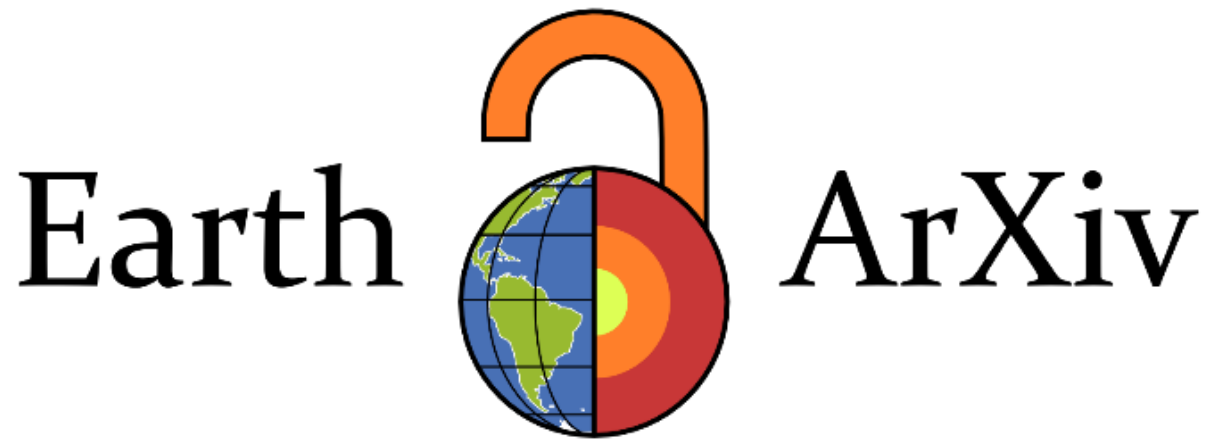




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Quantifying volumetric erosion from symbolic expression of landslide morphology

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1 **Highlights**

- 2 1. Landslide morphology refines first-order area–volume scaling.
- 3 2. Dimensionless relative width explains variability beyond source area alone.
- 4 3. The model generalizes across co-seismic inventories and lithologies.
- 5 4. Improved volume estimates constrain event-scale cumulative landslide
- 6 erosion.

7

8 **Abstract**

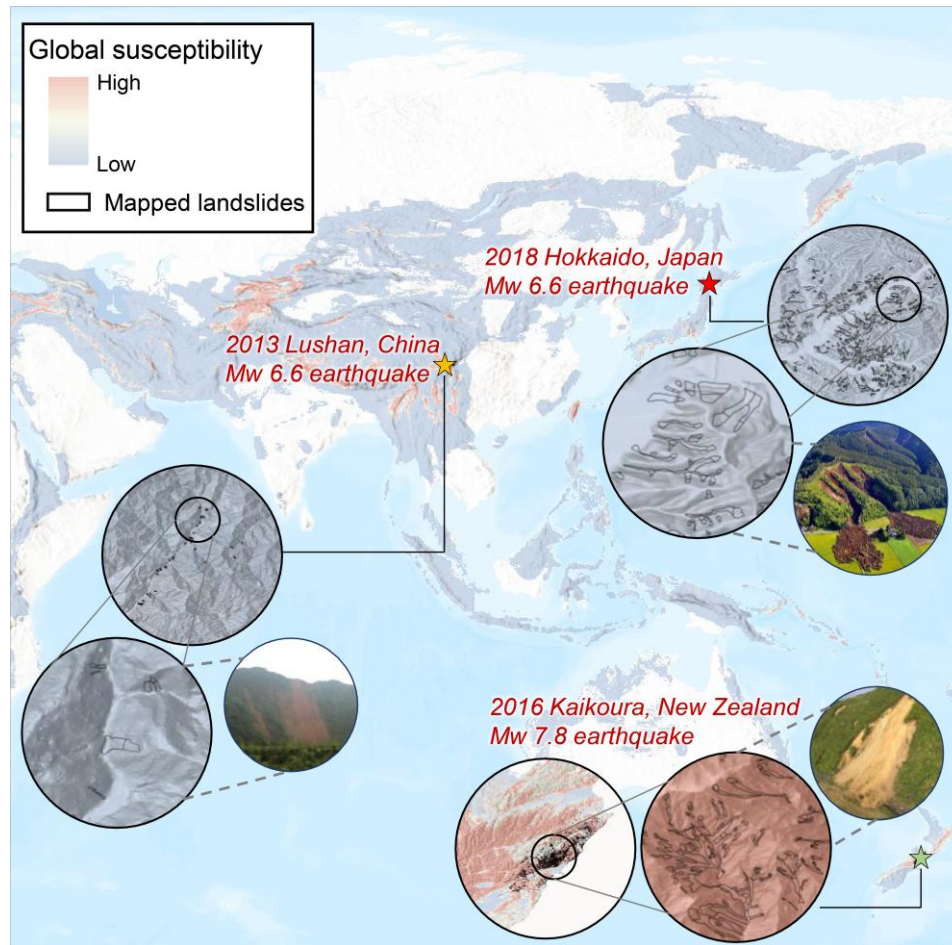
9 Landslide volumetric erosion is fundamental to regional sediment budgets and
10 downstream hazard assessment, yet accurately constraining material
11 mobilization remains a primary bottleneck in Earth-system research. Legacy
12 area–volume relations introduce substantial uncertainty when applied across
13 heterogeneous landslide populations. Here, we examine whether the erosional
14 and accumulation (i.e., runout) domains provide information beyond source area
15 alone for volumetric erosion. Using neural-guided symbolic regression, we
16 identify an expression that preserves source area as the first-order control on
17 erosional volume while introducing a dimensionless descriptor of the
18 accumulation counterpart, as a geometric correction. For the 2016 Kaikōura
19 earthquake inventory, the framework estimates a cumulative eroded volume of
20 54.9 Mm^3 , compared with the measured 56.5 Mm^3 . The formulation was
21 additionally applied without recalibration to the independent 2018 Hokkaidō
22 inventory and subsequently used for blind inference on 32 landslides from the
23 2013 Lushan earthquake, yielding a cumulative estimate of 1.95 Mm^3 of
24 volumetric erosion. Because independent volume observations are unavailable
25 for Lushan, this application is treated as inference rather than external validation.
26 Polygon-generalization experiments further indicate that our new formulation
27 remains stable across different mapping resolutions. These results show that
28 scale-normalized planform geometry can provide complementary information to
29 source area when constraining landslide erosion. The proposed framework is

therefore intended as an empirical extension to, rather than a replacement for, established area–volume scaling.

Keywords: Earthquake-triggered landslides, Landslide erosion, Volume, Landslide morphology, Symbolic regression, Neural network

1 Introduction

Landslide-driven erosion is a primary control on hillslope–channel coupling, the terrestrial flux of organic carbon, the long-term topographic evolution of orogens, and other such Earth-system geomorphic systems. These geomorphic systems are dominated by large-magnitude, stochastic events where total mobilized mass represents the primary physical determinant of erosional work. Not surprisingly, landslide planimetric area has been shown to be a first-order control on landslide erosion volume ($Volume = \alpha \cdot Area^\gamma$, γ is a scaling exponent and α is an intercept) first proposed over five decades ago (Simonett et al. 1967); however, the errors in simple area–volume relations frequently amounts to an order of magnitude, or even more in certain cases (Massey et al. 2020). This systematic bias arises because empirical scaling laws oversimplify the complex three-dimensional geomorphic information to two-dimensional planimetric area. Importantly, while the severity of catastrophic consequences e.g., the recent disasters in Wayanad, India (Yunus et al. 2025) and Gofa, Ethiopia (Li et al. 2025) depends on eroded mass, the magnitude of this erosion is physically modulated by topographic structure and substrate strength that are fundamentally obscured when relying on simple planimetric proxies.



49

50 *Figure 1: The diagram shows the study areas and epicentral locations of three*
 51 *earthquakes examined in this work: 2013 Lushan, China (Mw 6.6); 2016*
 52 *Kaikōura, New Zealand (Mw 7.8); and 2018 Hokkaidō (Japan) (Mw 6.6). Each*
 53 *panel shows a regional map with the respective epicentres of the earthquakes*
 54 *laid on top of the Global Landslide Hazard Map (World Bank Group 2021). Map*
 55 *credits: Esri, Maxar, Earthstar Geographics, and the GIS User*
 56 *Community (Environmental Systems Research Institute (ESRI) 2020).*

57 While these scaling laws facilitate rapid regional estimations, their application has
 58 revealed persistent misestimations of cumulative erosion (Marc and Hovius 2015;
 59 Xu et al. 2016; Massey et al. 2020) and poor transferability across distinct

lithological and tectonic regimes (Valagussa et al. 2021). This theoretical bottleneck derives largely from treating the landslide planform as a monolithic entity, effectively combining the erosion and accumulation domains. Physically, erosional loss is confined to the depleted area at the scarp; consequently, the inclusion of depositional zones in scaling relations often exaggerates failure depth, biasing regional inventories toward substantially inflated volumetric estimates (Massey et al. 2020).

A more rigorous description of surface erosion requires disentangling the specific geomorphic controls that govern failure geometry. While rapid detection methods can localize landslide movement (Fang et al. 2024), quantifying the resulting redistribution of material remains a challenge, as pre-event digital elevation models (DEM) are rarely available for remote volume calculations. In the absence of high-resolution substrate data or detailed field surveys, we propose that the volumetric signature of mass wasting is intrinsically embedded within the coupled morphological structure of the erosion and accumulation domains. Although, morphometric controls from both domains act as physical proxies for internal properties, such as thickness, confinement, and runout energetics (Taylor et al. 2018; Yunus et al. 2023; Schaller et al. 2025), yet their joint influence on volumetric erosion has remained largely unexplored.

This joint morphological constraint reveals critical information missing from legacy scaling laws without requiring additional environmental datasets (Tuganishuri et al. 2025) beyond mapped planforms. Here, we utilize neural-guided symbolic regression to identify expressions that capture these

morphological embeddings. Our approach yields a framework that identifies the geometric rules governing landslide bodies, providing closer estimates, i.e., 2-3 orders of magnitude of volumetric erosion than traditional models. We validate these expressions across diverse co-seismic events in New Zealand, Japan, and China (Figure 1), demonstrating the applicability to both shallow and bedrock regimes. Our developed method (see Figure 2 for the conceptual illustration) identifies a broad morphological pattern that reduces cumulative volumetric errors by up to two orders of magnitude, offering a scalable tool for quantifying the erosion of mass wasting which can be useful for hazard and landscape prognosis.

2 Data

Three distinct study areas were selected for developing our model, situated in New Zealand, Japan, and China. These regions were affected by seismically-induced landslides and are representative of contrasting geomorphic settings. These study areas have been previously documented extensively in the literature, highlighting their relevance for the analysis of landslide processes and behaviour. Consequently, we focus on these case studies which are described more in the subsequent sections.

2.1 The 2016 M_w 7.8 Kaikōura earthquake in New Zealand

New Zealand's Kaikōura affected region is situated in a highly active tectonic regime governed by the convergence of the Pacific and Australian Plates. The

relative motion between these plates is accommodated by the Alpine Transform Fault Zone, which fans out across the northeastern extent of the island to form the 80-km-wide Marlborough Fault Zone (MFZ). This rugged region is characterized by a complex network of NE-SW striking right-lateral strike-slip faults (Nicol et al. 2016). Regional tectonic strain is heavily partitioned across this zone, with the highest slip rates (20–25 mm/year) and shortest recurrence intervals (180–310 years) concentrated along the Hope fault in the south (Shi et al. 2017). On November 14, 2016, this intense regional strain culminated in the M_w 7.8 Kaikōura earthquake. The event exhibited extraordinary kinematic complexity, propagating across an anastomosing network of fault secondary structures. This violent and heterogeneous ground shaking triggered massive slope instability across the landscape, generating tens of thousands of landslides and mobilizing approximately 56.5 million cubic meters of rock and soil. To systematically evaluate these failures, we utilized a meticulously developed landslide inventory (Jones et al. 2025) with source areas separated from the runout zones. This catalog was acquired and verified by field surveys, historical sources, and aerial image interpretation with a vertical error of ± 1.83 m at one standard deviation (1σ) corrected for a regional systematic vertical bias. We selected about 10,000 polygonal landslide data points from this catalog for our study after careful polygonal post-processing (including removing coalescent landslides).

2.2 The 2018 M_w 6.6 Eastern Iburi earthquake in Japan

Hokkaidō, Japan's northernmost island, occupies one of the world's most tectonically complex regions, shaped by the westward subduction of the Pacific Plate beneath the North American and Eurasian Plates. The resulting collision zones have created a highly deformed landscape, particularly within the frontal fold and thrust belt of the Hidaka Mountains extending into the Ishikari Depression (Kimura 1994). The study area's rugged eastern terrain is underlain by structurally complex Neogene and Quaternary sedimentary rocks, transitioning to lowland alluvial and fluvial deposits in the west. Crucially, the surface lithology across this region is blanketed by layers of loosely consolidated pyroclastic tephra deposits, originating primarily from the Tarumae Caldera. These interbedded layers of pumice fall, paleosol, and humic soil reach depths of 4 to 5 meters (Tajika et al. 2016). While these highly porous volcanic deposits typically exhibit stable behavior, they become exceptionally vulnerable to slope failure when mechanically agitated under high moisture content (Yamagishi and Yamazaki 2018). The region is heavily forested and experiences a subarctic climate with significant annual precipitation. In August 2018, the area endured prolonged and intense rainfall, with cumulative totals exceeding 100 mm. Shortly thereafter, on September 6, 2018, the M_w 6.6 Hokkaidō Eastern Iburi earthquake struck the region. The intense seismic shaking, coupled with the antecedent moisture trapped within the thick, saturated tephra layers, resulted in catastrophic slope failures. The earthquake triggered thousands of shallow, rapid planar and spoon-shaped landslides, mobilizing vast quantities of the pyroclastic deposits.

The disaster caused widespread destruction, devastating local forestry, severing critical infrastructure, and resulting in 41 fatalities.

To evaluate this event, we utilized a curated post-earthquake inventory comprising of DEM difference obtained volumetric erosion data for ≈ 600 non-coalescent landslides from (Yunus et al. 2023), with the source areas distinctly separated from their respective runout zones (Bhuyan et al. 2025) to isolate the geomorphic signature of the initial failure geometries.

2.3 The 2013 M_w 7.0 Lushan earthquake in China

Situated at the abruptly transitioning eastern margin of the Tibetan Plateau, Lushan County in Sichuan Province, China, features topography that shifts from gentle eastern plains to severely rugged, mountainous terrain in the west. Hillslopes in this western sector are exceptionally steep, frequently exceeding gradients of 30° . The region is governed by the active southern segment of the Longmenshan thrust belt, a highly deformed structural zone driven by the ongoing collision between the Indian and Eurasian plates. The underlying bedrock is dominated by Cretaceous and Triassic sedimentary sequences, primarily composed of sandstone, mudstone, and shale. Subjected to abundant regional rainfall and active groundwater circulation, these sedimentary strata are deeply weathered along joints and bedding planes, significantly degrading their internal shear strength and preconditioning the steep ridges to instability. On April 20, 2013, the region was struck by the M_w 6.6 Lushan earthquake. Occurring just five years after the devastating 2008 Wenchuan earthquake, this

event was characterized as a typical reverse fault rupture with a focal depth of 13 km. It activated thrust structures such as the Shuangshi–Dachuan and Dayi faults without producing a distinct surface rupture (Chen et al. 2014; Xu et al. 2013). The intense ground shaking exploited the highly weathered, steep topography, triggering widespread and catastrophic shallow landslides across the county. We use the 32 landslides in this catalog for blind volumetric inference; we hand-mapped landslides in this region for which we wished to apply the model on.

3 Methods

3.1 Geometric space

The geometry of the planimetric footprint of a landslide encodes its mechanical history of failure initiation, run-out and eventual arrest (Li et al. 2021; Bhuyan et al. 2024). Traditionally, landslide volumes have been inferred from their planform areas using power-law fits of the form

$$V = \alpha \cdot A^\beta$$

where V is volume, A is area, and α, β are empirical constants (Equation 1). Using the source–run-out delineation workflow developed by Bhuyan et al. (2025), every mapped landslide polygon is divided into a *source* planform (head scarp) and the *total* planform (source + run-out). From each shape, we compute a gamut of morphometric indices (area, perimeter, convex–hull ratios, box dimensions, ellipse axes, eccentricity). We then assess feature relevance to source volume, $\log_{10}(V_S)$, via Pearson and Spearman coefficients, mutual

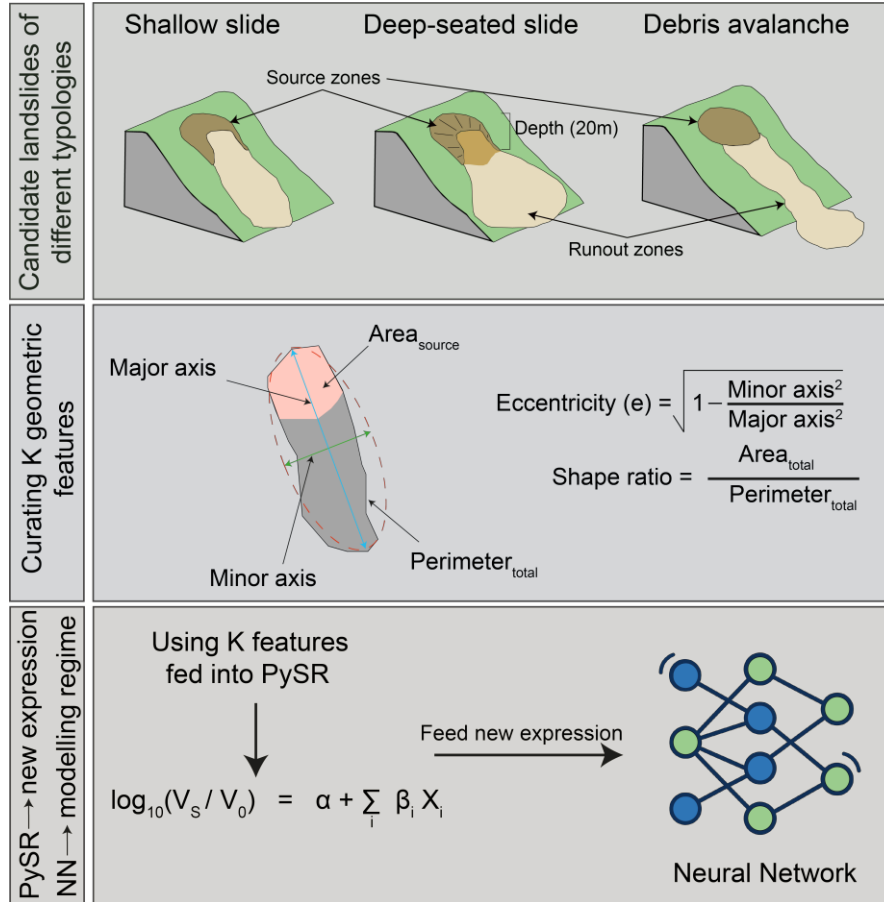
191 information, and ΔR^2 relative to $\log_{10}(A_s)$. The correlations among the various
 192 morphometric parameters can be seen in Table 1.

193 Table 1. Candidate morphometric parameters describing landslide source and
 194 total-footprint geometry.

Parameter Definition		Description
A_s	Source/scarp area (m^2)	Planimetric extent of the initial failure or source region.
A_t	Total planimetric area (m^2)	Planimetric extent of the complete landslide, including the source and run-out regions.
MAE_t	Minor axis of the total-footprint ellipse (m)	Approximate transverse breadth of the complete landslide footprint.
W_t	$MAE_t/\sqrt{A_t}$ (dimensionless relative width)	Relative breadth of the complete footprint after accounting for its overall planimetric size.
C_t	$P_t/[2\sqrt{(\pi A_t)}]$ (dimensionless compactness)	Degree to which the total footprint departs from a compact, approximately circular planform.

AR_t	Total-footprint aspect ratio	Elongation of the complete landslide footprint relative to its principal axes.
P_t	Total-footprint perimeter (m)	Length of the boundary enclosing the complete landslide footprint.

195 Next, since these parameters are derived from mapped polygon boundaries, their
 196 usage and practicality may depend on the geometric resolution at which those
 197 boundaries are represented. The disparity occurs due to mapper experience,
 198 institutional training, the resolution of the map used to draw polygonal boundaries,
 199 and more. In this regard and to account for these discrepancies, we evaluate an
 200 out-of-fold (OOF) performance of the morphometric parameters after simplifying
 201 the polygons to 5, 10, 20, and 50 m to analyze whether the volumetric signal is
 202 robust to boundary generalization while retaining the native polygons at the 0 m
 203 reference.



204

205 *Figure 2: The illustration showcases morphometric signatures of differing*
 206 *landslides are taken into consideration, following adaptations in the associated*
 207 *morphometries, and then embedded into neural networks. PySR refers to the*
 208 *Python library (Cranmer 2023) designed for interpretable symbolic expression.*
 209 *NN refers to neural networks.*

210 3.2 Symbolic representation: discovering a

211 morphologically-plausible volume relationship

212 Symbolic regression aims to discover an explicit, low-complexity analytical
 213 expression that maps a predictor vector to the response $\log_{10}(V_s/V_0)$, thereby

214 deriving a representation of the underlying relationship between landslide
215 morphometry and volume. Unlike purely data-driven curve-fitting, SR searches a
216 grammar-constrained space of candidate equations (or expressions) and
217 balances goodness-of-fit against mathematical parsimony (Schmidt and Lipson
218 2009; Udrescu and Tegmark 2020).

219 3.2.1 Search space syntax and multi-objective loss

220 We adopt minimalist grammar

$$221 \quad \mathcal{G} = \{ +, -, \times, \div, \log_{10}(\cdot) \},$$

222 and restrict exponents to $S = \{-2, -1, -1/2, 0, 1/2, 1, 2\}$. This design biases the
223 search toward interpretable, unit-sensible forms while still spanning the non-
224 linearities relevant to slope failure. Linearity in $\log_{10}$ space captures multiplicative
225 scaling; the discrete set S allows inverse, square-root, linear, and quadratic
226 responses (i.e., diminishing to amplifying returns) without inviting high-order
227 behavior. By excluding trigonometric and unconstrained exponential functions,
228 we avoid oscillatory or explosive fits that lack geomorphic meaning that tend to
229 overfit.

230 Crucially, this grammar does more than recast known power laws and encodings
231 (e.g., landslide area-volume scaling, $V \propto A^\beta$; sediment yield-drainage area
232 relationship, $Q_s \propto A^c$ (Summerfield and Hulton 1994; Montgomery and Brandon
233 2002); and Hack's Law, $L \propto A^h$ (Maritan et al. 1996). It also permits simple
234 interactions and ratios among morphometric descriptors (e.g., area, width

proxies), enabling the search to discover low-complexity expressions that are both parsimonious and transferable.

For each candidate expression $f(\mathbf{x}; \boldsymbol{\theta})$ we form

$$\mathcal{L} = \frac{1}{2} \left\| f(\mathbf{x}; \boldsymbol{\theta}) - \log_{10} \left(\frac{V_S}{V_0} \right) \right\|_2^2 + \lambda \|\boldsymbol{\theta}\|_0.$$

where the second term counts the number of active coefficients and λ sets the trade-off between accuracy and sparsity. Equation 2 is optimised by evolutionary search with L_0 pruning (`populations = 31` , `population_size = 27` , `ncycles_per_iteration = 380` , `niterations=1000` in our run `default_niterations=100`). At every generation we mutate both the algebraic tree and the real-valued parameters $\boldsymbol{\theta}$, retain the non-dominated Pareto front, and progressively increase λ to favour compact formulae.

3.2.2 Winning expression

Among the grammar-feasible candidates, we ranked each by 5-fold cross-validated error and selected the model at the *elbow* of the accuracy-complexity Pareto curve—i.e., the most parsimonious expression whose accuracy was statistically indistinguishable from the best. The winner (as found in the Results section) also passed bootstrap stability and basic physical checks (monotonicity in area; sensible responses to shape/depth proxies) and reduces to the classical $V \propto A^\beta$ in the appropriate limit. We then freeze this expression and use it as a symbolic backbone whose coefficients are later fine-tuned during neural network training (Cranmer et al. 2020; Cranmer 2023).

256 3.2.3 Morphometry-guided symbolic neural network

257 We treat the winning expression as a *symbolic backbone* and attach a small
 258 residual network r_ϕ that learns the remaining variance:

$$259 \quad \log_{10} \left(\frac{\hat{V}_S}{V_0} \right) = f_{\text{SR}}(\mathbf{x}; \theta^*) + r_\phi,$$

260 During training, we minimise

$$261 \quad J = \mathbb{E} \left[\left(\log_{10} \left(\frac{\hat{V}_S}{V_0} \right) - \log_{10} \left(\frac{V_S}{V_0} \right) \right)^2 \right] + \lambda_{\text{SR}} \sum_k (\theta_k - \theta_k^*)^2.$$

262 so that the network refines, but does not overwrite the interpretable parameters
 263 θ^* . The second term acts as a *symbolic anchor* and proved crucial for avoiding
 264 avoiding unconstrained parameter drift during later domain adaptation. r_ϕ is an
 265 MLP (hidden widths 64 and 32, ReLU activations, layer-norm, dropout = 0.1). We
 266 train with Adam (learning rate 10^{-4} , weight decay 10^{-6} , batch size 256, 7000
 267 gradient steps, cosine decay, early stopping with patience = 200). Weights are
 268 He-initialised (He et al. 2015). At last, the primary metric is the coefficient of
 269 determination (R^2), evaluated in normalized log-volume space, $\log_{10}(V_S/V_0)$.

270 With the coefficients trainable, the intention is to have a simple, yet interpretable
 271 approach. With ε_{A_S} , and ε_{W_T} , we can ascertain how the model ‘thinks’ when
 272 observing individual landslides in producing a certain value of volumes. This
 273 allows us to gauge the overall contribution of each morphometric feature in said
 274 volume production.

With this pipeline, we aim to fuse an interpretable symbolic expression with data-driven residual learning. This way, we enforce the model to respect first-order geomorphic reasoning while capturing local deviations, yielding volumes with quantified uncertainty and interpretable empirical elasticities.

3.2.4 Reading the morphological controls on landslide volume

We used SHapley Additive exPlanations (SHAP) (Lundberg and Lee 2017) to quantify how each morphometric predictor shapes the inferred landslide volume. SHAP approximates Shapley values from cooperative game theory, assigning to each feature a locally additive contribution to the deviation of a given prediction from the model's mean output. Treating our trained network as a black box that maps (A_S, W_T) to volume (in log-space), we wrapped it with the KernelExplainer and drew representative background sample of landslides to estimate these attributions. For every landslide–feature pair we obtained a SHAP value, then aggregated absolute values to derive global importance scores and to construct “budgets” of influence from both A_S and W_T . Here, SHAP allows us to verify that the learned relations remain geomorphically plausible and to diagnose where each morphometric control is most influential.

4 Results

4.1 Defining a new expression for volumetric erosional scaling

Traditional area-only scaling provides a useful first-order baseline but leaves unexplained variation in the Kaikōura inventory (Figure S1). The best area-based relation achieves $R^2 = 0.694$ ($N \approx 10,000$) (Jones et al. 2025), indicating that source area (A_S) cannot alone capture all of the geometric information associated with landslide erosional volume. We therefore constructed and screened candidate planimetric descriptors (see Table 1).

We then used symbolic regression on the log-transformed candidate descriptors to identify compact volume–morphology relationships. Among the parsimonious expressions on the Pareto front, we retained a relation containing A_S and W_T in the form of:

$$\log_{10} \left(\frac{V_S}{V_0} \right) = c + \beta_A \log_{10} \left(\frac{A_S}{A_0} \right) + \beta_W \log_{10} W_T.$$

The strong anticorrelation between C_T and W_T ($r = -0.998$) cautions against interpreting them as independent corrections. We favor the latter ellipse-based descriptor (W_T) over perimeter-based compactness (C_T) as the more directly interpretable morphological correction, while treating its inclusion in the scaling relation as an empirical selection rather than a derivation from failure mechanics.

311 In the present implementation, $A_0 = 1 \text{ m}^2$ and $V_0 = 1 \text{ m}^3$. The saved symbolic-
312 regression solution currently corresponds approximately to

313
$$c = -0.10, \beta_A = 1.196, \beta_W = 0.476$$

314 Thus, in the original volume scale,

315
$$V_S = V_0 \cdot 10^c \cdot (A_S/A_0)^{\beta_A} \cdot W_T^{\beta_W} .$$

316 Equivalently,

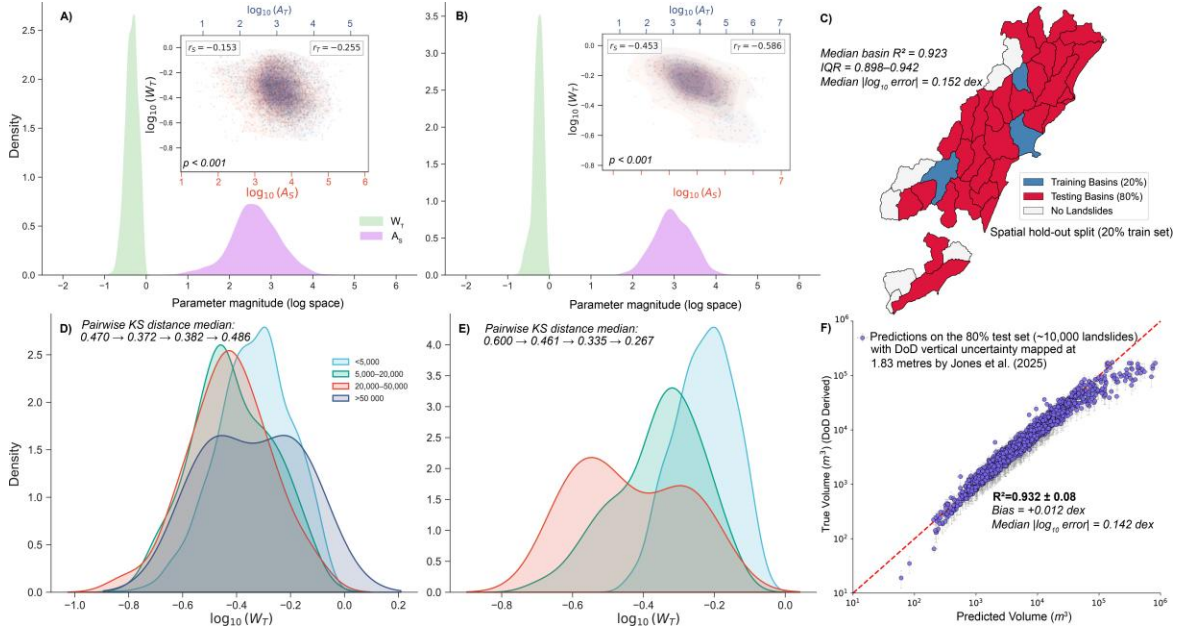
317
$$V_S = \alpha \cdot A_S^{\beta_A} \cdot W_T^{\beta_W}$$

318 where $\alpha = V_0 \cdot 10^c A_0^{-\beta_A}$ carries the unit required to produce volumes. This
319 formulation is dimensionally consistent because W_T is dimensionless and the
320 area term is expressed relative to a defined reference scale. More details
321 regarding the derivation can be found in Notes A1–A3. This selected symbolic
322 expression was then used as the interpretable backbone and initialization for the
323 neural model. As per how a neural residual component operates, it allows us to
324 depart from a global area–relative-width relationship while preserving its
325 mathematical structure. What this means is that the volumetric output does not
326 stray away from the bounds established in the expression.

327 Next, we investigate probability density functions which show that A_S spans a
328 substantially broader range than W_T , whereas W_T is comparatively tightly
329 distributed. This contrast indicates that A_S primarily captures the magnitude of the
330 source region, while W_T describes a more constrained aspect of the total
331 landslide morphology. The correlation analysis within panels A and B of Figure 3

further shows that W_T tends to decrease with increasing area, with the relationship being weak in Kaikōura and relatively more pronounced in Hokkaidō, respectively. When the inventories are stratified by total landslide area (A_T ; Figure 3-D,E), the distribution of W_T shifts toward lower values across progressively larger size classes, particularly for Hokkaidō. These differences are also reflected in the pairwise Kolmogorov–Smirnov distances between the size classes.

These observed shifts may reflect systematic changes in planimetric spreading and morphology as landslides become larger, although the present analysis does not by itself establish a specific process (e.g., increased incision or substrate penetration). Together, A_S and W_T may therefore provide complementary information where W_T may constrain volumetric differences across both small and large landslides. Given these morphological disparities, we apply a neural network to the identified symbolic expression to optimize and scale the resulting model across the Kaikōura inventory.



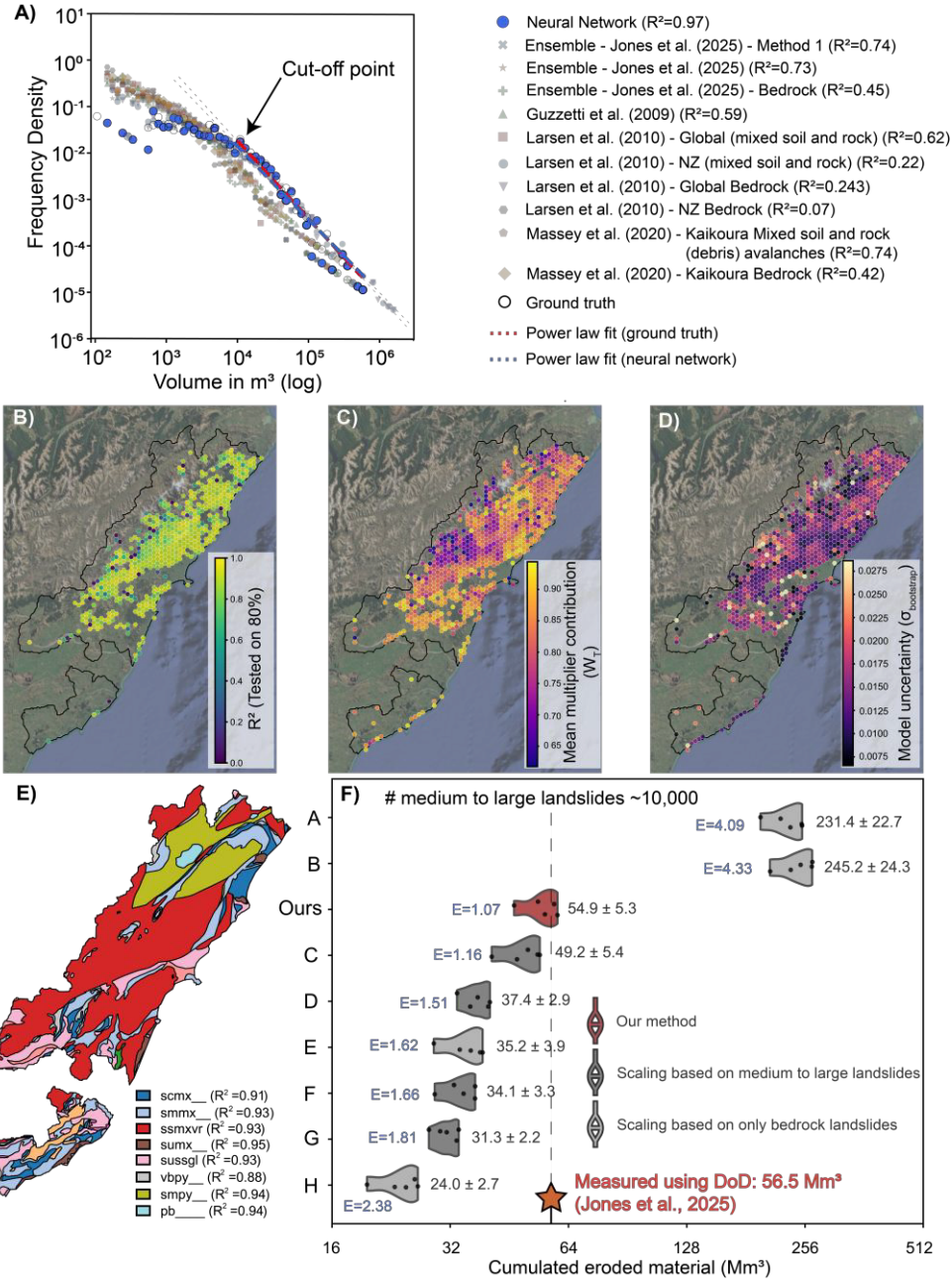
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348 Figure 3: (A) Kaikōura and (B) Hokkaidō probability-density functions of the
 349 logarithmically transformed relative-width parameter $\log_{10}(W_T)$ and source area
 350 $\log_{10}(A_S)$. The inset in each panel shows their joint distribution, with Pearson (r_P)
 351 and Spearman (r_S) correlations and the corresponding significance level. The
 352 upper horizontal axis provides the equivalent $\log_{10}(A_T)$ scale for the total-
 353 footprint area. (C) Regional map illustrating the strict spatial hold-out design, with
 354 the geographically isolated 20% training basins shown in blue, the 80% unseen
 355 testing basins in red, and basins without mapped landslides in white. (D)
 356 Kaikōura and (E) Hokkaidō distributions of $\log_{10}(W_T)$ stratified arbitrarily by
 357 landslide source-area classes of $< 5,000$, $5,000-20,000$, $20,000-50,000$, and $>$
 358 $50,000 \text{ m}^2$. The annotations report the median pairwise Kolmogorov–Smirnov
 359 distances for successive area-class comparisons, quantifying the degree to
 360 which the W_T distributions change with landslide size. (F) Scatter plot of true
 361 versus predicted landslide volumes evaluated strictly on the spatially unseen 80%

testing set ($> 10,000$ landslides) from the 2016 Kaikōura inventory. Vertical gray error bars represent the propagated ground-truth uncertainty associated with the reported ± 1.83 m (1σ) vertical uncertainty in the source elevation data (Massey et al. 2020; Jones et al. 2025). The dashed red line denotes the one-to-one relationship. The reported $R^2 = 0.932 \pm 0.08$ represents the bootstrap variability of the aggregate test-set performance; it is not interpreted as a $\pm 8\%$ uncertainty in individual linear-volume predictions. The accompanying bias and median absolute logarithmic error summarize prediction calibration and typical multiplicative error.

4.2 Model development on the 2016 M_w 7.8 Kaikōura, New Zealand co-seismic landslides

To systematically assess our modeling framework, we partitioned the Kaikōura (M_w 7.8) inventory using a strict spatial hold-out scheme based on basins. To aggressively test regional generalization and explicitly eliminate the risk of overfitting, we constrained the training regime to a single, geographically isolated subset consisting of only 20% of the landslide data (≈ 2500 , see Figure 3-C). The model was then forced to blindly predict on the remaining 80% of the unseen topography, evaluated against a vertical error constraint (± 1.83 m) reported by (Massey et al. 2020) and (Jones et al. 2025) (achieving $R^2 = 0.932 \pm 0.08$, Figure 3-F). We also mapped the epistemic model uncertainty ($\sigma_{bootstrap}$) across the spatial domain by implementing a 5-model bootstrap ensemble.



383

384 Figure 4: (A) Frequency–volume density distribution comparing the morphology-
 385 informed neural network and legacy empirical scaling laws against the ground-
 386 truth observations (hollow circles), overlaid with their respective power-law fits.
 387 (B–D) Spatial evaluation mapped across the regional testing hexagonal grids,
 388 illustrating (B) generalization performance (R^2), (C) the active mean shape

389 multiplier contribution (W_T), and (D) the epistemic model uncertainty ($\sigma_{bootstrap}$)
 390 derived from a 5-model bootstrap ensemble (darker is lower uncertainty). (E)
 391 Predictive performance (R^2) evaluated across discrete, completely unseen
 392 lithological units. (F) Cumulated erosion from the Kaikōura 2016 co-seismic
 393 landslides in New Zealand are shown here, compared across different scaling
 394 relationships. The ground-truth benchmark (red in line and text) is fixed at 56.5
 395 Mm^3 , against which our model and multiple scaling-law approaches are
 396 evaluated. Violin plots show variability (distribution of totals across 5-fold splits),
 397 with black points denoting individual fold outcomes. Mean ± 1 standard deviation
 398 values ($n=5$) are annotated above each box. E shows the order-of-magnitude
 399 error (e.g., $E=2$; folds error i.e., 10 times). A: Larsen et al.(2010) - Global Bedrock;
 400 B: Larsen et al. (2010) - NZ (mixed soil and rock) -Bedrock; C: Ensemble - Jones
 401 et al. (2025); D: Guzzetti et al. (2009); E: Massey et al. (2020) - Kaikōura
 402 Bedrock; F: Larsen et al. (2010) - Global (mixed soil and rock); G: Massey et al.
 403 (2020) - Kaikōura DA (Mixed); H: Larsen et al. (2010) - New Zealand Bedrock.

404 The power-law fit (Figure 4-A) derived from the neural network predictions (in
 405 blue color) closely mirrors the measured volumes (in red color) indicating that the
 406 model preserves the inventory-wide distribution of event sizes. The view that
 407 morphology, rather than area alone, governs volumetric erosion is supported by
 408 the stark contrast in performance against legacy models in Kaikōura. Spatially,
 409 we also report the R^2 (Figure 4-B), morphometry contribution (W_T in Figure 4-C),
 410 and model (bootstrapped) uncertainty (Figure 4-D) on a hexagonal grid to
 411 demonstrate the spatial divergence over the Kaikōura affected region.

412 Additionally, the geometric capability to implicitly capture landslides across
413 diverse lithologies is evidenced by the model's predictive capacity ($R^2 > 0.90$;
414 trained on the blue basins, Figure 3-F) across the vast majority of unseen
415 lithological units (e.g., sumx__, smpy__, smmx__) (Hartmann and Moosdorf
416 2012) (Figure 4-E).

417 The resolution ablation in Figure S2 shows that the parsimonious A_S and W_T
418 formulation is stable to polygon simplification: pooled out-of-fold R^2 remains
419 above 0.90 from the native geometry to 50 m resolution. The full-geometry model
420 is less stable at intermediate resolutions, indicating that additional boundary-
421 dependent descriptors do not consistently improve generalization. In this
422 framework, W_T is therefore interpreted as an empirical, scale-normalized
423 descriptor of total-footprint shape that adds information beyond source area; it is
424 not treated as a direct measurement of failure thickness or a standalone physical
425 law.

426 In terms of cumulative eroded volumes, our approach predicts volumetric erosion
427 (54.9 Mm^3) nearly identical to the measured cumulative total (56.5 Mm^3) of
428 medium to large landslides (Figure 4-F), while legacy models like (Larsen et al.
429 2010) deviated by a factor of more than four. While considering only deep-seated,
430 bedrock landslides ($N=25$; an independent within-event bedrock evaluation), our
431 approach maintained an order of magnitude error of only 1.19 and cumulative
432 erosion of 36.7 Mm^3 against 32.4 Mm^3 (see Figures S3, S4). The best traditional
433 model (Jones et al. 2025) was off by an order of 1.29 and the worst (Larsen et al.
434 2010) by 2.5. These bedrock subset in Kaikōura indicates that the morphology-

informed formulation remains informative for the tested deep-seated failures, although external validation on an independent deep-landslide inventory remains necessary.

4.3 Application on the 2018 M_w 6.6 Eastern Iburi Hokkaidō co-seismic landslides

Building on the strictly constrained model which was trained exclusively on a 20% spatial fold from Kaikōura (≈ 2500 landslides, see Figure 3-F blue basins), we applied it directly to the 2018 Eastern Iburi Hokkaidō, Japan (M_w 6.6) landslide inventory. We removed signs of coalescing landslides in order to accurately mask out the source zones from the runout (Bhuyan et al. 2025). By forcing the model to predict on a completely different location, we tested whether the relationship learned from Kaikōura remained informative under direct transfer to a contrasting tectonic and geomorphic setting. Despite Hokkaidō's unique geomorphic context, the model achieved an R^2 of 0.925 ± 0.03 (Figure 5-A) without any modification to the trained weights. To further visualize this transferability, we mapped the predictive performance (Figure 5-B) and the epistemic transfer uncertainty ($\sigma_{bootstrap}$) (Figure 5-C) across the affected region. The persistently low ensemble disagreement (i.e., uncertainty, darker tones) indicates that the transferred model produces mutually consistent estimates across much of the Hokkaidō inventory.

Similar to Kaikōura, the power-law fits (Figure 5-D) are very close between the observed data and our neural network-based model. Note that the trend of

landslide volumes prior to the cut-off point does not resemble the typical ‘curved’ distribution; we attribute this to the smaller sample pool compared to that of Kaikōura where the sample pool is much larger (≈ 2500 instances). Furthermore, an analysis of the multiplicative error factor (Figure 5-E) confirms that our framework maintains the tightest error distribution when compared against legacy empirical scaling models, bounding the vast majority of predictions within a single order of magnitude. So far, the results support transferability of the fitted relationship to this independent inventory.

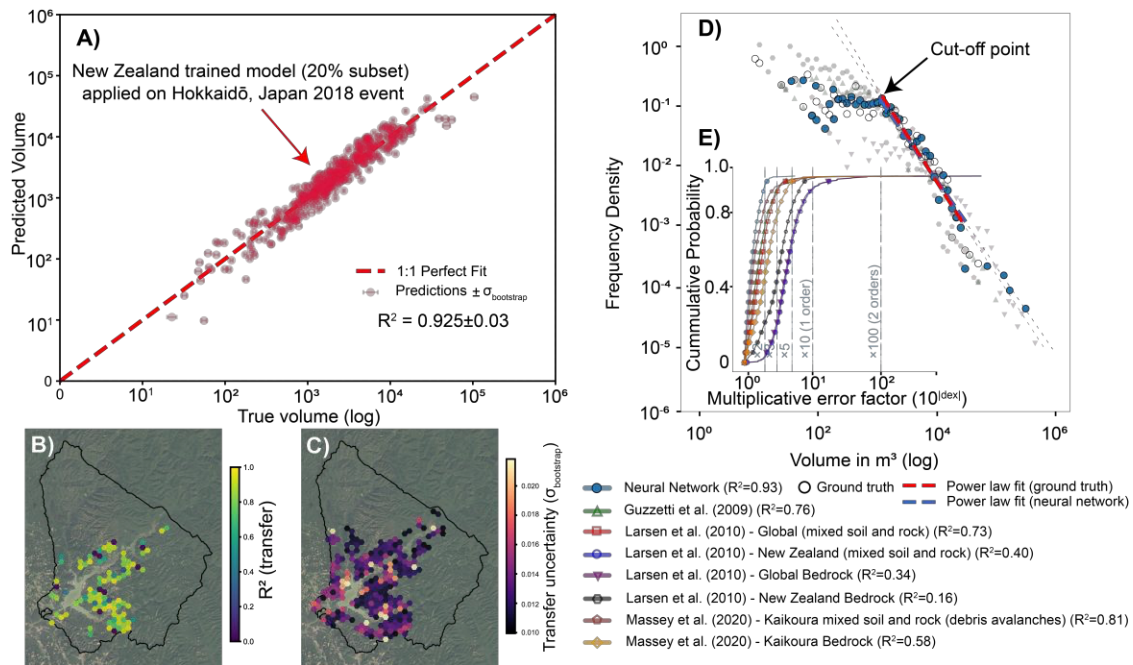


Figure 5: (A) Scatter plot of true versus predicted landslide volumes (log scale) demonstrating the model’s direct transferability to the unseen settings of Hokkaidō, Japan. Error bars on individual predictions represent the epistemic uncertainty ($\pm \sigma_{bootstrap}$) derived from the model ensemble. (B–C) Spatial evaluation mapped across the Hokkaidō region, illustrating (B) the local transfer

performance (R^2) and (C) the spatial distribution of the epistemic transfer uncertainty ($\sigma_{bootstrap}$). (D) Frequency–volume density distribution comparing the morphology-informed framework and legacy empirical scaling laws against the Hokkaidō ground-truth observations (hollow circles), overlaid with their respective power-law fits. (E) Cumulative probability of the multiplicative error factor, quantifying the magnitude of prediction deviations. Vertical dashed lines demarcate discrete order-of-magnitude thresholds; the rapid ascent of the neural network curve demonstrates a considerably tighter error distribution.

4.4 Inference on the 2013 M_w 6.6 Lushan earthquake in China

To demonstrate the framework’s operational utility, we deployed the same strictly constrained New Zealand-trained ensemble on the undocumented 2013 Lushan, China earthquake inventory ($N = 32$) in the context of blind inference (no ground-truth volume provided), and quantified volumetric information (Figure 6)-A. Without true labels to calculate standard error metrics, we evaluate the model by quantifying its internal epistemic confidence ($\sigma_{bootstrap}$) across the spatial domain (Figure 6-C). Mathematically, $\sigma_{bootstrap}$ represents the standard deviation of the individual volume predictions generated across the 5-model bootstrap ensemble. If the framework encountered an anomalous 2D planform shape or topological complexity that fell outside its calibrated understanding, the independent models within the ensemble would diverge significantly, producing a high $\sigma_{bootstrap}$. Conversely, the spatial evaluation reveals high model agreement across the

Lushan domain, with the maximum ensemble variance remaining tightly bounded ($\sigma_{bootstrap} \leq 0.05$). This $\sigma_{bootstrap}$ is quite low and shows low internal model disagreement for the 32 landslide cases; because independent volume observations are unavailable, this should not be interpreted as evidence of predictive accuracy or physical similarity to the Kaikōura calibration domain.

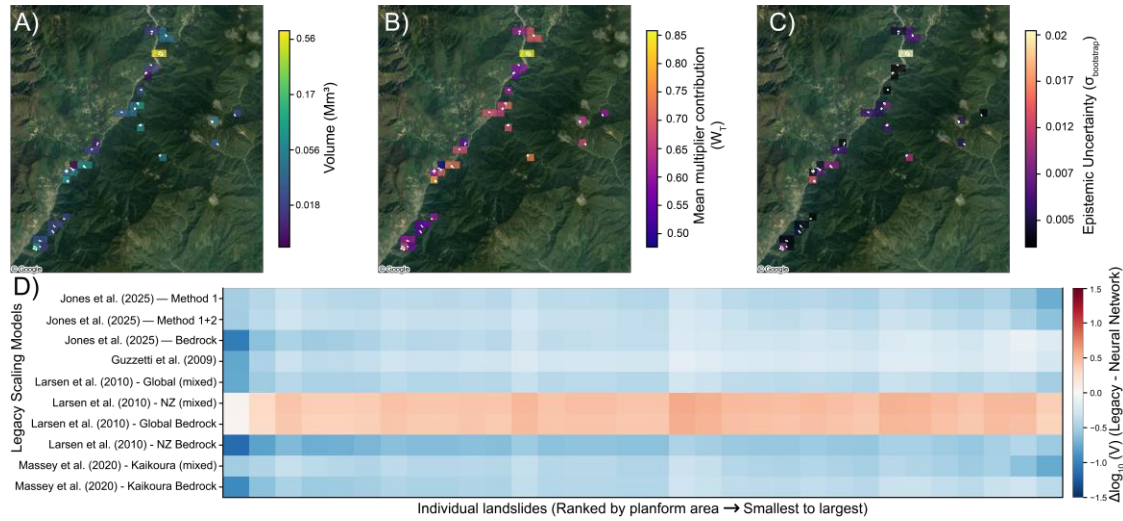


Figure 6: (A–C) Spatial mapping across the undocumented Lushan domain utilizing the New Zealand-trained ensemble, illustrating (A) the predicted individual landslide volumes (Mm^3), (B) the active morphological shape multiplier ($\log_{10} W_T$) driving the volumetric scaling, and (C) the tightly bounded epistemic model uncertainty ($\sigma_{bootstrap}$) mapped from the bootstrap ensemble. (D) Differential volumetric heatmap ($\Delta \log_{10} V_S$) comparing legacy empirical scaling estimates against our framework across the Lushan inventory. Individual landslides are ranked by planform area along the x-axis. Blue gradients indicate systematic underestimation by legacy laws, while red gradients highlight severe overestimation.

To visually conceptualize how the neural network interprets these boundary conditions, Figure 6-B maps the mean multiplier contribution of W_T . Geomorphologically, this multiplier functions as a dynamic scaling factor that actively calibrates the empirical area baseline. Because a 2D planform area (A_S) alone cannot distinguish between a shallow, superficial soil slip and a deeply incised, massive rock avalanche occupying the exact same footprint, the model relies on W_T and modifies the area-based estimate according to relative transverse geometry. Highly extended, directional runout axes (W_T) generate a higher multiplier (represented by brighter pixels). This mathematically drives the predicted volume upward, accounting for the massive amount of internal material required to sustain such highly mobilized, structurally expansive failures. Conversely, simpler, transversal footprints that are often indicative of shallow planar slides or rigid, block-like failures with limited internal deformation yield a lower multiplier (darker pixels), effectively dampening the area-based volume estimate. By synthesizing this morphometric parameter, the multiplier acts as a quantifiable proxy for the underlying mechanical behavior.

Crucially, Figure 6-D illustrates the resultant impact of the above mentioned active morphological correction through a differential volumetric expression heatmap ($\Delta \log_{10} V$). Unlike traditional empirical scaling laws ($V = \alpha \cdot A^\gamma$), which rigidly assign identical volumes to equivalent areas, our approach utilizes the multiplier to autonomously shift the volumetric estimate based on specific 2D transversal complexities. This heatmap shows severe deviations when using legacy models to this undocumented inventory: the majority of traditional laws

systematically underestimate the volumes compared to the neural network (indicated by blue gradients), while specific regional parameterizations (e.g., Larsen et al. 2010 - New Zealand mixed and Global Bedrock) severely overestimate them (red gradients) across the individual landslide size spectrum.

This per-landslide morphological correction cascades into massive discrepancies in the regional total eroded volume estimates. Our morphology-informed framework estimates a total cumulative volume of 1.95 Mm^3 for the event. In contrast, traditional empirical models exhibit a wide range of volumetric estimation, predicting regional totals ranging from as low as 0.53 Mm^3 (Massey et al. 2020 - Kaikōura mixed) to as high as 5.31 Mm^3 (Larsen et al. 2010 - NZ mixed) for the exact same 32 landslides. This divergence underscores that different formulations produce substantially different regional totals, and highlights the constraints introduced by our framework to provide a second lens of opinion.

4.5 Shifts in morphometric controls

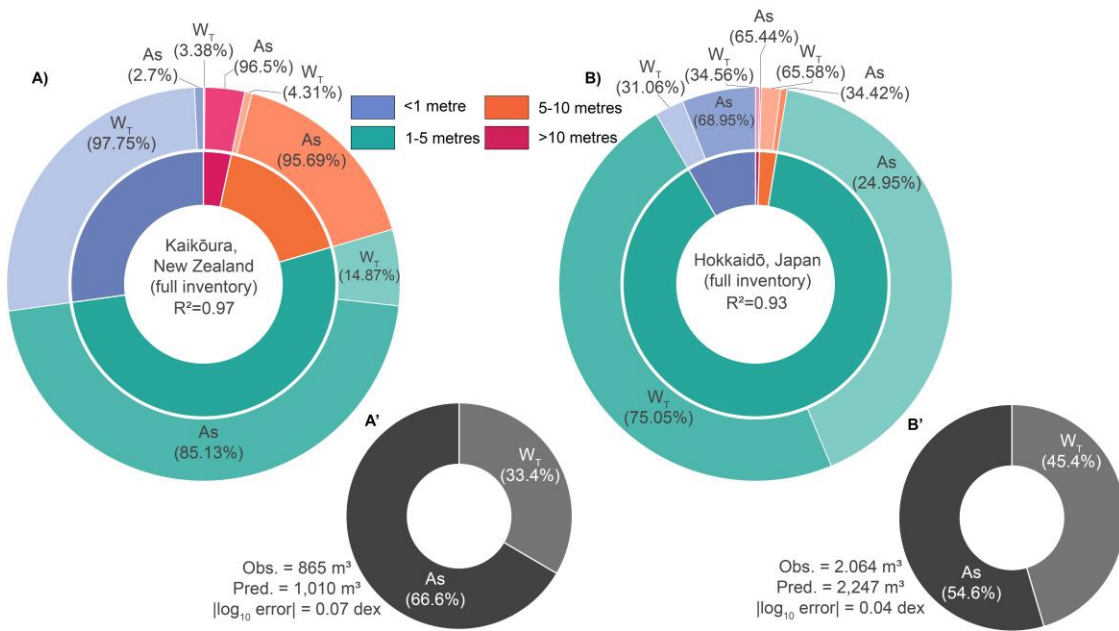
To understand whether the model relies on the two predictors in the same way across failure-depth regimes, we calculated their relative permutation contributions (Fig. 7; Note A3 expresses the quantification on how parameter contributions are measured). The inner ring shows the proportion of landslides in each class, while the outer ring partitions the associated increase in prediction error between A_S and W_T . The outer ring percentages describe model reliance

within each class; they are not measurements of physical volume fractions or causal effects.

The Kaikōura inventory shows a clear depth-dependent shift in predictor reliance. Failures shallower than 1 m are dominated by W_T (~97%), with little contribution from A_S . For deeper classes, A_S becomes the primary predictor, contributing 85% in the 1–5 m class and remaining dominant thereafter, with only modest contributions from W_T . Thus, we observe that the model shows greater reliance on W_T for the shallower group, whereas source area increasingly controls deeper events.

Conversely, the Hokkaidō transfer shows a different allocation. In most failures from the 1–5 m class, W_T contributes approximately 75% of the attribution and A_S approximately 25%. In the shallower class, A_S contributes approximately 69%, with the remainder assigned to W_T . The deeper classes contain relatively few observations and should therefore be interpreted cautiously, but their attributions indicate that both predictors remain active. The contrast between the two inventories shows that the relative value of source area and total-footprint width is dataset- and depth-dependent rather than fixed. The sample-level sunbursts reinforce this point (A' and B'). In the representative Kaikōura example, A_S and W_T contribute approximately 67% and 33%, respectively, while the Hokkaidō example is more evenly divided (approximately 55% and 45%). Both predictions have small absolute logarithmic errors, but note that these individual examples are illustrative rather than estimates of population-wide contribution.

575 Together with the resolution and ablation experiments (from Figure S2), these
576 results support using W_T as an empirical complement to source area. A_S supplies
577 the primary size-related signal in many regimes, while W_T provides additional
578 information about the total planimetric footprint when area alone is insufficient.
579 The attribution analysis does not, by itself, demonstrate that W_T measures failure
580 depth, identifies a specific failure mechanism, or recovers three-dimensional
581 geometry. It instead shows that the predictive information supplied by the two
582 geometric descriptors is redistributed across depth classes and inventories, and
583 W_T is able to extract that information rather well.



584

585 *Figure 7: Sunburst diagram for attribution of A_S and W_T across post-hoc observed*
586 *failure-depth groups across New Zealand and Japan. Each Sunburst (full*
587 *inventory averages: A-B; per-landslide examples: A'-B') shows how feature*
588 *contributions summarized on depth groups (< 1 m: blue, “1–5 m”: tortoise, “5–10*
589 *m”: orange, > 10 m”: magenta) to the total predicted volume sub-circle.*

Percentages next to each parameter label report its share of the total SHAP values for the sub-sector. Features are ordered with respect to the total SHAP contribution A_S (planform source area) and W_T (minor axis length of fitted ellipse on the total planform). The title of A–B reports the model’s average R^2 for the whole inventory; A’–B’ reports measured and neural-network volumes for a specific polygon (m^3). Reading the figure: it quantifies the magnitude of each parameter’s contribution and identifies the specific depth regime in which that contribution influences the final predicted volume.

5 Discussion

What is the nature of traditional scaling and its bias among diverse settings?

We demonstrated that landslide area is often insufficient to map monotonically to volumetric erosion. While legacy scaling accounts for larger variance in uniform regimes, it fails to capture the complexity of non-uniform failures. Much of this boils down to accrued systematic bias inherent in the original calibration environments. In Kaikōura, New Zealand, for example, complex landslide morphologies ensue from a variety of failure modalities, e.g., rock avalanches, bedrock landslides, and shallow failures. Consequently, legacy models exhibit larger variance ($R^2 = 0.74$) compared to our reformulated expression ($R^2 > 0.90$). This gain is rooted in the synergy captured by our symbolic expression, which defines volumetric erosion as a product of planform geometry rather than a simple area-dependent relationship. Such flexibility allows the framework to solve morphometric inversions where scarp area alone severely misestimates volume

and structural shape (in our case, transversal geometry) becomes the primary predictive signal for eroded mass. Therefore, utilizing symbolic regression and its identified latent "morphological signatures", we aid in finding a solution of complex morphometric variations that area-only scaling overlooks.

Why can a fixed scaling exponent fail to represent heterogeneous landslide populations? Fundamentally, while traditional area-volume scaling laws ($V = \alpha A^\gamma$) offer a mathematically elegant and easily applicable baseline, they remain empirical approximations that frequently exhibit orders-of-magnitude errors when applied across diverse lithologies and movement types (Guzzetti et al. 2009; Larsen et al. 2010; Massey et al. 2020). Landslides with similar erosional domains may develop substantially different accumulation geometries (i.e., runout) and occur within contrasting geological settings, producing volumetric variation that remains unresolved by area alone. This does not require a landslide-specific area exponent, nor does it imply multifractal or self-organised critical behaviour. Rather, it indicates that additional geometric information (e.g., our identified W_T) may explain part of the residual variance around the conventional area–volume relationship.

Landslide morphology refines the first-order area–volume relationship. In this context, our proposed formulation: $\log_{10}(V_S/V_0) = c + \beta_A \log_{10}(A_S/A_0) + \beta_W \log_{10}(W_T)$, operates as an empirical, dimensionally consistent morphology-informed model rather than as a universal physical scaling law. This adaptive structure allows the formulation to represent additional volumetric variation associated with differences in planform morphology that remains unresolved by

area alone. By embedding morphological constraints (W_T), the framework actively calibrates the empirical area baseline using observed geometric complexity of different landslide types (shallow and deep). This facet helps bring forth a single, unified mathematical logic. Practically, this morphology-informed logic directly mitigates the inherent variance of area-only scaling, which frequently misestimate eroded volumes by factors of 10^3 – 10^5 (Massey et al. 2020). This precision at the individual footprint translates directly to close agreement at the event scale; in Kaikōura (Figure 4-F), our framework predicted a cumulative eroded volume (54.9 Mm³) nearly identical to the measured total (56.5 Mm³), whereas legacy models systematically overestimated the regional budget by a factor of four (>200 Mm³). Because this mitigation is achieved using parsimonious geometric descriptors rather than high-dimensional, region-specific inputs (Tuganishuri et al. 2025), the framework effectively curtails systematic overestimation while remaining highly applicable to inventories without measured volumes, as illustrated by the Lushan inference experiment (Figure 6).

Lithological blindness on the new morphology–volume relationship.

Despite its improved precision, our model remains a geometric proxy and does not explicitly require lithological or hydrogeological parameters as direct inputs. Traditional scaling frequently require separate parameterizations for different rock types, as distinct materials fail with varying depth-to-area aspect ratios. However, our spatial prediction experiments indicate that the morphometric constraints may implicitly capture material properties. The model demonstrated higher agreement ($R^2 > 0.90$) across a variety of sedimentary and mixed rock

units (e.g., `sumx__`, `smpy__`, `smtx__`). In these materials, differences in failure geometry may be more clearly expressed in the mapped planform, allowing scale-normalized transverse breadth to retain information associated with eroded volume. Conversely, performance noticeably diminished ($R^2 \approx 0.63$) for massive, crystalline basic plutonic rocks (`pb__`). We posit that the failure of such hard, intact bedrock may be more strongly influenced by deep structural discontinuities (such as joint sets or intersecting faults) rather than surface-coupled mechanics. Such failures may produce comparatively simple, block-like planforms for which relative transverse breadth is weakly coupled to the subsurface failure depth. So, it maybe so that the 2D footprint decouples from the 3D failure depth and temporarily restricts the predictability of our morphological signatures.

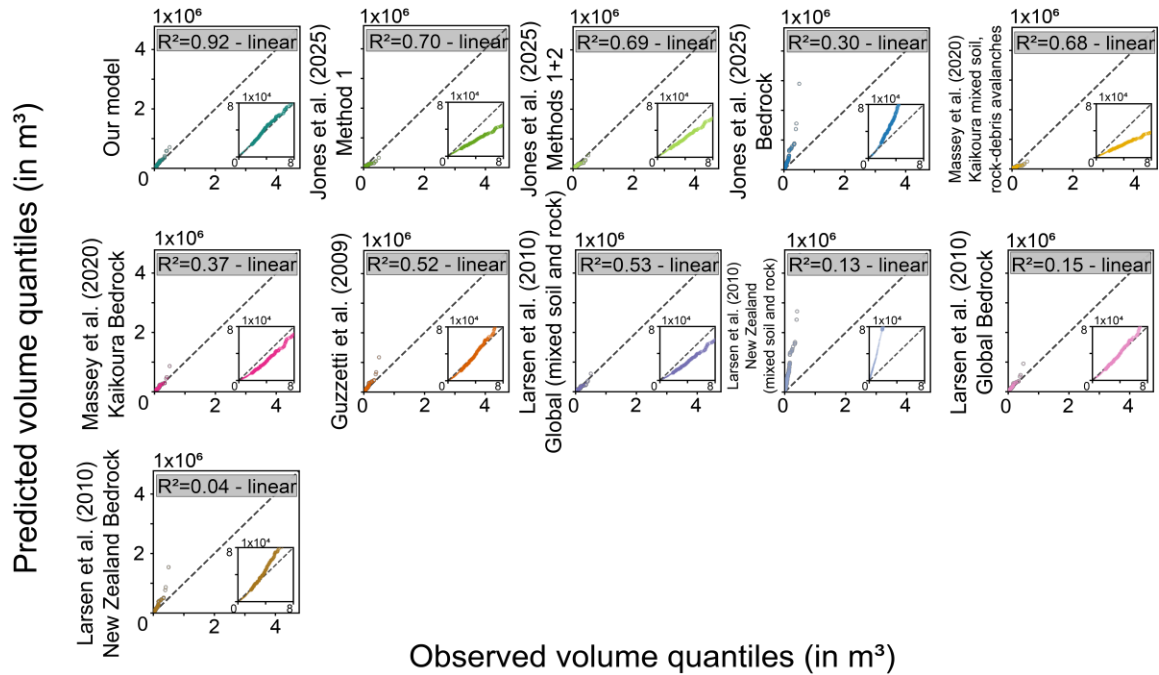


Figure 8: Observed and predicted landslide-volume quantiles for the Kaikōura inventory, comparing the morphology-informed neural network using A_S and W_T

with the considered literature-based scaling relations. Each subplot pairs observed quantiles on the x-axis with predicted quantiles on the y-axis in linear volume units (m^3); the dashed line denotes one-to-one agreement. The main panels show the full regional volume range, while the insets enlarge the lower-volume range up to $8 \times 10^4 m^3$. Semi-transparent points represent the interpolated quantile pairs, with upper-tail observations and raw maxima retained where visible. The R^2 values shown in each panel are calculated from the corresponding observed–predicted landslide pairs and summarize agreement on the linear-volume scale.

Limitations of our proposed morphology–volume relations to failure depth and triggering regime. Similarly, predictive skill for erosion diminishes for very shallow slides ($h < 1m$), most likely due to DEM resolution limits. The greater agreement observed for deeper failures ($R^2 = 0.97 \pm 0.03$ at the deepest levels) may reflect stronger morphology–volume coupling, reduced relative measurement uncertainty, or a combination of both. Furthermore, because our model is calibrated on co-seismic events, transfer to rainfall-induced flow-type regimes should be approached with caution, as transient pore pressures and fluid entrainment mechanisms may fundamentally alter the morphometric-volume relationship.

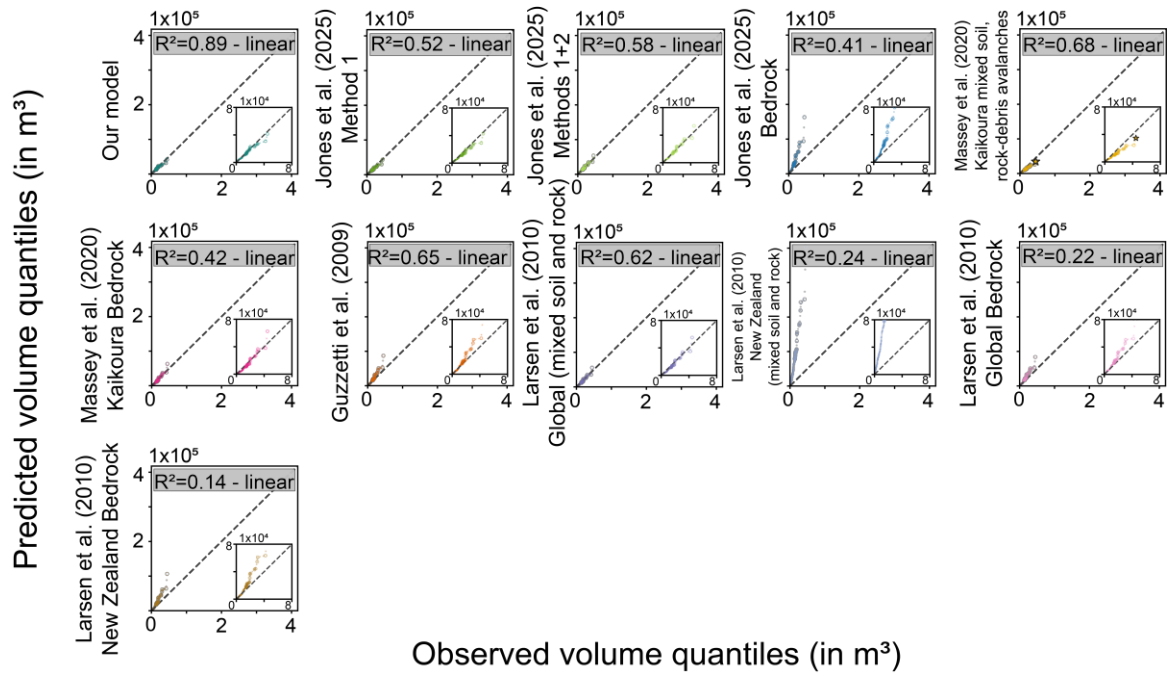


Figure 9: Observed and predicted landslide-volume quantiles for the Hokkaidō inventory, comparing the morphology-informed neural network using A_S and W_T with the literature-based scaling relations. Observed quantiles are plotted on the x-axis and predicted quantiles on the y-axis in linear volume units (m^3); the dashed line represents one-to-one agreement. The main panels show the complete volume range for Hokkaidō, whereas the insets provide an expanded view of volumes up to $8 \times 10^4 m^3$. Semi-transparent points show the interpolated quantile pairs, with upper-tail observations and raw maxima retained where visible. Panel annotations report the R^2 calculated from the paired observed and predicted volumes, allowing direct comparison of linear-scale predictive performance among the neural model and legacy relations.

Broader implications for sediment budgets and downstream geomorphic processes. Looking forward, the ability to disaggregate event-scale erosion by

failure depth (shallow vs. bedrock) may provide a critical bridge to modern sediment budgeting (Pearce and Watson 1986; Li et al. 2014; Francis et al. 2022; Xie et al. 2022), downstream erosion (Bernard et al. 2020), and perhaps even organic carbon cycling (Emberson et al. 2018; Croissant et al. 2021; Booth et al. 2023). Accurate eroded volume-depth profiles enable tighter coupling between mass-movement models and terrestrial carbon export frameworks. Furthermore, as future high-resolution DoD datasets become available to adequately calibrate localized in-situ mechanics and bulking factors, these highly constrained volumetric predictions could ideally serve to initialize dynamic runout simulations, advancing comprehensive downstream hazard and risk assessment workflows.

A tandem role for morphology-informed and traditional scaling. Taken together, our findings signal a direction in how landslide erosion is quantified from a new perspective. Parsimonious, accessible models may provide useful regional estimates of landslide erosion across regional scales. While we propose a new framework, we do not promote disentangling from legacy approaches; instead, we envision a complementary approach. By maintaining a dual perspective, legacy scaling provides a baseline for uniform failures while our morphological signatures (W_T) serve as a diagnostic correction for complex, non-uniform events (e.g., rock avalanches, shallow, and bedrock landslides). This integrated assessment is particularly critical for the world's under-instrumented/documented regions, where accurate erosion budgets are essential for broader landscape dynamic studies and cascade effects.

Scale considerations: logarithmic versus linear volumes. We have kept some important considerations for the end of this section. In this sense, we will acknowledge and reflect on two aspects in the current literature. On one side, geoscientists recognize the importance of accurate landslide volume estimates, usually referring to their use as input for landscape evolutionary modeling (e.g., Campforts et al. 2020, 2022), and/or for physics-based simulations (e.g., Mergili et al. 2017). On the other side, most of the studies focused on volume estimation still produce frequency volume distributions (e.g., Dai and Lee 2001). This inevitably creates an issue. In fact, neither landscape evolution models nor physics-based solvers allow for inputting volumes in logarithmic scales. In turn, this requires the log-volume estimates to be converted to the linear scale by calculating their exponential value. However, error estimates calculated on the basis of log-volume models are not the same as the error estimates calculated after converting back to actual linear volumes, something that inevitably produces very large discrepancies between observed and predicted volumes. With this idea in mind, we opted to challenge the volumetric erosion model we tested in this manuscript. Specifically, we assess the misfit between observed and predicted volumes in their linear expression. And in doing so, we benchmarked our results against other volume conversion approaches. Figures 8 and 9 showcases our results as Q-Q plots highlighting high R^2 both in the case of Kaikōura ($R^2 \approx 0.92$) and Hokkaidō ($R^2 \approx 0.89$). Across the board, the legacy scaling laws deviate substantially. For instance, compared with the scaling law of Guzzetti et al. (2009), in Kaikōura we yield improvements of 64% and 77% on the

logarithmic and linear scales, respectively. In Hokkaidō, improvements are observed by 22% and 37%. These results all indicate that our model has the potential to produce reliable erosional volumetric estimates directly in linear scale and across multiple landscapes.

6 Conclusion

Overall, the rationale of our work arises from revisiting legacy scaling laws by centering volumetric calculations on the core 2D morphology of the landslide footprint. We demonstrate that the reformulated relationship provides spatially consistent volume estimates within Kaikōura, retains useful transferability when applied without recalibration to Hokkaidō, and can be used for blind regional inference in Lushan where independent volume observations are unavailable. The Kaikōura results further indicate applicability across the observed range of shallow and deeper failures. Continuing on the obtained erosional volumes, our blind application to the Lushan earthquake sequence (in China) highlights the framework's operational utility for rapidly gauging regional volume estimates in undocumented, data-scarce environments. By mitigating the extreme variance that frequently limits area-only legacy models, this approach offers a highly accessible, grounded tool for constraining regional sediment budgets and post-disaster geohazard assessments following large-magnitude earthquake events.

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Declarations

The authors declare no competing interests.

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K.B. conceived the conceptualization of the research. Support was provided by U.O., X.F., F.C., L.L., and M.V.W.D.V; K.B. designed the research and C.F. assisted in developing the code. K.B. and C.F. performed data curation and formal analysis; X.W., L.N., and J.L contributed to ancillary data curation and reviewing; All authors contributed to writing, reviewing, and editing.

Data availability

The data used in this work can be found respectively from the original published work (Massey et al. 2020; Yunus et al. 2023). Lushan's data was manually mapped and can be requested to the authors.

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