Landslide Scaling: A Review

S. F. Tebbens1

1Department of Physics, Wright State University, Dayton, OH, USA

Abstract This paper is a review of landslide and rockfall studies of hilly and mountainous regions worldwide. Repositories of landslide inventories are available online (e.g., Tanyaş et al., 2017; https://doi:10.1002/2017JF004236). The landslide inventories predominantly record the surface area of deep-seated, fast-moving, landslides, generally triggered by an earthquake or rainfall event, and such landslides are the primary focus of this review. The size-frequency distributions of landslides and rockfalls are well described by a power function for larger (generally for the largest 2 orders of magnitude) of event sizes (e.g., Malamud et al., 2004; https://doi:10.1002/esp.1064; Tanyaş et al., 2018; https://doi:10.1002/esp.4359). Smaller event sizes are under-represented by the power function that describes the larger events (e.g., Stark & Hovius, 2001; https://doi.org/10.1029/2000GL008527). The deviation from a power function at smaller sizes is arguably not a simple detection issue and possible explanations include lack of temporal resolution in sampling, and amalgamation of smaller events into larger events when mapping (e.g., Tanyaş et al., 2019; https://doi:10.1002/esp.4543). Self-organized criticality models and cellular automata models have been developed that replicate the power scaling behavior (e.g., Hergarten, 2013). The self-organized criticality models are alluring in their simplicity but have shortcomings such as failing to recreate the same scaling exponent as observed in nature (e.g., Hergarten, 2002). Parameterized cellular automata models include one or more relevant variables that affect shear stress in the surface materials and come closer to replicating the scaling exponents observed for natural systems (e.g., D’Ambrosio et al., 2003; https://doi:10.5194/hess-3-545-2003). Mechanical models have also successfully replicated the observed power scaling (e.g., Jeandet et al., 2019; https://doi:10.1029/2019GL082351).

1. Introduction

Size-frequency distributions such as cumulative frequency, noncumulative frequency, probability density, and frequency density distributions can be used to analyze the scaling of natural hazards. Landslides and rock falls have been found to have size-frequency distributions that follow a power function for both area and volume of large events (Brardinoni & Church, 2004; Brunetti et al., 2009; Catani et al., 2005; Chien-Yuan et al., 2007; Crosta et al., 2003; Fujii, 1969; Guthrie & Evans, 2004a, 2004b; Guzzetti et al., 2002, 2005; Havenith et al., 2006; Hovius et al., 1997, 2000; Iwahashi et al., 2003; Korup, 2005; Malamud & Turcotte, 1999; Martin et al., 2002; Massey et al., 2018; Pelletier et al., 1997; Stark & Hovius, 2001; Zhang et al., 2019). Landslides have also been found to exhibit spatial (e.g., Goltz, 1996; Guthrie & Evans, 2004b; Liucci et al., 2015; Qiu et al., 2019), geometric (e.g., Larsen et al., 2010), and temporal (e.g., Qiu et al., 2019) scaling or clustering. The above referenced landslide studies have been conducted in different locations and are associated with different triggering mechanisms including earthquakes, precipitation, and snow melt. The landslide inventories predominantly record deep-seated, fast-moving, landslides, generally triggered by an earthquake or rainfall event, and such landslides are the primary focus of this review.

Factors that contribute to landslide events include topographic variations, soil moisture, vegetation, land use, and climate (e.g., Posner & Georgakakos, 2015). Models have been developed that generate events with the scaling behavior observed in nature, including self-organized criticality (SOC) (e.g., Bak et al., 1987), parameterized cellular automata models (e.g., Hergarten, 2013), and mechanical models (e.g., Jeandet et al., 2019).

Landslides pose a threat to people, property, infrastructure (e.g., Dilley et al., 2005; Hungr et al., 2005). An accurate determination of landslide scaling is a key component for understanding related processes and risks, as enumerated below. First, by determining the size-frequency scaling relationship of landslides one can determine which sizes dominate the overall process. For power scaling, the lower the scaling exponent, or less steep the power function, the greater the contribution of large events relative to small events (e.g.,
Hergarten, 2003). Second, landslide scaling can form the basis for probabilistic landslide hazard assessment for a region over a given time interval (e.g., Guzzetti et al., 2005; Marc et al., 2019). Third, the scaling observed in a natural system can be used to calibrate and assess the applicability of models. A model that generates landslides where the frequency-size distribution does not match the distribution of natural occurrences fails to characterize a known parameter of the natural system (e.g., Hergarten, 2013). Fourth, the scaling exponent is a means of quantifying a landslide inventory. For inventories of landslides triggered by individual events, the scaling exponent provides a means of comparing one triggering event to another. To facilitate such comparisons, scales to quantify landslide event magnitude have been proposed by Malamud et al. (2004) and Tanyaş et al. (2018). Fifth, landslide scaling provides a means of estimating erosion rates in a region due to landslides and, thus, the landslide contribution to a regional sediment budget (e.g., Jeandet et al., 2019; Marc et al., 2019). Finally, more complicated processes may be informed by the parameters of landslide scaling, such as the reworking of sediment following a landslide by river sediment export (Croissant et al., 2019) and the impact of landslides on organic carbon cycling in a montane forest (Hilton et al., 2011).

2. Landslide Databases

Beyond the data compilations of individual authors, there are national data repositories online for landslide inventories in New Zealand (http://data.gns.cri.nz/landslides) (Rosser et al., 2017) and Italy (http://www.ceri.uniroma1.it/index_cedit.html) (Martino et al., 2014). A global-scale centralized repository with sixty-six digital inventories for earthquake-triggered landslide from numerous authors was compiled by Tanyaş et al. (2017) and is available through the U.S. Geological Survey’s ScienceBase Catalog landslide inventories webpage (https://www.sciencebase.gov/catalog/item/586d824ce4b0f5ce109fc9a6). These repositories store landslide data in formats importable by Geographic Information System (GIS) software packages.

3. Landslide and Rockfall Size-Frequency Distributions

Landslide and rockfall inventories are often quantified by plotting event area or volume versus the probability density. A typical probability density distribution is shown in Figure 1. In plots of landslide probability density versus size, the largest 1 to 2 orders of magnitude of events, typically for areas larger than about 10,000 m², tend to be well described by a power function. For smaller sizes, the data tends to deviate from the power function, and this point is called the cutoff point (Stark & Hovius, 2001). For even smaller event sizes, the distribution changes from negative slope to positive slope, between which is a rollover region (e.g., Malamud et al., 2004; Tanyaş et al., 2019; Van Den Eeckhaut et al., 2007).

The probability density function (PDF) of landslide area, \( p(A_L) \) can be defined as

\[
p(A_L) = \frac{1}{N_{LT}} \frac{\delta N_L}{\delta A_L}
\]

where \( A_L \) is landslide area, \( N_{LT} \) is the total number of landslides in the inventory, \( \delta N_L \) is the number of landslides with areas between \( A_L \) and \( A_L + \delta A_L \), and \( \delta A_L \) is the bin width (e.g., Florsheim & Nichols, 2013; Frattini & Crosta, 2013; Malamud et al., 2004). Malamud et al. (2004) defined a method for creating variable bin widths, \( \delta A_L \) that are approximately equal in logarithmic coordinates, to minimize or avoid empty bins at larger sizes.

We consider landslides triggered by the 1994 magnitude M 6.7 Northridge, California earthquake mapped by Harp and Jibson (1995, 1996) to demonstrate analysis methods. The data was obtained at the U.S. Geological Survey’s ScienceBase Catalog landslide inventories webpage (https://www.sciencebase.gov/catalog/item/
For this dataset, the probability density distribution for landslides with areas larger than 100 m², binned using a constant logarithmic (base 10) bin size of 0.1, is shown in Figure 2a.

Two functions have been applied to mathematically describe the probability density distributions of landslides over the range of sizes above and below the rollover, the Double Pareto function (Stark & Hovius, 2001) and the Inverse Gamma function (Malamud et al., 2004). In some papers, the frequency density versus size distribution is analyzed, which is the product of the probability density and the total number of events (e.g., Hergarten, 2013).

The method of Stark and Hovius (2001) describes the probability density distribution as a five parameter Double Pareto function which can be written as

$$p(A_L) = \text{pdf}(A_L | \alpha, \beta, t, c, m)$$

$$= \frac{\beta t (1 - \frac{1 + \left(\frac{A_L - c}{m}\right)^{\beta}}{1 + (\frac{A_L - c}{m})^{\beta}}) - 1}{\beta (1 + \left(\frac{A_L - c}{m}\right)^{\beta})^2 \frac{\Gamma(\rho)}{\Gamma(\rho + 1)}}$$

where $$\alpha$$ is the scaling exponent that primarily controls the power function for the large sizes, $$\beta$$ is the scaling exponent that primarily controls the power function for the small sizes, $$t$$ constrains the rollover position (although it is not exactly equal to the largest probability density distribution value at the peak of the rollover), and $$c$$ and $$m$$ are minimum and maximum sizes of $$A_L$$, respectively. The form of equation (2) is from Rossi and Malamud (2014); this form was presented because the terms and form are more readily compared to equation (3) than the form originally published by Stark and Hovius (2001). By setting $$c$$ and $$m$$ to zero and in finity, respectively, equation (2) can be simplified to a three parameter version (Malamud et al., 2004; Rossi & Malamud, 2014).

An example of fitting the 1994 Northridge data with the Double Pareto function is shown in Figure 1b.

The second method (Malamud et al., 2004) describes the PDF as a three parameter Inverse Gamma function

$$p(A_L) = \text{pdf}(A_L | \rho, a, s)$$

$$= \frac{1}{a \Gamma(\rho) \left[\frac{a}{A_L - s}\right]^\rho \exp \left[-\frac{a}{A_L - s}\right]}$$

where $$\rho$$ is the parameter that primarily controls the power-function decay for medium and large landslide areas, $$\Gamma(\rho)$$ is the gamma function of $$\rho$$, $$A_L$$ is landslide area (m²), $$a$$ is the parameter primarily controlling the location of the maximum of the probability distribution and is the rollover point of the distribution, $$s$$ is the parameter primarily controlling the exponential rollover for small landslide areas, and $$-(\rho + 1)$$ is the power-function scaling exponent for large landslide areas. The function effectively fits a power function to medium and large events and an exponential rollover to events smaller than $$a$$ (Malamud et al., 2004). If one is only interested in describing the larger event sizes, the gamma function can be applied with the exponential term omitted with the parameter $$s$$ set to zero (Malamud et al., 2004).

A third method (Tanyaş et al., 2018), similar to the early studies of landslide scaling, is to fit a power function to the cumulative distribution of only the largest events, above a cutoff value, following the relationship

$$p(A_L) = \frac{1}{a \Gamma(\rho) \left[\frac{a}{A_L - s}\right]^\rho \exp \left[-\frac{a}{A_L - s}\right]}$$
where $X$ is landslide area (binned values), $c$ is a normalization constant, and $-\alpha$ is the power function scaling exponent. The cutoff size was found by Tanyaş et al. (2018) using the method of Clauset et al. (2009). This method may result a cutoff size larger than suggested in Figure 1. For instance, for the 1994 Northridge inventory, the cutoff was determined to be $9,189 \times 10^3$ m$^2$ (Tanyaş et al., 2018), as shown on Figure 2a.

4. Scaling Properties

4.1. Size Scaling

An early study by Fujii (1969) of approximately 650 rainfall-induced landslide events in upland areas of Japan found that for events with areas ranging from $10^{-3}$ to $10^{-1}$ km$^2$, the noncumulative size-frequency distribution followed a power function with a scaling exponent of $-0.96$, which corresponds to $-1.96$ for a cumulative frequency size distribution.

Numerous subsequent studies have been conducted in different regions and with different triggering mechanisms, as cited in the Introduction. Van Den Eeckhaut et al. (2007) assembled landslide inventory studies from around the world and reported the determined scaling frequency distributions for twenty-seven landslide studies in mountainous regions and found they all exhibited power scaling of event areas. For larger event sizes, scaling exponents of noncumulative distributions were reported to range from $-1.4$ to $-3.5$ with a mean of $-2.3$ (with one standard deviation of 0.56; Table 1) Van Den Eeckhaut et al. (2007). Tanyaş et al. (2019) examined forty-five landslide inventories, compiled by various authors, for 32 earthquake triggered landslide events that occurred between 1976 and 2016. Tanyaş et al. (2019) found the scaling exponent for noncumulative frequency density distributions for the landslide areas of different inventories ranges from $-1.8$ to $-3.3$ with a mean of $-2.5$ (Table 1), consistent with previous studies cited above. Both Van Den Eeckhaut et al. (2007, Table 1) and Tanyaş et al. (2019, Table 1) provide tables documenting, for each inventory, the study references, location, rollover size, and noncumulative scaling exponent for large events.

Systematic variations in scaling exponent have been identified. Qiu et al. (2018) examined the cumulative frequency size distributions in Ningquing County, China and found that the scaling exponent changed as a function of the relative relief (difference in elevation between two nearby points) with higher scaling exponents associated with higher relative relief.

Power scaling has also been documented for rockfalls (e.g., Malamud et al., 2004; Strunden et al., 2015). Since rockfalls are measured in volume and landslides tend to be measured in area, it is necessary to transform the distributions in order to compare the observed scaling exponents. The simplest of these conversions assumes isotropic scaling for landslides, $V \propto A^{3/2}$ (e.g., Hovius et al., 1997). Later studies found evidence for anisotropic scaling and with $V \propto A^\gamma$, with $\gamma$ values ranging from 1.32 to 1.38 (Klar et al., 2011). Malamud et al. (2004), Brunetti et al. (2009), and Hergarten (2013) compared rockfalls to landslides and found that the comparable scaling exponent of rockfalls is significantly smaller than that for landslides. For instance, landslide frequency density distributions, determined as a function of landslide volume, have a scaling exponent of $-1.93$, which is considerably steeper than observed for the scaling exponent for frequency density distribution for rockfall volumes of $-1.07$ (Malamud et al., 2004).

Measures of landslide volume are of interest for quantifying erosion rates. The isotropic scaling assumption ($\gamma = -1.5$) in the relationship $V \propto A^{\gamma}$, is not a complete characterization. The $\gamma$ value for landslides has been found to vary depending upon the failure material: soil landslides tend to be shallower and are described by lower scaling exponents ($-1.09$ to $-1.40$); mixed soil and bedrock slides are described by intermediate scaling exponents ($-1.36$ to $-1.45$); while bedrock landslides tend to have a deeper scar area and larger volume and are described by steeper scaling exponents ($-1.34$ to $-1.92$; Larsen et al., 2010; values from Table S1 In the supporting information). Cha et al. (2018) apply Larsen et al.’s (2010) scaling analysis methods and report a slightly less steep scaling exponent ($-1.02$) for analysis of 930 rainfall-triggered landslides in Jinbu, Korea that were predominantly shallow (<1 m) soil slides.

The ability to extrapolate volume measurements from area measurements is of particular interest as landslide volume measures can be used to estimate erosion rates due to landslides. Larsen et al. (2010) demonstrate that slight variations in the $\gamma$ value from $-1.5$ (isotropic) can result in significant differences in

$$p(X) = c X^{-\alpha}$$
estimates of volume loss (erosion). For instance, using $\gamma = -1.5$ instead of $\gamma = -1.4$ can overestimate the total landslide volume for a given inventory of landslides by at least a factor of two (Larsen et al., 2010).

### 4.2. Geometrical Scaling
The relationships between landslide volume and area and between landslide depth and area both exhibit power scaling (Larsen et al., 2010). Larsen et al. (2010), using measurements for 604 bedrock landslides and 2,136 soil landslides, document power scaling of area versus volume over nine orders of magnitude in area measurements and twelve orders of magnitude in volume measurements, with a scaling exponent of $-1.33$ (Larsen et al., 2010). Similarly, they observe power scaling between area and depth (with depth measurements spanning 4 orders of magnitude) with scaling exponent $-1.09$ (Larsen et al., 2010). For these relationships, they find soil landslides correspond to smaller volumes, areas and depths, while bedrock landslides are observed over essentially the full range of observed volume, area and depth measurements (Larsen et al., 2010). This study also found that scar depth for soil landslides increase by less than one order of magnitude with increasing landslide area. In contrast, for bedrock landslides, the failures tend to become deeper and the deposits thicken by 2–3 orders of magnitude with increasing landslide area (Larsen et al., 2010).

### 4.3. Temporal Scaling
Qiu et al. (2019) studied 295 historical landslides (2005–2014) in a 74,000-km$^2$ region of the Qinba Mountains, China. Qiu et al. (2019) found the cumulative frequency distribution of the number of landslides occurring per day followed a power function distribution with a scaling exponent of $-1.18$ (with number of landslides per day ranging from 1 to 100). Most days in the time series had zero landslides; this value was not included in the scaling analysis.

### 4.4. Spatial Scaling and Patterns
Spatial patterns of landslide locations have been found to exhibit power scaling properties (Goltz, 1996; Guthrie & Evans, 2004b; Liucci et al., 2015; Qiu et al., 2019). Guthrie and Evans (2004b) and Qiu et al. (2019), using nearest neighbor analysis and density contour methods, found that the spatial distribution of landslides cluster and that intraday rainfall magnitudes and earthquake occurrences correlate with the clustering of landslides within the study areas.

### 5. Rolloff Observed at Small Event Sizes
As observed in the section "Landslide and Rockfall Size-frequency Distributions," smaller landslide event sizes are under represented by the power function that describes the largest events. The underrepresentation at sizes below the cutoff point (Figure 1), including the rollover (Figure 1) and smaller events, will be collectively termed "rolloff" for this discussion. Some studies attribute this rolloff to under sampling of the smallest event sizes, as has been documented for earthquake frequency-size statistics where the smallest event sizes are often under sampled (Guzzetti et al., 2002; Malamud et al., 2004; Stark & Hovius, 2001). However, the rolloff has been documented to occur at landslide sizes that are well above detection thresholds (Guthrie & Evans, 2004a, 2004b; Pelletier et al., 1997; Turcotte et al., 2002). Turcotte et al. (2002) proposed that under sampling occurs due to an inability to measure the areas of the smaller landslides on aerial photographs.

---

**Table 1**

| Reference             | Location          | Type of inventory                                                                 | Relation                                                                 | Location of rollover, m$^2$ | Scaling Exponent for large events$^a$ |
|-----------------------|-------------------|-----------------------------------------------------------------------------------|--------------------------------------------------------------------------|------------------------------|--------------------------------------|
| Van Den Eeckhout et al. (2007) | Global; 27 inventories | Mixture of historical inventories and inventories from various rainfall, snow melt, and earthquake triggered events | Cumulative and non-cumulative frequency distribution of landslide areas | Where reported: 4 × 10$^2$ m$^2$ 7 × 10$^4$ m$^2$ | Min slope: $-1.4$ Max slope: $-3.5$ Mean: $-2.3$ Std Dev: 0.56 |
| Tanyaş et al. (2019)  | Global; 45 inventories | 32 earthquake triggered events                                                    | Frequency density distribution of landslide areas                        | Where reported: 3.9 × 10$^1$ m$^2$ 1.6 × 10$^7$ m$^2$ | Min slope: $-1.8$ Max slope: $-3.3$ Mean: $-2.5$ |

$^a$Reported scaling exponent values are for noncumulative distributions.
and/or erosion or other mass wasting that obscures the smaller events. Fan et al. (2018) studied high resolution imagery (0.5- to 2.5-m resolution) and observed rolloffs at sizes between 1,000 to 10,000 m², well above a detection threshold, which indicates the rolloff is not due to incomplete sampling. Tanyaş et al. (2019) demonstrate how unlikely an under sampling explanation is by calculating the level of under sampling needed in each of forty-five earthquake inventories to bring the number of small events up to a value consistent with the power function scaling found for larger event sizes. For instance, for the 1994 Northridge earthquake landslide inventory of Harp and Jibson (1995, 1996), Tanyaş et al. (2019) show that if you extend the power function scaling found for large events to landslides smaller than the cutoff, with areas between 1,000 to 9,189 m², over 20,000 of these landslides are predicted to be missing from the inventory. This is over twice as many landslides as are in the entire inventory; Tanyaş et al. (2019) suggest it is not reasonable that so many small events in this size range would have been “missed” when mapping.

The rolloff could be due to a change in the physics of the processes behaving at large and small scales (Fan et al., 2018; Pelletier et al., 1997). The change in physics would likely vary for different regions and triggering mechanisms. One proposal is that there is a difference in the parameters (e.g., local conditions and/or material properties) controlling large deep landslides versus small shallow landslides (Crosta et al., 2013; Frattini & Crosta, 2013; Guzzetti et al., 2002; Katz & Aharonov, 2006). Stark and Guzzetti (2009) propose that the power function distribution observed for larger landslides is controlled by the relatively strong cohesion of bedrock while the scaling of small, shallow failures is the result of the low cohesion of soil and regolith. A mechanical model of Jeandet et al. (2019) for bedrock landslides produces a rollover that is due to the contribution of cohesion to slope instability, similar to mechanisms proposed by Stark and Guzzetti (2009) and Frattini and Crosta (2013).

Similarly, Van Den Eeckhaut et al. (2007) conclude that in the hilly Flemish Ardennes there is a different scaling regime for small (<10⁻² km²) shallow landslides due to local human activities that increase soil moisture near the surface such as construction projects, poor and insufficient sewage systems, and the obstruction of springs, that together result in a decrease in shear strength of slope materials at shallow depths. A related physical explanation for the rolloff was suggested by Pelletier et al. (1997) who modeled slope-stability based on a combination of topography and soil moisture content that controlled shear stress. They proposed that smoother topography at smaller scales results in a break-up of larger soil moisture patches which results in fewer small landslides and could explain the observed change in scaling for smaller events.

An alternative physical explanation for the rolloff is related to geomorphology. Guthrie and Evans (2004a, 2004b) and Guthrie et al. (2008) reasoned that most landslides initiate in middle and upper slopes and grow in size as they travel downslope, generating long runout landslides that grows until they reach a natural barrier such as a stream and this process results in events larger than the rollover size. In contrast, small landslides occur where long runout is improbable, and they assert such locations are less likely to generate landslides, thereby resulting in fewer (relative to the power function fit) small events. This finding is supported by Chung et al. (2001) who found that the mid- and upper slopes on Vancouver Island, coastal British Columbia, were most susceptible to precipitation-initiated landslides.

It has also been proposed that the rolloff may be an artifact of how landslide areas are sampled from imagery, where small landslides scars are included as part of larger adjacent/surrounding slides (Frattini & Crosta, 2013; Tanyaş et al., 2019). This explanation builds on the suggestion of under sampling caused by obscured events (e.g., Turcotte et al., 2002) with a clearer explanation of the cause. Frattini and Crosta (2013) noted that even for accurate landslide inventories of single events, a large number of smaller landslides may be undetectable because of reworking during the event by larger coalescent landslides. Tanyaş et al. (2019) further examined the concept that smaller slides may be amalgamated into larger slides and thereby be undersampled. Tanyaş et al. (2019) demonstrated that the same photograph of landslides near the town of Gümda, Nepal can be sampled using maximum amalgamation, resulting in 88 separate landslides; or with moderate amalgamation, resulting in 184 separate landslides; or minimal amalgamation, separating landslides to the maximum extent possible, resulting in 253 separate landslides. Variations in the choice of how to delineate landslides in imagery is evident in published landslide inventories. Tanyaş et al. (2019) note that the same landslide image near Gümda that they analyzed has been mapped by different researchers who variously report the number of landslides as 19 (Kargel et al., 2016), 32 (Zhang et al., 2016), 40 (Tanyaş et al., 2018), 42 (Gnyawali & Adhikari, 2017), and 151 (Roback et al., 2018). A comparison of
frequency-area distributions at different amalgamations levels as sampled by Tanyaş et al. (2019) shows that the data set with more individual landslides has a smaller rollover value and steeper frequency density scaling exponent (−1.97 vs −1.59). As a further demonstration of the amalgamation effect, Tanyaş et al. (2019) demonstrate that, theoretically, an ideal landslide database with a single power function scaling across all event sizes would appear to have a rolloff if small landslides were not individually distinguished and instead were mapped as parts of larger ones. Tanyaş et al. (2019) work demonstrates the need for standardized mapping methodology to obtain consistent inventories.

Another factor that can cause rolloff is lack of temporal resolution when sampling. Samia et al. (2017) found that landslides preferentially occur at sites of previous landslides. Thus, a mapping effort on any given date may document a landslide scar that was the site of numerous landslides. A rockfall study found that sampling through time captures many smaller events than observed in an instantaneous mapping (Barlow et al., 2012; Williams et al., 2018). Williams et al. (2018) compared distributions for rockfalls measured from observations taken at approximately 1-hour intervals to those observed with a 30-day sampling interval. For the shorter sampling interval, the scaling exponent was steeper, at −2.27, compared to −1.78 for the 30-day sampling interval. Further, there appears to be no rolloff observed for data collected at the shorter sampling rate while there appears to be a rolloff for the 30-day sampling interval.

6. Modeling of Landslide Scaling

This paper focuses on models that generate the power scaling behavior observed in size-frequency analysis of natural data sets. For a broader view of landslide modeling, review articles include van Westen et al. (2008) and Reichenbach et al. (2018).

An early model that reproduces the observed power function scaling of event size distributions is the SOC model of Bak et al. (1987). The SOC model produces power function scaling of the cumulative frequency distribution of event sizes and has been applied to several natural systems that exhibit power function scaling. SOC models have been developed for landslides, forest fires and earthquakes (e.g., Turcotte, 1999).

SOC models have several defining characteristics. First, they are a cellular automata model where each cell follows the same set of instructions; there is no “tuning” of cell parameters or response to represent spatial variations. Second, there are no initial conditions specifying a starting configuration for the grid. Third, the same set of instructions are executed in each step (or in a cycle of steps for the forest fire model where a match is periodically dropped at a random location). Fourth, the set of steps is executed completely, with any cascading events completed, before the next step is initiated. Fifth, once the system has been running for a while and is initialized, the grid will be in a critical state where the next step could result in no event, a large event, or any size in between. Sixth, the frequency size distributions of both event sizes and the time interval between events are well described by power functions.

The SOC model that has been applied to landslides is termed the sandpile model. The sandpile model has been extensively described in books and papers (e.g., Bak, 1996; Hergarten, 2002; Jensen, 1998; Turcotte, 1997, 1999) and is briefly summarized here. The sandpile model consists of a two-dimensional quadratic lattice. In each step, a grain of sand is added to a randomly selected cell. If this results in fewer than four grains of sand in the cell, nothing further happens and that step is complete. In the next step, another grain of sand is added to a randomly selected cell. When a cell has four grains of sand, the grains are redistributed to each of the non-diagonal adjacent cells (one per cell). This redistribution is sometimes called relaxation of the grid (e.g., Hergarten, 2003). If this redistribution results in four grains of sand in any neighboring cells, the grains in those cells are also redistributed. This process of redistribution is continued until all cells contain three or few grains. If grains are redistributed such that they leave the edge of the grid, those grains are lost from the system. The “area” of an event is the number of cells that participate in a cascading event. The cumulative frequency size distribution is a power function with a scaling exponent of one.

Shortly after Bak et al.’s (1987) paper was published, several groups studied the behavior of actual piles of sand, or beads, in the laboratory. Evesque (1991) using spherical glass beads and Nagel (1992) using granular sand, both studied the behavior of the material in a container where the angle of repose was slowly increased to induce failure. Both found that avalanches occurred, but the associated frequency size distributions were not described by power functions. These findings were used to argue against the possibility that piles of
granular material are in a critical state (Nagel, 1992). Held et al. (1990) designed a laboratory experiment that slowly added grains of sand to the center of circular disk resting on a Mettler balance and measured events as the changes in the weight measured by the scale. They used sand sieved to a nearly uniform grain size with an average mass of 0.6 mg. For sandpiles grown on disks, with base diameters ranging from 9.7 mm to 38 mm, they found the size frequency distribution of events exhibit power function scaling with an exponent near one and interpreted this to be SOC behavior. For disks with larger base diameters of 3 inches, avalanches occurred without falling off the pile, and the frequency size distribution for events where sand left the system did not follow a power function. Puhl (1992) also studied the behavior of granular sand, sieved to be a nearly uniform size, and found that by adding grains to the center of a surface of finite area, and only considering events that do not reach the side of the raised surface (which occur as the pile is growing upward and outward without events spilling over the edge), power function scaling of event sizes was observed and it was concluded that the process was exhibiting SOC behavior. SOC behavior was not observed for avalanches that overflowed the edges of the raised surface. Later experiments with grains of rice observed SOC behavior for elongated grains of rice but not for less elongated grains (Frette et al., 1996).

Hergarten (2002) points out a number of inconsistencies between the SOC model and actual landslides. For instance, the stability of an actual sandpile depends on local slope gradient, not the number of grains at a given location as defined in the SOC model. Further, the driving mechanism of periodically dropping a grain of sand in the SOC model cannot be directly related to the tectonic and fluvial processes that dominate landscape formation. In addition, Hergarten (2002) note that the scaling exponent for event sizes obtained by the SOC model is one, which differs from the values observed for natural systems. Finally, the behavior of landslides to be more likely to occur at location of previous landslides, as documented by Samia et al. (2017), is not a behavior replicated by SOC models.

Hergarten (2013) provides a review of mechanical numerical models that have been applied to landslides. This includes application of the Olami-Feder-Christensin slider-block SOC earthquake model to operate on a slope to model landslide failure. The model generates events with power function scaling, but the scaling exponent is approximately −1.2, which is less than the value of approximately −2.4 observed in nature (Hergarten, 2002, 2013). By adding a constraint of time-dependent weakening to the model, Hergarten and Neugebauer (2000) obtain a power function distribution of event sizes with scaling exponent near two, which is in closer agreement with observations.

Alternatives to the SOC model have been proposed to model landslide scaling. Pelletier et al. (1997) develop a cellular automata model that models slope-stability as a combination of topography and soil moisture content that control shear stress and find a power function noncumulative frequency-area distribution with scaling exponent −2.6, comparable to values found for natural events.

Non-SOC cellular automata models have been successfully developed to model landslide events in China (Segre & Deangeli, 1995), Japan (Di Gregorio et al., 1999), and Italy (Avolio et al., 2000; Clerici & Perego, 2000; D’Ambrosio et al., 2003). These models include parameters such as soil properties, depth of soil cover, rheological properties, cohesion, slope and elevation.

Jeandet et al. (2019) propose a mechanical model for bedrock landslides which assumes the rocks and soil behave as Mohr-Coulomb materials, and failure occurs when shear stress on rupture surfaces exceeds resisting shear strength of the material, which is controlled by the frictional angle and cohesion. They model landslides as a planar failure and include the criterion that the rupture plane must intersect the topographic surface in the downslope direction; this results in shallower planes having a higher rupture probability than deeper planes (Jeandet et al., 2019). Jeandet et al.’s (2019) model produces power scaling of landslide depth and area, with a rollover for small landslides due to the contribution of cohesion to slope instability, as proposed earlier by Stark and Guzzetti (2009) and Frattini and Crosta (2013). The model also captures the scaling behavior of a cutoff at large events sizes caused by the topographic criterion combined with the finite size of hillslopes (Jeandet et al., 2019).

7. Future Directions

Technological advances in surveying, terrain modeling and GIS are improving landslide measurements and modeling (Gatter et al., 2018). LIDAR (Light detection and ranging) surveys (e.g., Roering et al., 2013),
digital photogrammetry (e.g., Liu et al., 2019; Romeo et al., 2019), and satellite surveys (e.g., Wang et al., 2018) are being used to create digital elevation models (DEMs) to study landslide events. Pre- and post-event DEMs can be compared to obtain three-dimensional estimates of volumetric change (e.g., Bossi et al., 2015; Calista et al., 2019; Fanos & Pradhan, 2019; Riquelme et al., 2019). As methods improve and additional pre- and post-event DEMs are collected for more regions, there will be a reduced need to use landslide area measures to estimate volume measures. Direct volume measures should improve erosion estimates and either inform modeling parameters or evaluate the success of model outputs (e.g., do the size-volume scaling relationships generated by a model match the relationships observed in nature?). Improved characterization of size-volume scaling relationships may form the basis for probabilistic forecasting of events of a given size occurring in a given time interval in a given region. In addition, pre- and post-event studies at individual locations can be used to inform dynamic computer models and provide risk assessments for a range of hazard scenarios before subsequent landslides occur (e.g., Bossi et al., 2015).

Future advances in landslide modeling may incorporate additional parameters beyond physical processes and local conditions, such as climate change affects. Handwerger et al. (2019) argue that northern California is a region that is likely to experience increased rainfall due to climate change and may therefore be prone to increased landslide risk. Climate change is likely to affect landslide risk in additional regions worldwide.

An unanswered question is what controls the range in observed power scaling exponent for different locations and inventories. For example, Tanyaş et al. (2019) found the scaling exponent for noncumulative frequency density distributions for the landslide areas of different inventories ranges from $-1.8$ to $-3.3$. What are the primary and secondary controls of this variability?

### 8. Summary

Power scaling has been documented for both landslide and rockfall events. The landslide studies have been conducted in different locations and associated with different triggering mechanisms including earthquakes, precipitation, and snow melt. Data repositories have been compiled for landslide inventories for New Zealand (Rosser et al., 2017), Italy (Martino et al., 2014), and globally (Tanyaş et al., 2017). Landslide frequency-size distributions are commonly plotted as probability density or frequency density distributions. The largest landslide events, with areas larger than about 10,000 m² are well-described by a power function. A compilation of landslide studies from mountainous regions found that the scaling exponent of the power function that describes the largest events in a noncumulative distribution ranges from $-1.42$ to $-3.26$ (Van Den Eeckhaut et al., 2007). A compilation for 32 earthquake triggered landslide events reported a narrower range of $-1.8$ to $-3.3$ (Tanyaş et al., 2019). For smaller event sizes, the distribution tends to deviate from the power function below a cutoff point (Stark & Hovius, 2001). For even smaller event sizes, the distribution changes from negative slope to positive slope, between which is a rollover region (e.g., Malamud et al., 2004; Tanyaş et al., 2019; Van Den Eeckhaut et al., 2007). The probability density distributions of landslides over a range of sizes, both above and below the rollover, can be described by the Double Pareto function (Stark & Hovius, 2001) or the Inverse Gamma function (Malamud et al., 2004). In addition to scaling in size, Qiu et al. (2019) found the cumulative frequency distribution of the number of landslides occurring per day follows a power function distribution with a scaling exponent of $-1.18$. The spatial distribution of landslides has also been found to be clustered, with intraday rainfall magnitudes and earthquake occurrences found to correlate with the clustering of landslides (Guthrie & Evans, 2004a; Qiu et al., 2019). At events sizes smaller than the cutoff, the cause for the shallower power function slope, compared to the scaling for larger sizes, and for the rollover, may have several contributing factors. Possible factors include sampling amalgamation that results in under sampling of small events (Tanyaş et al., 2019), lack of detection of smaller events due to lack of temporal resolution resulting in multiple events occurring in the same location being recorded as one event (Williams et al., 2018), and different physical processes controlling small versus large events (Fan et al., 2018). The power scaling exponent that describes the largest events provides a means of quantifying landslide events and has been used as the basis for landslide magnitude scales (Malamud et al., 2004; Tanyaş et al., 2018). Models have been developed that generate events with the size-frequency scaling behavior observed in nature. SOC models replicate the power function scaling of event size, temporal scaling, and spatial clustering (e.g., Bak, 1996; Hergarten, 2002; Jensen, 1998; Turcotte, 1997, 1999). SOC models have a number of shortcomings including that the scaling exponent for event sizes obtained by the SOC model is...
one, which differs from the values observed for natural systems (e.g., Hergarten, 2002). Parameterized cellular automata models that include one or more variables that affect shear stress in the surface materials, such as precipitation, soil properties, and topography, come closer to replicating the size-frequency scaling exponents observed for larger event sizes of natural landslides (Avolio et al., 2000; Clerici & Perego, 2000; D’Ambrosio et al., 2003; Di Gregorio et al., 1999; Segre & Deangeli, 1995). Mechanical models also replicate the observed power scaling, including a rolloff and cutoff (Jeandet et al., 2019).

Acknowledgments
I thank one anonymous reviewer and Chris Barton for helpful critical reviews. My thanks to Daniel Koehl, Tristan Coffey, and Doyle Watts who imported the 1994 Northridge landslide inventory of Harp and Jibson (1995) into a GIS software package and extracted the landslide areas shown in Figure 2. The data used in this paper was obtained and is available at the U.S. Geological Survey’s ScienceBase Catalog landslide inventories webpage (https://www.sciencebase.gov/catalog/item/586d824ac4b0f5c109f659a4).

References
Avolio, M. V., Di Gregorio, S., Mantovani, F., Pasuto, A., Rongo, R., Silvano, S., & Spataro, W. (2000). Simulation of 1992 Tessina landslide by a cellular automata model and future hazard scenarios. International Journal of Applied Earth Observation and Geoinformation, 2(1), 41–59. https://doi.org/10.1016/S0303-2434(00)00025-4
Bak, P. (1996). How Nature Works – the science of self-organized criticality. New York, NY: Copernicus, Springer.
Bak, P., Tang, C., & Wiesenfeld, K. (1987). Self-organized criticality: an explanation of 1/f noise. Physical Review Letters, 59, 381, 1987–384. https://doi.org/10.1103/physrevlett.59.381
Barlow, J., Lim, M., Rossé, N., & Pefley, D. (2012). Modeling cliff erosion using negative power law scaling of rockfalls. Geomorphology, 139–140, 416–424. https://doi.org/10.1016/j.geomorph.2011.11.006
Bosi, G., Cavalli, M., Crema, S., Frigerio, S., Quan Luna, B., Mantovani, M., et al. (2015). Multi-temporal LiDAR-DTM as a tool for modelling a complex landslide: a case study in the Rotolot catchment (eastern Italian Alps). Natural Hazards and Earth System Sciences, 15, 715–722. https://doi.org/10.5194/nhess-15-715-2015
Brardinoni, F., & Church, M. (2004). Representing the landslide magnitude–frequency relation: Capilano River Basin, British Columbia. Earth Surface Processes and Landforms, 29(1), 115–124. https://doi.org/10.1002/esp.1029
Brunetti, M. T., Guzzetti, F., & Rossi, M. (2009). Probability distributions of landslide volumes. Nonlinear Processes in Geophysics, 16, 179–188. https://doi.org/10.5194/npg-16-179-2009
Calista, M., Masiocchi, F., Menna, V., Micciedei, E., & Piacentini, T. (2019). Recent geomorphological evolution and 3D Numerical modelling of soft clastic rock cliffs in mid-western Adriatic Sea (Abruzzo, Italy). Geosciences, 9(7). https://doi.org/10.3390/geosciences9070309
Catani, F., Casagli, N., Ermini, L., Righini, G., Mondini, G. (2005). Landslide hazard and risk mapping at catchment scale 2005 Arno River basin. Landslides, 2(4), 329–342. doi:https://doi.org/10.1007/s10346-005-0021-0
Cha, D., Hwang, J., & Choi, B. (2018). Landslide detection and volume estimation in Jinbu area of Korea. Forest Science and Technology, 14, 61–65. https://doi.org/10.1007/s12455-018-1446-37
Chien-Yuan, C., Fan-Chieh, Y., Sheng-Chi, L., & Kei-Wai, C. (2007). Discussion of Landslide Self-Organized Criticality and the Initiation of Debris Flows. Earth Surface Processes and Landforms, 32(2), 197–209. https://doi.org/10.1002/esp.1400
Chung, C., Bobrowsky, P., & Guthrie, R. H. (2001). Quantitative prediction model for landslide hazard mapping. Tisitika and Schmidt creek watersheds, Northern Vancouver Island, British Columbia. In P. Bobrowsky (Ed.), Geoenviromental mapping—method, theory and practice (pp. 697–716). Lisse, Netherlands: A.A. Balkema Publishers.
Clauset, A., Shalizi, C. R., & Newman, M. E. J. (2009). Power-law distributions in empirical data. Society for Industrial and Applied Mathematics Review, 51(4), 661–703. https://doi.org/10.1137/071071111
Clerici, A., & Perego, S. (2000). Simulation of the Parma river blockage by the Corniglio landslide (Northern Italy). Geomorphology, 33, 1–23. https://doi.org/10.1016/S0169-555X(99)00095-1
Croissant, T., Steer, P., Lague, D., Davy, P., Jeandet, L., & Hilton, R. G. (2019). Seismic cycles, earthquakes, landslides and sediment fluxes: Linking tectonics to surface processes using a reduced-complexity model. Geomorphology, 339, 87–103. https://doi.org/10.1016/j.geomorph.2019.04.017
Crosta, G. B., Dal Negro, P., & Frattini, P. (2003). Soil slips and debris flows on terraced slopes. Natural Hazards and Earth System Sciences, 3, 31–42. https://doi.org/10.5194/nhess-3-31-2003
Crosta, G. B., Frattini, P., & Agliardi, F. (2011). Deep seated gravitational slope deformations in the European Alps. Tectonophysics, 605, 13–33. https://doi.org/10.1016/j.tecto.2010.04.028
D’Ambrosio, D., Di Gregorio, S., & Iovine, G. (2003). Simulating debris flows through a hexagonal cellular automata model: SCICCCA S 3 hex. Natural Hazards and Earth System Sciences, 3, 545–559. https://doi.org/10.5194/nhess-3-545-2003
Di Gregorio, S., Rongo, R., Siciliano, C., Sorriso-Valvo, M., & Spataro, W. (1999). Mount Ontake landslide simulation by the cellular automata model SCICDCCA 3. Physics and Chemistry of the Earth, 24, 97–100. https://doi.org/10.1016/S1464-1895(99)00008-3
Dilley, M., Chen, R. S., Deichmann, U., Lerner-Lam, A. L., & Arnold, M. (2005). Natural disaster hotspots: a global risk analysis. Washington, USA: The World Bank Hazard Management Unit.
Evesque, P. (1991). Analysis of statistics of sandpile avalanches using soil mechanics results and concepts. Physical Review A, 43, 2720–2740. https://doi.org/10.1103/PhysRevA.43.2720
Fan, X., Donnénech, G., Scaringi, G., Huang, R., Xu, Q., Hales, T. C., et al. (2018). Spatio-temporal evolution of mass wasting after the 2008 Mt 7.9 Wenjuch earthquake revealed by a detailed multi-temporal inventory. Landslides, 15(12), 2325–2341. https://doi.org/10.1007/s10346-018-1054-5
Fanos, A. M., & Pradhan, B. (2019). A novel rockfall hazard assessment using laser scanning data and 3D modelling in GIS. Catena, 172, 435–450. https://doi.org/10.1016/j.catena.2018.09.012
Forsheim, J. L., & Nichols, A. L. (2013). Landslide area probability density function statistics to assess historical landslide magnitude and frequency in coastal California. Catena, 109, 129–138. https://doi.org/10.1016/j.catena.2013.04.005
Frattini, P., & Crosta, G. B. (2013). The role of material properties and landscape morphology on landslide size distributions. Earth and Planetary Science Letters, 361, 310–319. https://doi.org/10.1016/j.epsl.2012.10.029
Frette, V., Christensen, K., Malthe-Sorensen, A., Feder, J., Jossang, T., & Meakin, P. (1996). Avalanche dynamics in a pile of rice. Nature, 379, 49–52. https://doi.org/10.1038/379049a0
Fujii, Y. (1969). Frequency distribution of the magnitude of landslides caused by heavy rainfall. Seismological Society of Japan, 22, 244–247. https://doi.org/10.4249/ziisin1948.22.3_244
Gatter, R., Cavalli, M., Crema, S., & Rossi, G. (2018). Modelling the dynamics of a large rock landslide in the Dolomites (eastern Italian Alps) using multi-temporal DEMs. PeerJ. https://doi.org/10.7717/peerj.5903
Gruyewali, K. R., & Adhikari, B. R. (2017). Spatial Relations of Earthquake Induced Landslides Triggered by 2015 Gorkha Earthquake Mw = 7.8. In M. Mikol, N. Casaghi, Y. Yin, & K. Sassa (Eds.), Advancing Culture of Living with Landslides (Vol. 4, pp. 85–93). Cham, Switzerland: Springer International Publishing. https://doi.org/10.1007/978-3-319-53485-5_10
Goltz, C. (1996). Multifractal and entropic properties of landslides in Japan. Geologische Rundschau, 85(1), 71–84.
Guthrie, E. L., & Jibson, R. L. (1995). Landslides triggered by the 1994 Northridge, California earthquake. Geophysical Research Letters, 22(19), 2382–2385. https://doi.org/10.1029/95GL02970
Handwerger, A. L., Fielding, E. J., Huang, M. H., Bennett, G. L., Liang, C., & Schulz, W. H. (2019). Widespread Initiation, Reactivation, and Acceleration of Landslides in the Northern California Coast Ranges due to Extreme Rainfall. Journal of Geophysical Research: Earth Surface, 124, 1782–1797. https://doi.org/10.1029/2019EF005035
Harp, E. L., & Jibson, R. L. (1995). Inventory of landslides triggered by the 1994 Northridge, California earthquake. US Geological Survey Open File Report, 95-213. https://doi.org/10.3133/ofr95213
Harb, E. L., & Jibson, R. L. (1996). Landslides triggered by the 1994 Northridge, California earthquake. Seismological Society of America Bulletin, 86, S319-S332
Havenith, H. B., Torgev, I., Melekhov, A., Alioshin, Y., Torgev, A., & Danneels, G. (2006). Landslides in the Mailu-Su Su valley, Kyrgyzstan – hazards and impacts. Landslides, 3(2), 137–147. https://doi.org/10.1007/s10346-006-0035-2
Held, G. A., Solina, D. H., Keane, D. T., Haag, W. J., Horn, P. M., & Grinstein, G. (1990). Experimental Study of Critical-Mass Fluctuations in an Evolving Sandpile. Physical Review Letters, 65(9), 1120–1123. https://doi.org/10.1103/PhysRevLett.65.1120
Hergarten, S. (2002). Self-Organized Criticality in Earth Systems. Berlin, Germany: Springer-Verlag.
Hergarten, S. (2003). Landslides, sandpiles, and self-organized criticality. Natural Hazards and Earth System Sciences, 3, 505–514. https://doi.org/10.5194/nhess-3-505-2003
Hergarten, S. (2013). SOC in landslides. In M. J. Ashwanden (Ed.), Self-Organized Criticality Systems (pp. 379–401). Warsaw, Berlin: Open Academic Press.
Hergarten, S., & Neugebauer, H. J. (2000). Self-organized criticality in two-variable models. Physical Review E, 61(3), 2382–2385. https://doi.org/10.1103/PhysRevE.61.2382
Hilson, G. R., Muenier, P., Hovius, N., Bellingham, P. J., & Galy, A. (2011). Landslide impact on organic carbon cycling in a temperate montane forest. Earth Surface Processes and Landforms, 36(12), 1670–1679. https://doi.org/10.1002/esp.2191
Hovius, N., Stark, C. P., & Allen, P. A. (1997). Sediment flux from a mountain belt derived by landslide mapping. Geology, 25(3), 231–234. https://doi.org/10.1130/0091-7613(1997)025<0231:SFFAMB>2.3.CO;2
Hovius, N., Stark, C. P., Hao-Tsu, C., & Jiu-Chuan, L. (2000). Supply and removal of sediment in a landslide-dominated mountain belt: Central Range, Taiwan. The Journal of Geology, 108(1), 73–89. https://doi.org/10.1086/314387
Hunger, O., Fell, R., Couture, R., & Eberhardt, E. (2005). Landslide Risk Management. London, England: CRC Press.
Iwahashi, I., Watanabe, S., & Fujuya, T. (2003). Mean slope-angle frequency distribution and size frequency distribution of landslide masses in Higashikubiki area, Japan. Geomorphology, 50(4), 349–364. https://doi.org/10.1016/S0169-555X(02)00222-2
Jeantet, L., Steer, P., Lague, D., & Davy, P. (2019). Coulomb mechanics and relief constraints explain landslide size distribution. Geophysical Research Letters, 46(8), 4258–4266. https://doi.org/10.1029/2019GL082351
Jensen, H. J. (1998). Self-Organized Criticality. Cambridge, UK: Cambridge University Press.
Kargel, J. S., Leonard, G. J., Shugar, D. H., Haritashya, U. K., Bevington, A., Fielding, E. J., et al. (2016). Geomorphic and geologic controls of geohazards induced by Nepal’s 2015 Gorkha earthquake. Science, 351, 6269. https://doi.org/10.1126/science.aac8353
Katz, O., & Aharonov, F. (2006). Landslides in vibrating sand box: What controls types of slope failure and frequency magnitude relations? Earth Planet. Science Letters, 247, 280–294. https://doi.org/10.1016/j.epsl.2006.05.009
Klar, A., Aharonov, E., Calderon-Asiel, B., & Katz, O. (2011). Analytical and observational relations between landslide volume and surface area. Journal of Geophysical Research, 116, F02001. https://doi.org/10.1029/2009JF001604
Korup, O. (2005). Distribution of landslides in southwest New Zealand. Landslides, 2, 43–51. https://doi.org/10.1007/s10346-004-0042-0 “Landslide Inventories.” U.S. Geological Survey ScienceBase Catalog, https://www.sciencebase.gov/catalog/item/586d824ce4b0f6c6109fc9a6
Larsen, I. J., Montgomery, D. R., & Korup, O. (2010). Landslide erosion controlled by hillslope material. Nature Geoscience, 3, 247–251. https://doi.org/10.1038/NGEO776
Liu, C., Liu, X. L., Peng, X. C., Wang, E. Z., & Wang, S. J. (2019). Application of 3D-DDA integrated with unmanned aerial vehicle-laser scanner (UAV-LS) photogrammetry for stability analysis of a blocky rock mass slope. Landslides, 16(9), 1645–1661. https://doi.org/10.1007/s10346-019-01396-6
Luciuc, I., Melelli, L., & Sutena, C. (2015). Scale-invariance in the spatial development of landslides in the Umbria region (Italy). Pure and Applied Geophysics, 172(7), 1959–1973. https://doi.org/10.1007/s00024-014-0877-9
Malamud, B. D., & Turcotte, D. L. (1999). Self-organized criticality applied to natural hazards. Natural Hazards, 20(2-3), 93–116. https://doi.org/10.1023/A:1008014000515
Malamud, B. D., Turcotte, D. L., Guzzetti, F., & Reichenbach, P. (2004). Landslide inventories and their statistical properties. Earth Surface Processes and Landforms, 29(6), 687–711. https://doi.org/10.1002/esp.1064
Marc, O., Behling, R., Andermann, C., Turowski, J. M., Illien, L., Roessner, S., & Hovius, N. (2019). Long-term erosion of the Nepal Himalayas by bedrock landsliding: the role of monsoons, earthquakes and giant landslides. Earth Surface Dynamics, 7, 107–128. https://doi.org/10.5194/esurf-7-107-2019
Martin, Y., Rood, K., Schwab, J. W., & Church, M. (2002). Sediment transfer by shallow landslides in the Queen Charlotte Islands, British Columbia. Canadian Journal of Earth Sciences, 39, 189–205. https://doi.org/10.1139/E01-068
Martino, S., Prestininazi, A., & Romeo, R. W. (2014). Earthquake-induced ground failures in Italy from a reviewed database. Natural Hazards and Earth System Sciences, 14(4), 799–814. https://doi.org/10.5194/nhess-14-799-2014
Massey, C., Townsend, D., Rathee, E., Allstadt, K. E., Lukovic, B., Kaneko, Y., et al. (2018). Landslides triggered by the 14 November 2016, M7.8 Kaikoura earthquake, New Zealand. Bulletin of the Seismological Society of America, 108(3B), 1630–1648. https://doi.org/10.1785/0220170305

Nagel, S. R. (1992). Instabilities in a sand-pile. Reviews of Modern Physics, 64, 321–325. https://doi.org/10.1103/RevModPhys.64.321

Pelletier, J. D., Malamud, B. D., Blodgett, T., & Turcotte, D. L. (1997). Scale- invariance of soil moisture variability and its implications for the frequency-size distribution of landslides. Engineering Geology, 48(3-4), 255–268. https://doi.org/10.1016/S0013-7952(97)00041-0

Posner, A. J., & Georgakakos, K. P. (2015). Soil moisture and precipitation thresholds for real-time landslide prediction in El Salvador. Landslides, 12(6), 1179–1196. https://doi.org/10.1007/s10346-015-0618-x

Pühl, H. (1992). On the modelling of real sand piles. Physica A, 182(3), 295–310. https://doi.org/10.1016/0378-4371(92)90344-P

Qiu, H., Cui, Y., Hu, S., Yang, D., Pei, Y., & Yang, W. (2019). Temporal and spatial distributions of landslides in the Qinba Mountains, Shaanxi Province, China. Geomorphics: Natural Hazards and Risk, 10(1), 595–5621. https://doi.org/10.1080/19475705.2018.1536080

Qiu, H., Cui, Y., Regmi, A. D., Hu, S., Zhang, Y., & He, Y. (2018). Landslide distribution and size versus relative relief (Shaanxi Province, China). Bulletin of Engineering Geology and the Environment, 77(4), 1311–1342. https://doi.org/10.1007/s10064-017-1121-5

Reichenbach, P., Ross, M., Malamud, B. D., Mihir, M., & Guzzetti, F. (2018). A review of statistically-based landslide susceptibility models. Earth-Science Reviews, 180, 60–91. https://doi.org/10.1016/j.earscirev.2018.05.003

Riquelme, A., Del Soldato, M. Tomas, R., Cano, M., Bordehore, L.J., Moretti, S. (2019) Digital landform reconstruction using old and recent open access digital aerial photos. Geomorphology, 329, 206-223. https://doi.org/10.1016/J.GEOMORPH.2019.01.003

Roback, K., Clark, M. K., West, A. J., Zekkos, D., Li, G., Gallen, S. F., et al. (2018). The size, distribution, and mobility of landslides caused by the 2015 Mw 7.8 Gorkha earthquake, Nepal. Geomorphology, 301, 121–138. https://doi.org/10.1016/j.geomorph.2017.01.030

Roering, J. J., Mackey, B. H., Marshall, J. A., Sweeney, K. E., Deligne, N. L., Booth, A. M., et al. (2013). “You are HERE”: Connecting the dots with airborne lidar for geomorphic fieldwork. Geomorphology, 200, 172–183. https://doi.org/10.1016/j.geomorph.2013.04.009

Romeo, S., DiMatteo, L., Kieffer, D. S., Tosi, G., Stoppini, A., & Radicioni, F. (2019). The Use of Gigapixel Photogrammetry for the Understanding of Landslide Processes in Alpine Terrain. Geosciences, 9(2). https://doi.org/10.3390/geosciences9020099

Rosser, B., Dellow, S., Haubrock, S., & Glassy, P. (2017). New Zealand’s national landslide database. Landslides, 14(6), 1949–1959. https://doi.org/10.1007/s10346-017-0843-6

Rossi, M., & Malamud, B. D. (2014). D. 5.3. Prototype SW for determination of landslide statistics from inventory maps. LAMPRE report. http://www.lampré-project.eu/index.php?option=com_phocadownload&view=category&download=117&wp5-report-on-prototype-software-for-landslide-statistics&id=6:wp5-triggered-event-landslides&Itemid=203.

Samia, J., Temme, A., Bregt, A., Wallinga, J., Guzzetti, F., Ardizzone, F., & Rossi, M. (2017). Do landslides follow landslides? Insights in path dependency from a multi-temporal landslide inventory. Landslides, 14(2), 547–558. https://doi.org/10.1007/s10346-016-0739-x

Segre, E., & Deangeli, C. (1995). Cellular automaton for realistic modelling of landslides. Nonlinear Processes in Geophysics, 2, 1–15. https://doi.org/10.5194/npg-2-1-1995

Stark, C. P., & Hovius, N. (2001). The characterization of landslide size distributions. Geophysical Research Letters, 28(6), 1091–1094. https://doi.org/10.1029/2000GL008527

Strunden, J., Ehlers, T. A., Brehm, D., & Nettesheim, M. (2015). Spatial and temporal variations in rockfall determined from TLS measurements in a deglaciated valley, Switzerland. Journal of Geophysical Research: Earth, 120, 1251–1273. https://doi.org/10.1002/2014JF003274

Tanyas, H., Allstadt, K. E., & van Westen, C. J. (2018). An updated method for estimating landslide-event magnitude. Earth Surface Processes and Landforms, 43(9), 1836–1847. https://doi.org/10.1002/esp.4359

Tanyas, H., van Westen, C. J., Allstadt, K. E., Jessee, M. A. N., Gürüm, T., Jibson, R. W., et al. (2017). Presentation and analysis of a worldwide database of earthquake-induced landslide inventories. Journal of Geophysical Research: Earth Surface, 122(10), 1991–2015. https://doi.org/10.1002/2017JF004236

Tanyas, H., van Westen, C. J., Allstadt, K. E., & Jibson, R. W. (2019). Factors controlling landslide frequency-area distributions. Earth Surface Processes and Landforms, 44, 900–917. https://doi.org/10.1002/esp.4543

Turcotte, D. L. (1999). Fractals and Chaos in Geology and Geophysics (2nd ed.). Cambridge, UK: Cambridge University Press.

Turcotte, D. L. (1997). Self-organized criticality. Reports on Progress in Physics, 62(10), 1377–1429. https://doi.org/10.1088/0034-4885/62/10/201

Turcotte, D. L., Malamud, B. D., Guzzetti, F., & Reichenbach, P. (2002). Self-organization, the cascade model, and natural hazards. Proceedings of the National Academy of Sciences, 99(suppl 1), 2530–2537. https://doi.org/10.1073/pnas.012582399

Van Den Eeckhaut, M., Poosen, J., Gover, G., Verstraeten, G., & Demoulin, A. (2007). Characteristics of the size distribution of recent and historical landslides in a populated hilly region. Earth and Planetary Science Letters, 256, 586–603. https://doi.org/10.1016/j.epsl.2007.01.040

van Westen, C. J., Castellanos, E., & Kuriakose, S. L. (2008). Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview. Engineering Geology, 102(3-4). https://doi.org/10.1016/J.ENGEO.2008.03.010

Wang, S., Yang, B., Zhou, Y., Wang, F., Zhang, R., & Zhao, Q. (2018). Three-Dimensional information extraction from GeoFen-1 satellite images for landslide monitoring. Geomorphology, 309, 77–85. https://doi.org/10.1016/j.geomorph.2018.02.027

Williams, J. G., Rossier, N. J., Hardy, R. J., Brian, M. J., & Alana, A. A. (2018). Optimising 4-D surface change detection: an approach for capturing rockfall magnitude-frequency. Earth Surface Dynamics, 6, 101–119. https://doi.org/10.5194/esurf-6-101-2018

Zhang, J., Liu, R., Deng, W., Khanal, N. R., Gurung, D. R., Murthy, M. S. R., & Wahid, S. (2016). Characteristics of landside in Koshi River Basin, Central Himalaya. Journal of Mountain Science, 13(10), 1711–1722. https://doi.org/10.11629/016-4017-0

Zhang, J., van Westen, C. J., Tanyas, H., Mavrouri, O., Ge, Y., Bajracharya, S., et al. (2019). How size and trigger matter: analyzing rainfall- and earthquake-triggered landslide inventories and their causal relation in the Koshi River basin, central Himalaya. Natural Hazards and Earth System Sciences, 19, 1789–1805. https://doi.org/10.5194/nhess-19-1789-2019