact with the slope. While some of the cubes slowed down significantly from contact with vegetation, none of the cubes came to rest along the slope. For both rectangular prism sizes, many were stopped on the slope or lost substantial energy to vegetation interactions. The 17 kg rectangular prisms end locations were distributed along the slope while the 34 kg prisms either stopped near the crest or the toe. Similar to the cubes, the rectangular prisms also rolled down the majority of the slope, bouncing but not sliding. Both cubes and rectangular prisms would experience larger bounces if an edge or corner came in contact with a large cobble on the slope.

4.2. Preliminary Modeling Results

Based on the DCP data and typical COR values for the slope material, initial COR values were selected for each material region in the model. These values were all increased simultaneously by increments of 0.05 until there were four sets of models to compare to the field results. The four models consisted of COR ranges of 0.2–0.3, 0.25–0.35, 0.3–0.4, and 0.35–0.45, with the top and bottom of the slopes having higher COR values and the COR decreasing towards the middle of the slope (see Figure 6).

For the spheres, as the COR range increased, the runout distances and dispersion areas also increased. Within each COR range, the same increases were seen as the block size increased, which matches how the spheres behaved in the field. Although this is the same pattern seen for spheres in the field, the models do not accurately represent dispersion areas, runout distances, or modes of motion observed in the field.

For the cubes and prisms, no consistent patterns were observed in the models, seemingly unrepresentative of the field results. In the models, both shapes had very narrow,

short dispersion areas with a significant number of blocks coming to rest on the slope. Additionally, for the cubes and prisms, there was no consistent increase or decrease in dispersion areas as the COR range was increased. Table 2 presents the field and RocFall3 dispersion and deposition areas.

Table 2. (a) Seeder 1 Runout, Dispersion and Deposition with Varying COR Values. (b) Seeder 2 Runout, Dispersion and Deposition with Varying COR Values.

(a)											
			Sphere			Cube			Rectangular Prism		
			17 kg	34 kg	68 kg	17 kg	34 kg	68 kg	17 kg	34 kg	68 kg
Deposition Areas (m ²)	Runout Distance (m)	Field	-	34.1	41.6	-	26.5	26.5	-	22.9	23.5
		0.20–0.30	30.1	31.4	34.7	23.9	23.9	23.2	24.9	25.2	25.1
		0.25–0.35	30.2	33.3	35.9	34.3	29.3	29	26.8	27.4	27.3
		0.30–0.40	30.3	34	39.2	29.3	26.2	25.2	25.5	25.8	25.2
		0.35–0.45	33.8	37.5	37.9	30.7	30.6	32.5	29.4	29.9	29.1
	Dispersion Areas (m ²)	Field	-	99.9	154.8	-	86.5	49.8	-	52.4	56.8
		0.20–0.30	190.6	323.3	418.1	150.8	88	169.1	293.3	25.9	31.5
		0.25–0.35	166.5	345.3	538.3	158.3	216.6	191	230.9	190.5	78.1
		0.30–0.40	148.1	514.4	696.2	215.1	159.7	227.5	103.7	51.2	42.2
		0.35–0.45	445.2	498.2	822.9	207.1	354.9	282.2	301.6	145	170.5
	Model COR Range	Field	-	43.2	47.7	-	7.9	4.7	-	6.4	11.1
		0.20–0.30	61.1	318	413.2	145.9	79.4	165.7	286.6	24	27.5
		0.25–0.35	136.4	340.6	532.9	154.3	194.6	176.9	222.6	184.4	23.2
		0.30–0.40	56.6	510.1	692.4	98.6	156.6	220.7	100.5	48.8	40.4
		0.35–0.45	187.2	270.5	816.7	201.3	349.4	166.5	270	114.9	54.1
(b)											
			Sphere			Cube			Rectangular Prism		
			17 kg	34 kg	68 kg	17 kg	34 kg	68 kg	17 kg	34 kg	68 kg
Deposition Areas (m ²)	Runout Distance (m)	Field	39.1	46.0	51.3	33.5	34.7	35.6	19.7	17.8	-
		0.20–0.30	33.8	39	43.5	6.4	6.6	2.9	8.4	4.7	3.3
		0.25–0.35	36.8	37.8	47.2	27.6	22.2	21.2	27.6	23.6	24.7
		0.30–0.40	34.7	37	43.7	5.2	5.2	1.8	6.8	5.5	3
		0.35–0.45	38.3	38.5	48.5	22.8	20.5	19	22.5	20.3	16.5
	Dispersion Areas (m ²)	Field	155.2	193.3	243.8	160.7	94.4	147.7	97.5	117.9	-
		0.20–0.30	154.4	313.3	539.1	47.5	39.8	14.3	32.5	31.4	24.2
		0.25–0.35	213.6	250.9	606	136.1	85.4	81.9	68.7	48.2	74.5
		0.30–0.40	235.5	285.8	942.7	40.9	89.5	4.6	59.2	32.7	25.9
		0.35–0.45	193.2	388.7	1051.2	107	133.8	72.4	77.4	74.7	62.1
	Model COR Range	Field	49.6	57.7	55	20.3	8.8	22.8	81	111.4	-
		0.20–0.30	136.4	92.6	237.9	37.9	30.3	6.7	20	19.9	13.1
		0.25–0.35	61.8	121.1	331	120.3	72.9	71.1	56.3	36.7	61.9
		0.30–0.40	190	272.3	759.7	29.3	77.8	3.3	46	19.9	14.3
		0.35–0.45	56.3	371.9	1022.2	96.7	118.9	62.2	62.2	62.9	48.5

Although no single coefficient of restitution range was suitable for all three shapes, some ranges more closely matched field results. For the spheres, the COR range of 0.2–0.3 closely modeled the field results. For the cubes, the most suitable COR range was 0.25–0.35. For the prisms, the most suitable COR range was 0.3–0.4. These best-fit models are shown below in Figure 9, while all models are shown in Appendix A.1.

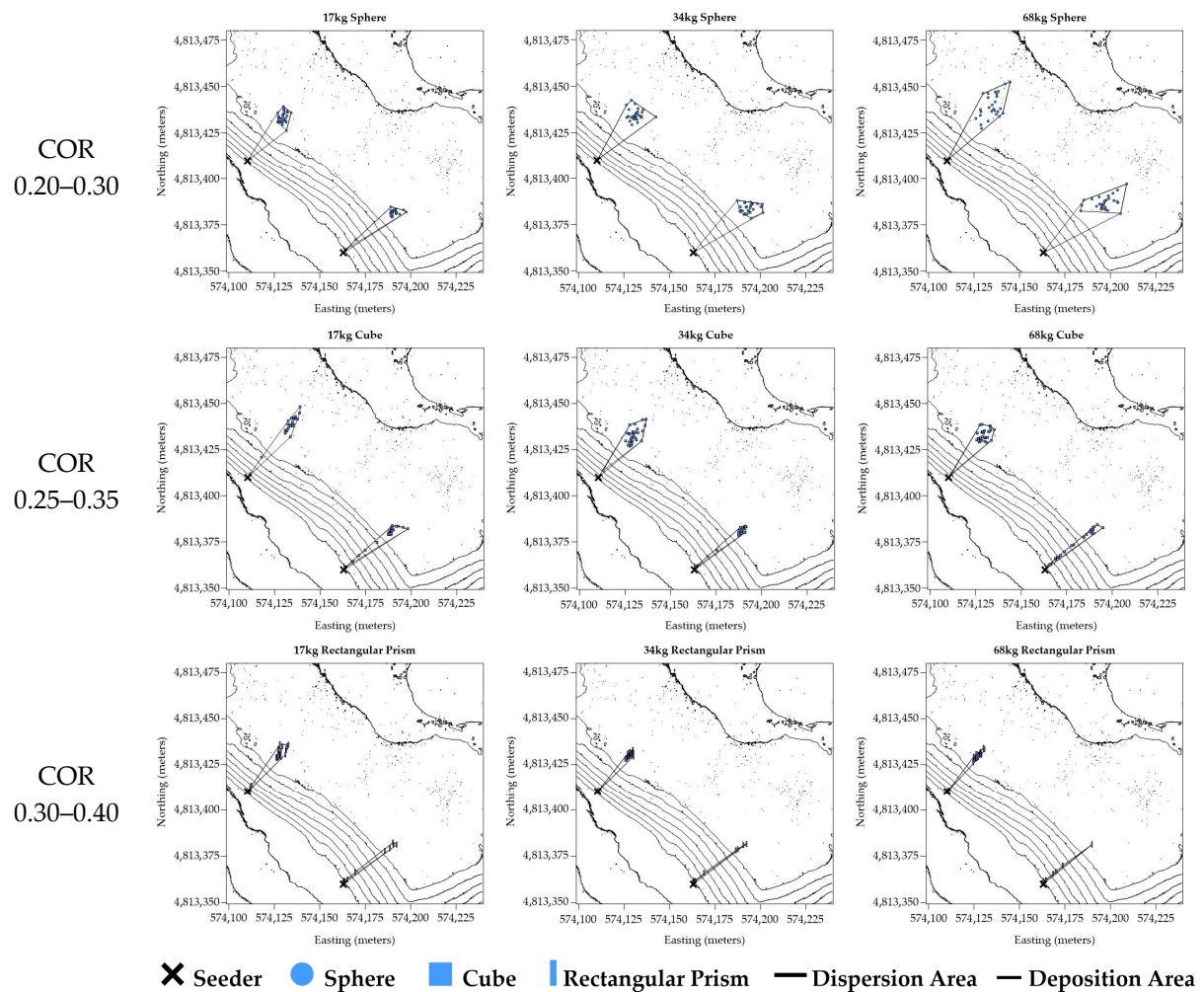


Figure 9. Best Initial Modeled Results.

One main difference between the model and field results was that the cubes and rectangular prisms showed sliding as the initial mode of motion as they progressed downslope. At Seeder 1, the model showed cubes sliding down the top section (approximately 1/3 of slope length) before they began to roll and bounce. The model showed prisms sliding down the first half of the slope before they began to roll and bounce. However, the video recording show the actual movement was rolling and bouncing for both shapes.

Since the slope associated with Seeder 2 is less steep than the slope associated with Seeder 1, the model shows both cubes and prisms sliding down nearly the entire slope. Some of the cubes begin to show rolling near the very bottom of the slope, but the prisms show strictly sliding down the entirety of the slope. Figure 10 below shows the rotational velocity of the 34 kg rectangular prisms as they travel down the slope in Rocfall3. The solid blue rock paths illustrate a rotational velocity of zero, which represents sliding.

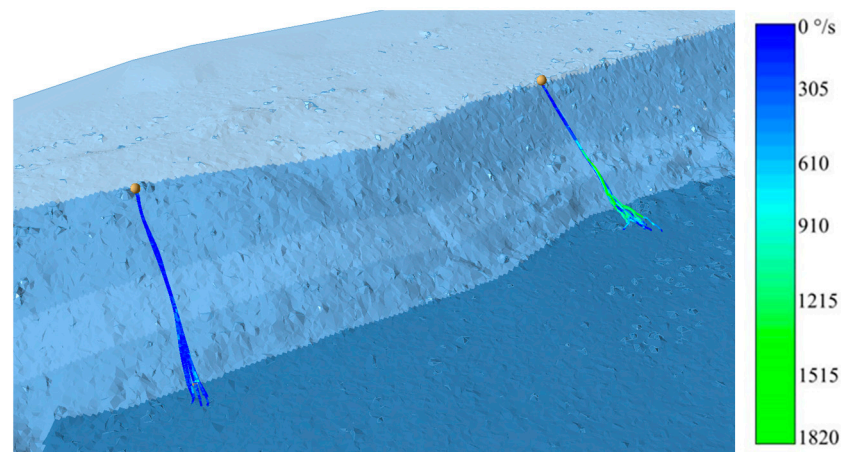


Figure 10. Sliding of Rectangular Prisms in Rocfall3.

4.3. Varying Initial Conditions Modeling Results

To improve the accuracy of the modes of motion in the models, the initial conditions (translational and rotational velocities) were adjusted for each shape. Using rotational velocity data collected from the enDAQ sensor during field drops, an initial rotational velocity was obtained for all shapes as they left the ramp. These initial conditions were applied to the simulated blocks in RocFall 3. Figure 11 shows the rotational velocity of the 34 kg rectangular prism as it travels down the slope. The graph verifies that the blocks were not sliding down the slope but rather rolling and bouncing. Each color represents the rotation about either the X-, Y-, or Z-axis. Initial rotational velocity values of 280, 24, and 18 degrees per second were used for the spheres, cubes, and rectangular prisms, respectively, in the models.

Applying initial field rotation conditions to the models allowed the simulated blocks to exhibit more accurate behavior than what was observed during field testing. The cubes and prisms that previously only exhibited sliding were now bouncing and rolling as expected. This was a promising result as the mode of motion is indicative of block energy, which influences runout distance, dispersion, and deposition area. With the corrected mode of motion, significantly more blocks could travel down both slopes.

This change also increased the number of dispersion areas from the models that fall within 20% of what was observed in the field, especially at Seeder 2. Preliminary models had only three blocks within 20% of the field results, whereas models with initial rotational velocity had five. For Seeder 1, the adjusted initial conditions made the runout distances for cubes and rectangular prisms more accurate over fewer COR ranges. This meant that we could further narrow down which COR range was most applicable for each shape. Once initial conditions were added, the COR range of 0.20–0.30 was the only range suitable for both cubes and prisms at Seeder 1.

With the added initial conditions, many of the dispersion areas remained similar to those found in the preliminary models, especially at Seeder 2. However, at Seeder 1, there were more decreases in dispersion areas seen in blocks. The 34 kg spheres had dispersion areas between 282 and 476.3 square meters through the different COR ranges while they were between 323.3 and 514.4 square meters for the preliminary models. Decreases like this were also observed in the 17 kg sphere, 68 kg cube, and 17 and 68 kg prisms. These smaller dispersion areas are closer to the field findings.

Additionally, at Seeder 2, runout distances for cubes and prisms in 0.20–0.30 and 0.30–0.40 COR ranges increased significantly when the initial rotational velocity was added. In the preliminary models, the largest average runout distances for COR 0.20–0.30 were 6.6 m for the cubes and 8.4 m for the prisms. Once the initial rotational velocity was

introduced, the average runout distances for those same blocks and COR range were 24.8 m for the cube and 30.1 m for the prism, more closely matching field results.

While improvements were achieved by adding initial rotational velocity to the models, this still did not cause the dispersion areas and runout distances from the models to match the field results. Dispersion and deposition areas, along with runout distances, for both seeders are shown in Table 3 below.

Table 3. (a) Seeder 1 Runout, Dispersion and Deposition with Varying COR Values. (b) Seeder 2 Runout, Dispersion and Deposition with Varying COR Values.

(a)												
				Sphere			Cube			Rectangular Prism		
				17 kg	34 kg	68 kg	17 kg	34 kg	68 kg	17 kg	34 kg	68 kg
Runout Distance (m)	Model COR Range	Field	-	34.1	41.6	-	26.5	26.5	-	22.9	23.5	
		0.20–0.30	29.6	35.4	37.5	28.8	28.6	27.7	28.4	24.2	25.3	
		0.25–0.35	32	34.8	39.6	27.3	28.7	29.7	26.4	26.9	27.3	
		0.30–0.40	32.8	35.7	38.6	30.8	29.8	29.5	29.5	27.1	27.1	
		0.35–0.45	31.7	36.1	40	30.8	31.6	29.8	28.4	28	26.6	
Dispersion Areas (m ²)	Model COR Range	Field	-	99.9	154.8	-	86.5	49.8	-	52.4	56.8	
		0.20–0.30	84.1	368.2	427.7	155	289.9	136.5	141	183.4	34.2	
		0.25–0.35	158.5	476.3	726.3	216.6	110.6	199.2	143.4	70.8	112.5	
		0.30–0.40	199.1	282	693.9	471.2	255.4	197.4	196	116.5	106.1	
		0.35–0.45	195.4	351.4	852.4	235.4	501	247.4	140.7	208.1	140.2	
Deposition Areas (m ²)	Model COR Range	Field	-	43.2	47.7	-	7.9	4.7	-	6.4	11.1	
		0.20–0.30	79.6	204.6	423.2	147.6	258.4	62.8	58	179.7	32.4	
		0.25–0.35	57.8	234	721.1	213.1	98.1	81.5	132.3	67.9	34.3	
		0.30–0.40	78.7	143.1	687.1	432.8	119	187.3	110.1	113	103.7	
		0.35–0.45	78.9	236.5	845.7	231.6	280.4	218.9	61.5	202.1	130.9	

(b)												
				Sphere			Cube			Rectangular Prism		
				17 kg	34 kg	68 kg	17 kg	34 kg	68 kg	17 kg	34 kg	68 kg
Runout Distance (m)	Model COR Range	Field	39.1	46.0	51.3	33.5	34.7	35.6	19.7	17.8	-	
		0.20–0.30	36.4	37.5	44.3	24.8	22.6	20.6	30.1	20.4	22.9	
		0.25–0.35	34.7	35.4	42.3	28.2	24.9	22.8	28.2	22.1	20.9	
		0.30–0.40	36.4	38.9	46.9	28.4	23.3	21.3	26.9	25.7	21.8	
		0.35–0.45	35.8	40.7	47.3	29.3	26.7	22.3	25.9	26	25.6	
Dispersion Areas (m ²)	Model COR Range	Field	155.2	193.3	243.8	160.7	94.4	147.7	97.5	117.9	-	
		0.20–0.30	144.4	230.3	769.6	98.7	63.5	101.7	98.5	55.7	54.3	
		0.25–0.35	153.9	279.6	676.2	154.9	64.8	57.2	60.3	55.7	43.7	
		0.30–0.40	165.1	419.2	913.4	96.5	114.4	91.9	71.4	52.8	52.1	
		0.35–0.45	267.4	307.4	1073.5	123.4	107.1	87.7	87.1	73.7	52.9	
Deposition Areas (m ²)	Model COR Range	Field	49.6	57.7	55	20.3	8.8	22.8	81	111.4	-	
		0.20–0.30	37.9	128.5	490.6	84.2	51.1	89.2	88.7	42.5	42	
		0.25–0.35	102.6	264.3	590	139.2	51.1	47.5	48.7	44.1	32.6	
		0.30–0.40	79.2	402.3	486.1	81.5	102.5	81	59.6	40.7	41.3	
		0.35–0.45	218.3	122.8	888.8	106.9	95.5	76.5	74.9	61.4	39.4	

Of the models that included the initial conditions, the COR range for each shape that is closest to the field results is shown below in Figure 12. All results are shown in Appendix A.2. For the spheres, the COR range was 0.20–0.30. For the cubes and rectangular prisms, the COR range was 0.35–0.45.

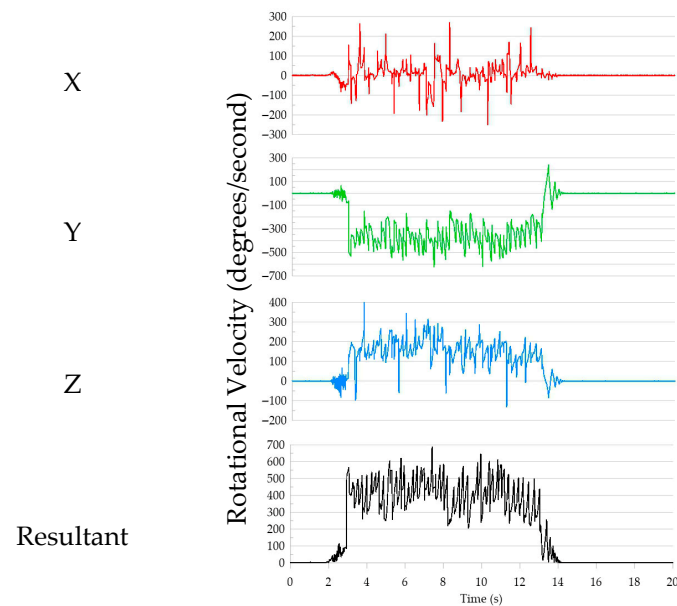


Figure 11. Example enDAQ Sensor Data from Rockfall Event.

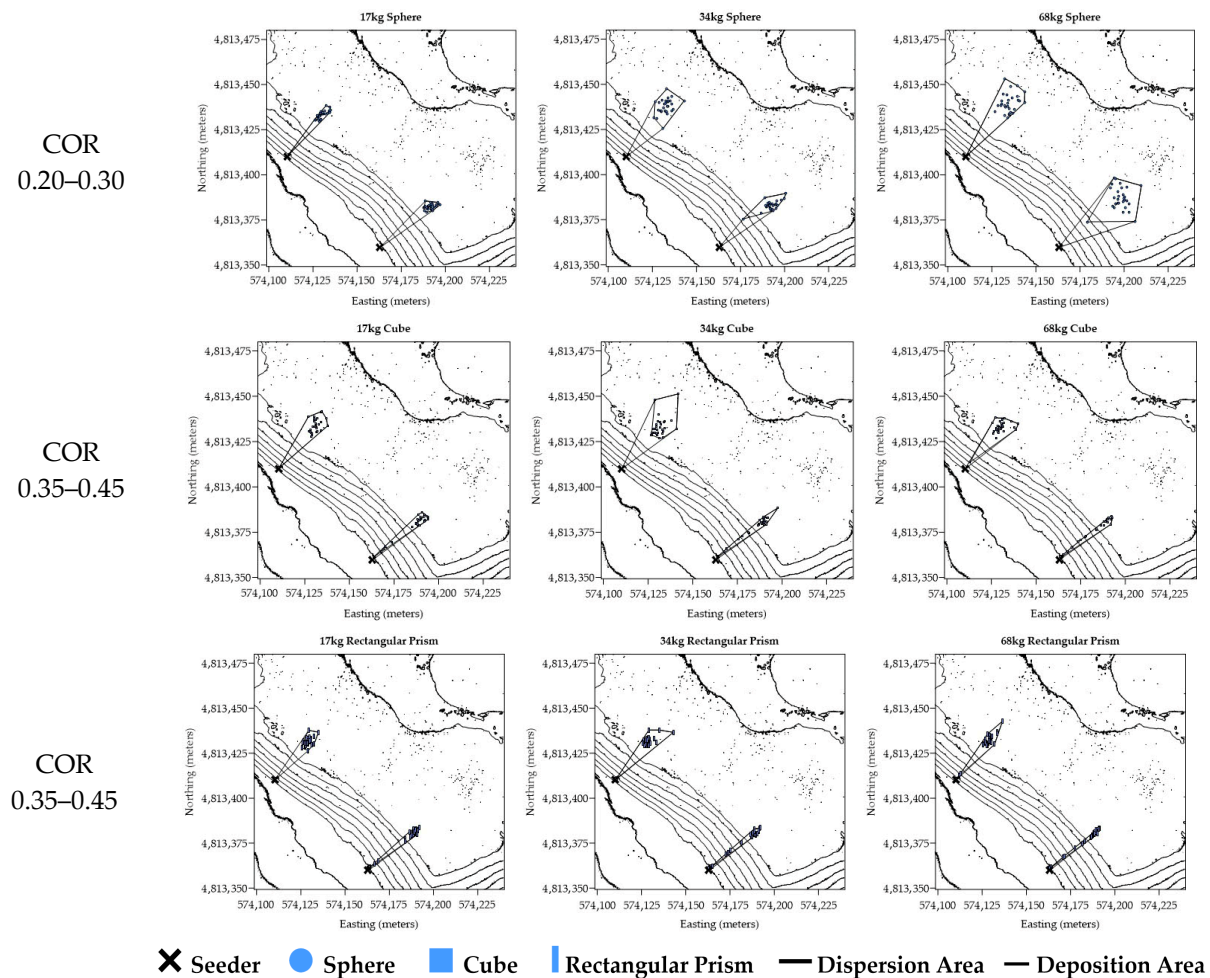


Figure 12. Best Modeled Results with Initial Rotational Velocity.

Variations between modeling and field results were likely due to the loss of small-scale surface intricacies during the importing of the LiDAR point cloud into the software. To create a surface in RocFall3, a point cloud is imported, and the user must down-sample

it to a resolution the software can handle. The points are then triangulated to create the surface. This means that cobbles and vegetation on the slope are lost, which decreases the representation of the slope surface in the model. The cobbles on the slope will share the same material properties. For example, if a block came into contact with a cobble in the field, the same reaction would not be produced in the models, since it was simulated as contacting soil.

The second step in creating the surface is to smooth and repair the slope geometry. Triangulation from the point cloud often exaggerates or creates localized surface depressions. Smoothing and repairing address this, but cause additional details to be lost. For example, if the seeder location is in a depression, the simulated rocks cannot travel down the slope because they must first travel uphill to exit the depression.

Although the results are promising, improvements can be made on two fronts. Firstly, using a dynamic cone penetrometer is unique to characterize the slope material for rockfall modeling. DCP provides a measure of penetration resistance with depth below the surface slope, it does not provide a surface-based modulus value which can be better correlated to a COR value. Such measurements can be obtained with a lightweight falling deflectometer.

Secondly, LiDAR-based slope surface scanning produces a highly representative digital twin of the slope surface. Small features such as cobbles and vegetation can be classified visually or by using laser return pulse intensity. It is possible, but not practical, to assign a high-fidelity COR map to materials other than the primary soil slope material. Additionally, the rough slope surface geometry had to be simplified. These are limitations of common physics-based rockfall software.

While the present study focused on idealized block geometries to isolate effects of sphericity and elongation on restitution behavior, future experiments would benefit from incorporating more naturalistic block shapes characterized by rounded edges, irregular faces, and asymmetric mass distributions. Such geometries more closely reflect in situ rockfall blocks and are expected to influence rotational energy transfer, multi-point contacts, and effective coefficients of restitution during impact. These non-idealized shapes could be captured using close-range three-dimensional scanning techniques, such as handheld laser scanners or structured-light triangulation systems, which allow rapid generation of high-resolution surface meshes. The resulting digital models could then be imported directly into rigid-body numerical simulations, enabling systematic evaluation of how edge rounding, surface roughness, and geometric asymmetry modify impact mechanics, rolling resistance, and trajectory dispersion.

5. Conclusions

Large-scale rockfall experiments were conducted on two slopes of varying inclination. Three sizes of three differently shaped blocks were dropped, and all initial and end drop locations were geolocated. A LiDAR scan of the site was also performed to replicate the slopes in Rocfall3. The preliminary models used initial translational and rotational block-velocity values of zero, a constant frictional coefficient along the slopes, and varied COR values based on dynamic soil-penetration results. These model results were not representative of field results, both in terms of modes of motion as blocks traveled downslope, in deposition and dispersion areas of the resting locations of the blocks, and runout distance.

To address this, a second round of modeling was performed that incorporated non-zero initial rotational velocities, which were based on sensor data obtained during field testing. This corrected the modes of motion for all shapes and improved the models, but did not fully resolve discrepancies in deposition and dispersion areas, as well as runout distances.

Two possible improvements are suggested. COR values should be correlated with a more appropriate field soil test that captures elastic response, such as the lightweight

falling deflectometer. Modeling software can also be improved to handle more complex and detailed slope geometry.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

COR	Coefficient of Restitution
LiDAR	Light Detection and Ranging
UAV	Unmanned Aerial Vehicle
DCP	Dynamic Cone Penetrometer

Appendix A.

Appendix A.1. Preliminary Modeling Results

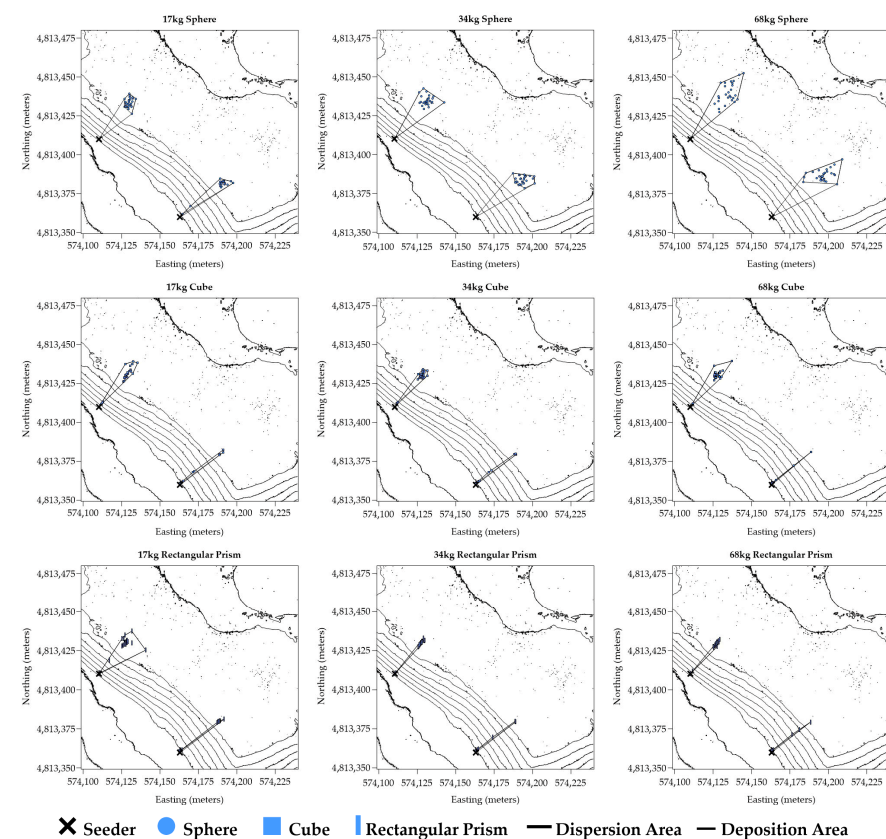


Figure A1. COR 0.20–0.30.

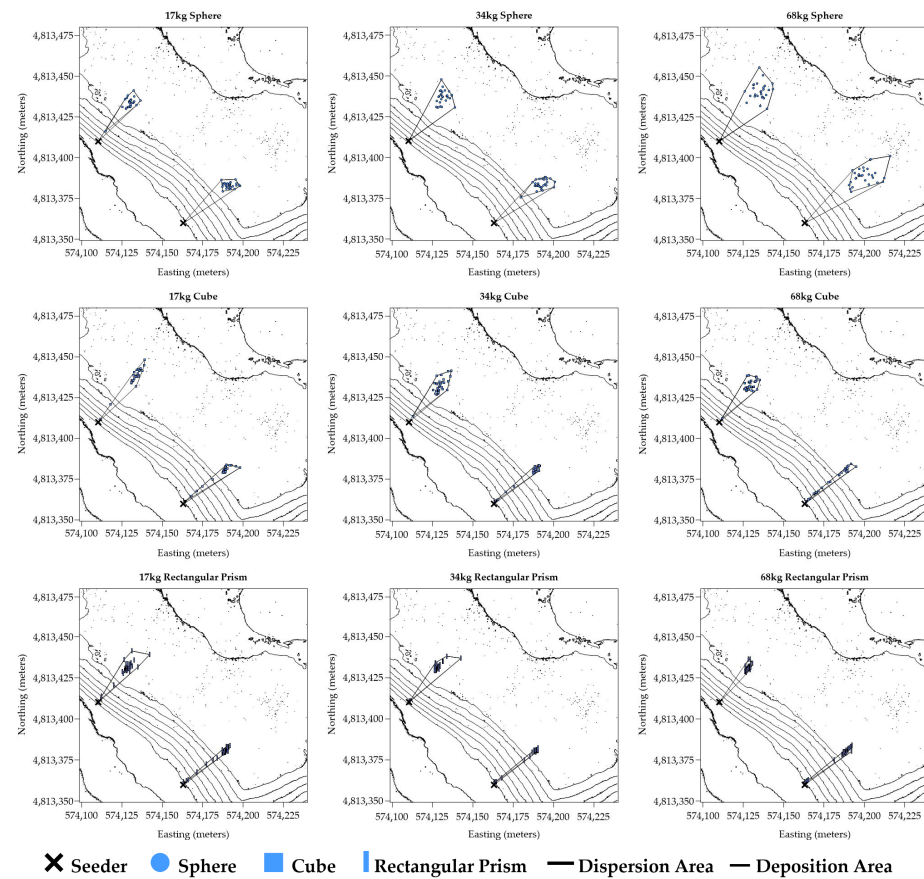


Figure A2. COR 0.25–0.35.

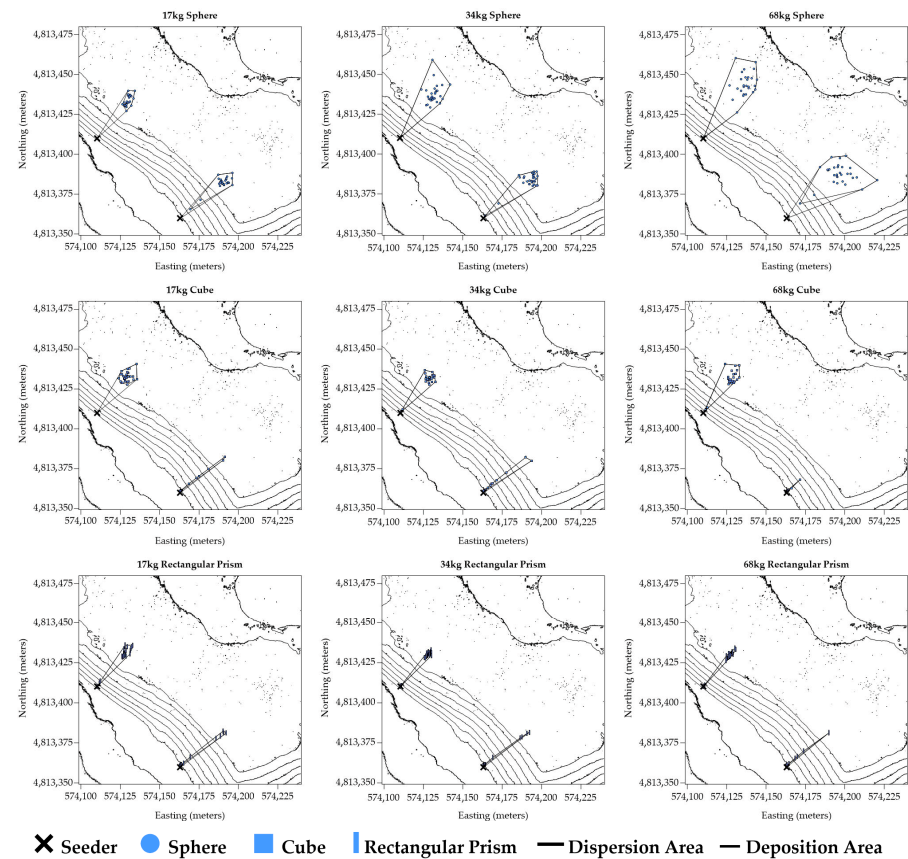


Figure A3. COR 0.30–0.40.

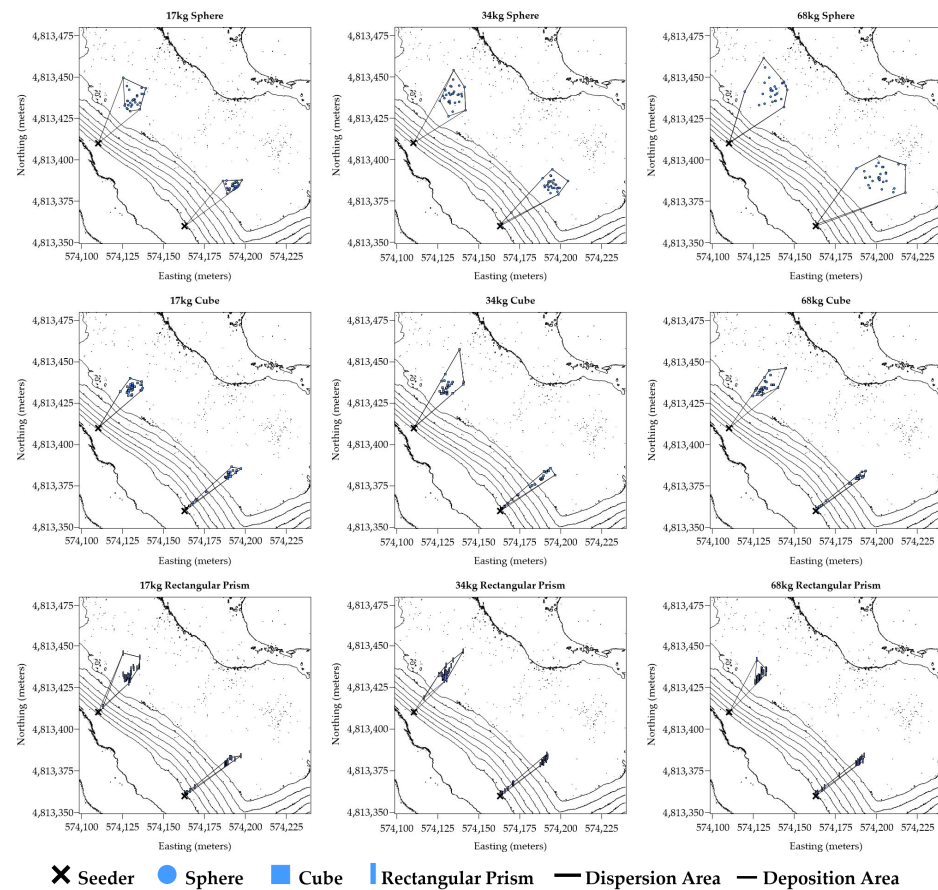


Figure A4. COR 0.35–0.45.

Appendix A.2. Initial Conditions Modeling Results

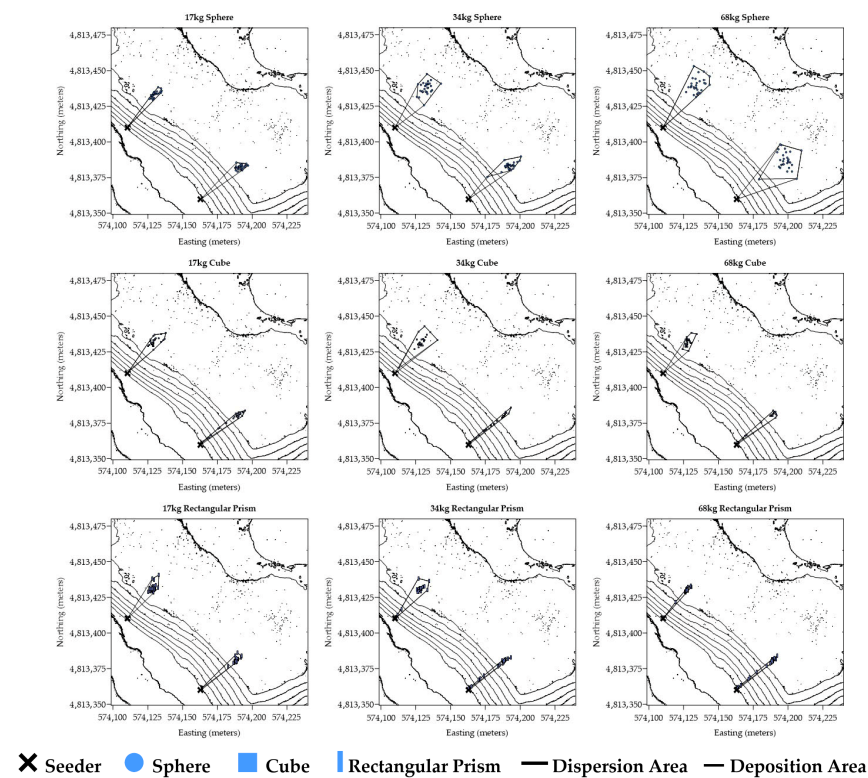


Figure A5. COR 0.20–0.30 with Initial Rotational Velocity.

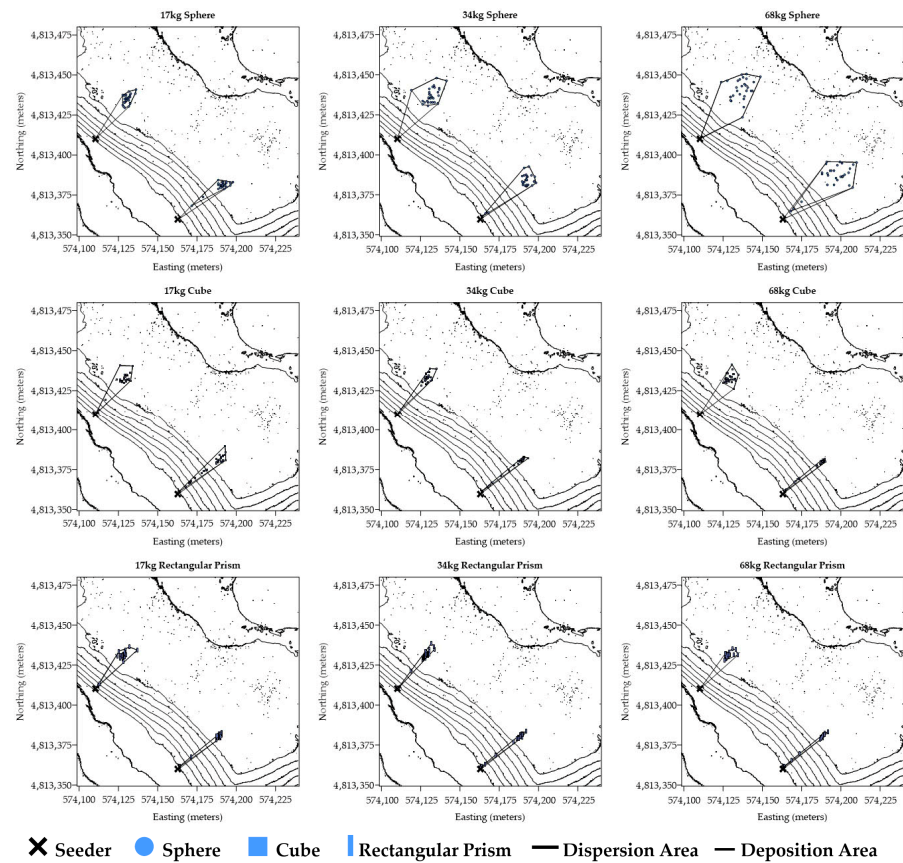


Figure A6. COR 0.25–0.35 with Initial Rotational Velocity.

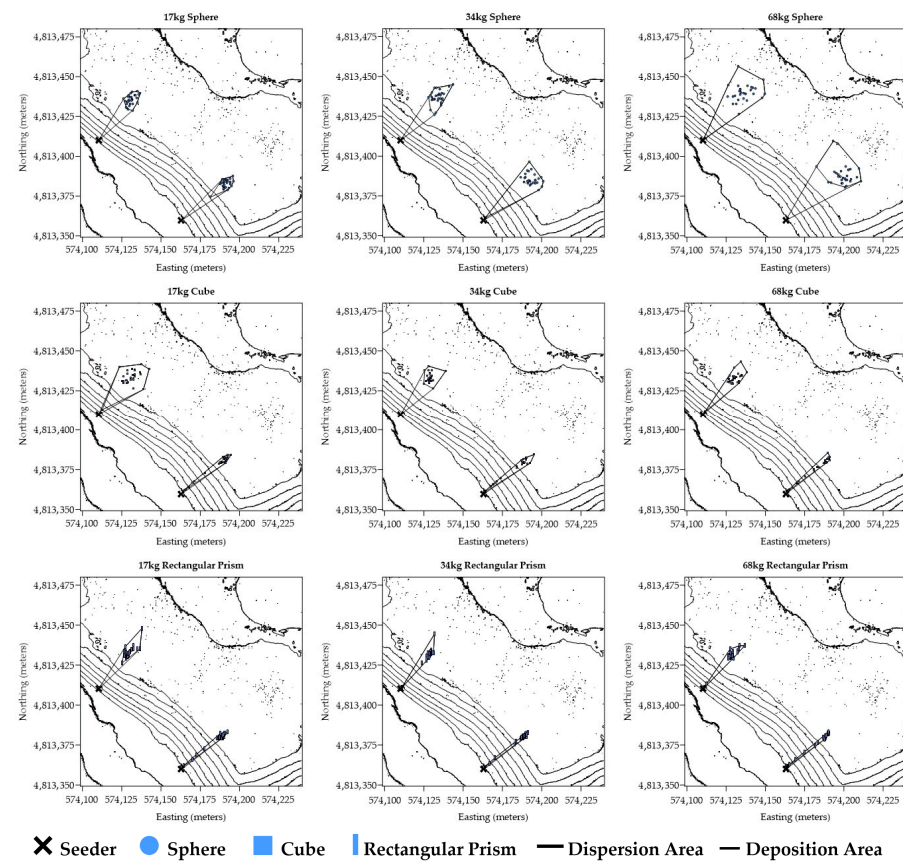


Figure A7. COR 0.30–0.40 with Initial Rotational Velocity.

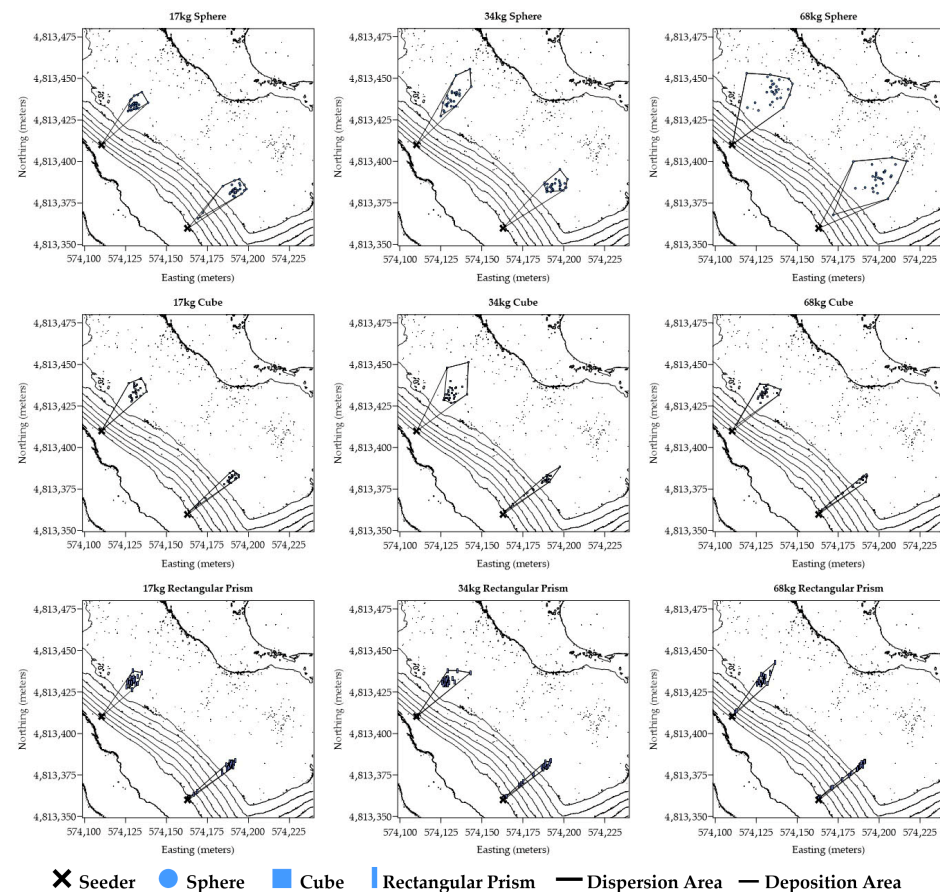


Figure A8. COR 0.35–0.45 with Initial Rotational Velocity.

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